DS 7333 | Quantifying the World

FINAL EXAM | COST OPTIMIZED CLASSIFICATION

JOEY HERNANDEZ | DANNY CHANG

Introduction

Background

In an increasingly data-driven business environment, the ability to accurately predict outcomes is paramount. The challenge often lies not just in the prediction itself but in the cost associated with the inaccuracies of such predictions. False predictions can be classified into two main categories: false positives and false negatives, each carrying its own implications and costs. A false positive occurs when the model incorrectly predicts a positive outcome, while a false negative is when the model fails to identify a positive outcome. The impact of these inaccuracies varies based on the nature of the business and the specific circumstances surrounding the predictive model's application.

Objective

The primary objective of our predictive modeling endeavor is to develop a binary classification model that can discern between 'Yes' (positive) and 'No' (negative) outcomes with the highest possible accuracy. The model will be applied to an anonymized dataset with undisclosed features, emphasizing the minimization of the associated cost of incorrect predictions. Given the cost structure, where a false positive is penalized five times more heavily than a false negative (\$100 versus \$40), the model must prioritize the reduction of false positives without significantly increasing the false negatives. The ideal model will strike a balance between sensitivity (true positive rate) and specificity (true negative rate) to achieve the lowest possible total cost to the business. Various modeling techniques will be explored and evaluated based on their performance against this cost function to ensure the most economically advantageous outcome.

Data Inspection

Target Distribution

The dataset at hand comprises 160,000 original observations, aimed at predicting a binary outcome—essentially a 'Yes' (1) or 'No' (0). The target variable distribution indicates a relatively balanced dataset with 95,803 instances of the 'No' class and 64,197 of the 'Yes' class. Such a distribution is beneficial as it does not heavily favor one class over the other, which can be a common issue in binary classification problems leading to a biased model.

Missing Values

Upon initial inspection, the dataset contains 1,608 missing values. The missing data represents 1% of the total observations, which is a relatively small proportion. There is no discernible pattern or correlation between the missing values and other variables in the dataset. Given the

absence of a relationship and the comparatively low percentage of missing data, the decision has been made to proceed with the removal of these instances. This approach is deemed appropriate as it simplifies the modeling process without the risk of introducing bias or inaccuracies that could come with imputation methods.

Numerical Variables

The numerical features in the dataset exhibit a wide range of magnitudes, indicating the presence of variables measured on different scales. This observation suggests a need for normalization or standardization in the preprocessing phase to ensure that no single attribute dominates the model due to its scale.

Categorical Variables

The dataset includes several categorical variables which provide classificatory information:

- Country of origin with categories such as Asia, Europe, and America.
- Month of the year from January to December.
- Day of the week covering Monday to Friday.

These categorical variables are crucial for the model as they might hold significant predictive power. They will require appropriate encoding to transform them into a format that can be effectively utilized by the predictive algorithms.

Financial Values

Some columns represent financial figures initially in dollar terms, which have been converted to floating-point numbers to maintain consistency and to facilitate computation. Likewise, a percentage column has been adjusted by dividing by 100 and converting to a float. These transformations are essential for aligning all numerical variables on a similar scale and for preparing the data for analysis by various statistical and machine learning methods.

In summary, the initial data inspection has laid the groundwork for further preprocessing. The subsequent steps will involve handling missing values, transforming categorical variables, and normalizing numerical values to ensure the data is in an optimal form for modeling.

Target Distribution

80000 - 60000 - 20000 - 20000 - 1

Target Variable

Figure 1: Count plot illustrating the distribution of the classification target.

Description: The count plot displays the class distribution for our target variable, highlighting the difference between the two instances. This visualization aids in identifying class balance present in the dataset.

Table 1: Table detailing the distribution of target class.

Distribution of Target Variable					
Class Counts Class Percentag					
0 (No)	95803	59%			
1 (Yes)	64197	41%			

Description: The table presents the distribution of occurrences of the data *target* variable. It succinctly highlights the number of instances for each class and the corresponding percentages.

Modeling

Preprocessing

Data Splitting:

- Initially, the dataset (df) is split into features (X) and target (y). The features are all columns except the target column 'y'.
- The data is then split into training and test sets using train_test_split from sklearn.model_selection. This is a common practice in machine learning to evaluate the performance of models on unseen data.
- The split is done in a way that 80% of the data is used for training (X_train_main, y train main) and 20% for testing (X test, y test).
- The stratify parameter ensures that the proportion of classes in the target variable is maintained in both training and test sets, which is crucial for maintaining a representative distribution, especially in imbalanced datasets.

Feature Scaling:

- Before splitting the data, feature scaling is applied using StandardScaler from sklearn.preprocessing. This is important because many machine learning algorithms perform better when numerical input variables are scaled to a standard range.
- The scaler is fitted and transformed on the columns specified in col_to_scale. This standardizes features by removing the mean and scaling to unit variance.
- The scaled data is then reassigned back to the corresponding columns in X.

Validation Set Creation:

- The main training set (X_train_main, y_train_main) is further split into a training set and a validation set.
- This split is again 75% for training (X_train, y_train) and 25% for validation (X_validation, y_validation), which allows for a separate dataset to tune hyperparameters and prevent overfitting.
- The use of stratify on y_train_main for this split ensures that the class distribution is consistent across the training and validation sets.

Random State:

• The random_state parameter set to 12 ensures reproducibility. It fixes the way the data is split, so the same results can be achieved if the code is rerun.

Random Forest – (Benchmark) Base Model

In the initial phase of our case study, we sought to establish a benchmark for performance using a base model. The Random Forest Classifier was selected for its versatility and robustness, particularly in managing datasets with potential class imbalances. Random Forest, an ensemble learning method, constructs a multitude of decision trees during training and outputs the class that is the mode of the classes for classification. Its inherent mechanism of averaging helps to prevent overfitting, often resulting in a solid baseline performance.

Upon configuring our Random Forest Classifier with a balanced class weight to adjust for imbalanced classes, we proceeded to fit the model on our training set, composed of X_train for the features and y_train for the labels. Following the training process, we predicted outcomes on a validation set, X_validation, to assess the model's generalization capabilities.

The performance metrics were derived using a confusion matrix and a classification report on the test data. The confusion matrix revealed the number of true positive and true negative predictions, alongside the false positives and negatives, allowing us to gauge the model's predictive accuracy in a binary classification context. The classification report provided further insight with precision, recall, and f1-score metrics for each class, as well as overall accuracy. These metrics are indispensable for understanding the model's performance nuances, particularly in the context of an imbalanced dataset where traditional accuracy may not fully reflect the model's effectiveness.

Our base model demonstrated commendable predictive power, with an overall accuracy of 0.91. The macro and weighted averages for precision, recall, and the f1-score were consistent at approximately 0.91, indicating a balanced performance between the sensitivity and specificity of the model. These results provide a solid foundation for comparison as we proceed to explore more complex models and techniques. The elucidation of these findings will inform our subsequent steps in model refinement and selection, ensuring that any improvements are measured against a robust and well-understood baseline.

Test Data Prediction Matrix - Random Forest - 18000 - 16000 윤 -18381 589 - 14000 - 12000 - 10000 - 8000 - 6000 Yes 691 12018 4000 2000 No Yes

Figure 2: A visual of the Random Forest Base model prediction matrix.

Description: The plot above illustrates the confusion matrix for the predictions made by the Random Forest Baseline model. On the x-axis, we have the predicted labels, and on the y-axis, we have the true labels.

Table 2 : Classification Report for Random Forest Base Model

Random Forest - Classification Report								
	Precision	Precision Recall F1- Score Support						
No	0.90	0.95	0.93	18970				
Yes	0.92	0.85	0.88 1270					
Accuracy			0.91	31679				
Macro Avg	0.91	0.90	0.90	31679				
Weighted Avg	Weighted Avg 0.91 0.91 0.91		31679					

Description: The classification report indicates that the model achieved a precision of 0.90 for class No and 0.92 for class 1, a recall of 0.95 for class No and 0.85 for class Yes, and an overall accuracy of 91%

Table 3: Misclassification Cost Report for Random Forest Base Model

Random Forest – Cost of Misclassification Report							
	Cost Per Number of Total Cost Total Cost Misclassification Misclassifications Combined						
False Positive	\$100	977	\$97,700	¢172.040			
False Negative	\$40	1906	\$76,240	\$173,940			

Description: Table 3 provides a breakdown of the costs associated with misclassifications for the Random Forest base model, detailing the financial impact of false positives and false negatives, leading to a total combined misclassification cost of \$173,940.

XGBoost Model – F1 Optimized

Following the establishment of a Random Forest baseline, the case study advanced to incorporate the XGBoost algorithm, a sophisticated and powerful machine learning technique that stands for Extreme Gradient Boosting. XGBoost is particularly renowned for its speed and performance, which is largely attributed to its capability of parallel processing and its efficient handling of sparse data.

In preparation for model training and validation, data matrices for training, validation, and testing were constructed using the XGBoost library's DMatrix data structure, which optimizes both memory efficiency and speed. The datasets, denoted as dtrain, dvalidation, and dtest, were subsequently utilized within the XGBoost training framework.

The process of parameter tuning is vital in optimizing the XGBoost model's performance. A systematic search across a range of hyperparameters was conducted, including max_depth for controlling the depth of the trees, subsample and colsample_bytree to manage the sampling of the dataset, and eta as the learning rate. This search was operationalized through a randomized search strategy, iterating over combinations of these hyperparameters to identify the configuration that minimizes the loss function, in this case, the log loss, which is suitable for binary classification problems.

The final model was subjected to cross-validation with the identified optimal parameters, a crucial step in assessing the model's robustness and generalizability. A 5-fold cross-validation was employed, which partitions the data into five sets, iteratively using one set for validation and the remaining four for training. This technique provides a thorough insight into the model's stability across different subsets of the data.

The cross-validation phase employed 1000 boosting rounds with an early stopping of 5 rounds to prevent overfitting. This means that the training would cease if the validation metric does not improve for five consecutive iterations, thereby ensuring that the model does not learn the noise in the training data.

Results:

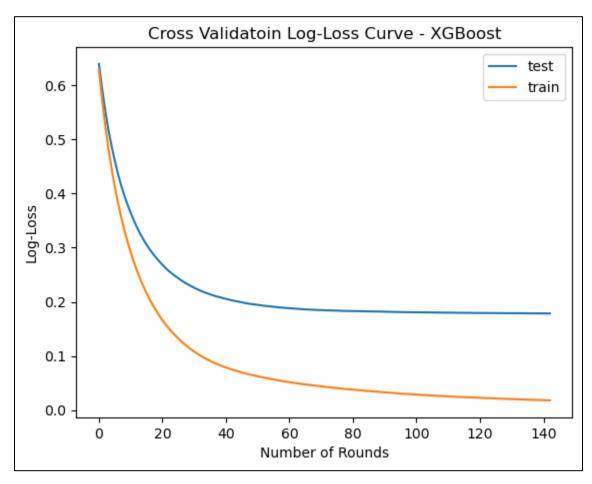
the performance of the XGBoost model, which has been optimized using an F1 score-based threshold determination. The F1 score serves as a harmonic mean of precision and recall, providing a balance between the two metrics, particularly in scenarios where the class distribution is uneven. This optimization is critical in applications where the cost of false negatives and false positives is high, and a trade-off between precision and recall is necessary.

To optimize the threshold for binary classification, a series of potential thresholds ranging from 0 to 1 were evaluated. The model's prediction probabilities were converted to binary outputs based on these thresholds, and the corresponding F1 scores were calculated. Through this method, the threshold that yielded the highest F1 score was determined to be the optimal point for classifying the test data.

The optimal threshold was identified to be notably different from the default of 0.5, indicating that a tailored threshold was indeed beneficial for model performance in this specific context. Upon applying this optimized threshold, the model achieved a refined balance between precision and recall, as evidenced by the improved F1 scores for both classes.

The resulting confusion matrix and classification report reveal that the model, with the F1 optimized threshold, exhibits a higher degree of precision and recall compared to the base model. This is demonstrated by precision and recall scores of 0.94 and 0.92 for class 0 and class 1, respectively, leading to an F1 score of 0.94 for class 0 and 0.92 for class 1. The overall accuracy of the model stands at 0.93, with the macro and weighted averages across precision, recall, and the F1 score mirroring this figure. These metrics underscore the model's robustness and its capability to generalize well on unseen data.

Figure 3: Cross validation Log-Loss Curve



Description: This plot illustrates the model's cross validation log loss per round, demonstrating how the losses decrease and stabilize over time, indicating the model's learning and stabilization, with minimal overfitting as evidenced by the parallel trajectories of both curves.

Testing Data Prediction Matrix - XGBoost Model F1 Optimized - 16000 14000 윤 -17923 1047 12000 - 10000 8000 6000 1062 11647 4000 2000 No Yes

Figure 4: A visual of the XGBoost prediction matrix

Description: The plot above illustrates the confusion matrix for the predictions made by the XGBoost Model with threshold optimized for the best F1 Score. On the x-axis, we have the predicted labels, and on the y-axis, we have the true labels.

Table 4 : Classification Report for XGBoost F1 Optimized Classification Model

XGBoost Classification Report							
	Precision Recall F1- Score Support						
No	0.94	0.94	0.94	18970			
Yes	0.92	0.92	0.92 1270				
Accuracy			0.93	31679			
Macro Avg	0.93	0.93	0.93	31679			
Weighted Avg	0.93	0.93	0.93	31679			

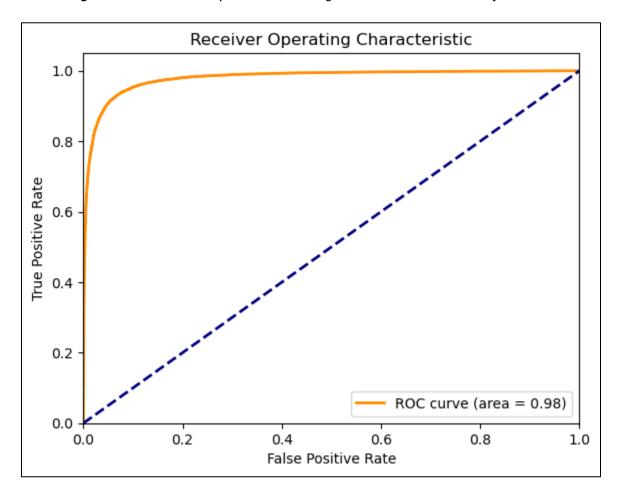
Description: The classification report indicates that the model achieved a precision of 0.94 for class No and 0.92 for class Yes, a recall of 0.94 for class No and 0.92 for class Yes, and an overall accuracy of 93%

Table 5: Misclassification Cost Report for XGBoost Base Model

XGBoost – Cost of Misclassification Report						
Cost Per Number of Total Cost Total Cost Misclassification Misclassifications Combined						
False Positive	\$100	1047	\$104,700	\$147,180		
False Negative	\$40	1062	\$42,480	\$147,180		

Description: Table 5 provides a breakdown of the costs associated with misclassifications for the XGBoost model optimized for the best F1 Score, detailing the financial impact of false positives and false negatives, leading to a total combined misclassification cost of \$147,180.

Figure 5: ROC Curve Analysis Demonstrating Model's Discriminative Performance



Description: The plot above illustrates the Receiver Operating Characteristic (ROC) curve, highlighting the model's excellent capability in distinguishing between the classes with a high area under the curve (AUC) of 0.98.

XGBoost Model – Threshold Optimized for Misclassification

In refining our XGBoost model, we incorporated a cost-sensitive approach to optimize the decision threshold based on the financial impact of misclassifications. This optimization is particularly crucial in scenarios where the consequences of false positives and false negatives carry different cost implications. By defining a cost of \$100 for false positives and \$40 for false negatives, we sought a threshold that minimized the total cost of errors made by the model.

A rigorous search across a spectrum of thresholds was executed, assessing the resultant confusion matrix for each to calculate the total cost. This cost-optimized strategy yielded an updated threshold that deviates from the standard 0.5, chosen to minimize the financial loss due to prediction errors.

Upon applying this optimized threshold, the confusion matrix and classification report were updated. The new confusion matrix shows a decrease in false positives to 386 (from 1047), an improvement that significantly reduces the cost associated with this type of error. However, this reduction in false positives resulted in an increase in false negatives to 2354 (from 1062), reflecting a trade-off inherent in the cost-optimization process.

The updated classification metrics show a slight decrease in overall accuracy from 0.93 to 0.91, and shifts in precision and recall for the positive class, which now stands at 0.96 precision and 0.81 recall, compared to the previous 0.92 for both. This indicates a higher cost for false negatives has led to a model that prioritizes reducing false positives.

Comparatively, while the optimized model may have a lower overall accuracy and altered precision-recall balance, the reduction in the total number of false positives is financially advantageous. This cost-optimized threshold approach demonstrates that model performance cannot be solely judged on conventional metrics when the cost of errors is asymmetrical. It emphasizes the importance of aligning model evaluation with the specific cost structure of the application at hand. The results underscore the necessity of a holistic view of model performance, where financial implications are factored into the optimization process, potentially offering substantial savings despite a modest sacrifice in accuracy.

Test Data Prediction Matrix - XGBoost Cost Optimized - 17500 15000 윤 -18584 386 12500 - 10000 - 7500 Yes 2354 10355 - 5000 - 2500 No Yes

Figure 6: A visual of the XGBoost prediction matrix

Description: The plot above illustrates the confusion matrix for the predictions made by the XGBoost Model with threshold optimized for business cost savings. On the x-axis, we have the predicted labels, and on the y-axis, we have the true labels.

Table 6 : Classification Report for XGBoost Cost Optimized Classification Model

XGBoost Classification Report								
	Precision Recall F1- Score Support							
No	0.89	0.98	0.93	18970				
Yes	0.96	0.81	0.88 127					
Accuracy			0.91	31679				
Macro Avg	0.93	0.90	0.91	31679				
Weighted Avg	0.92	0.91	0.91	31679				

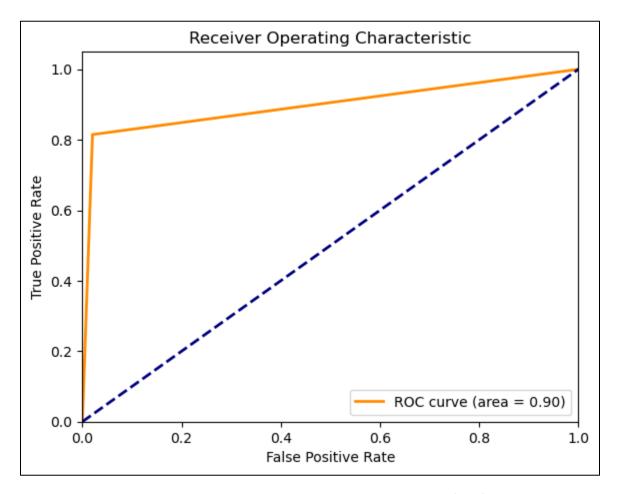
Description: The classification report indicates that the model achieved a precision of 0.89 for class No and 0.96 for class Yes, a recall of 0.98 for class No and 0.81 for class Yes, and an overall accuracy of 91%

Table 7: Misclassification Cost Report for XGBoost Model

XGBoost Cost Optimized – Cost of Misclassification Report							
	Cost Per Number of Total Cost Total Cost Misclassification Misclassifications Combined						
False Positive	\$100	386	\$38,600	\$132,760			
False Negative	\$40	2354	\$94,160	\$132,760			

Description: Table 7 provides a breakdown of the costs associated with misclassifications for the XGBoost model optimized for the best business savings, detailing the financial impact of false positives and false negatives, leading to a total combined misclassification cost of \$132,760.

Figure 7: ROC Curve Analysis Demonstrating Model's Discriminative Performance



Description: The plot above illustrates the Receiver Operating Characteristic (ROC) curve, highlighting the model's excellent capability in distinguishing between the classes with a high area under the curve (AUC) of 0.90.

Neural Network

In the progression of our case study's modeling endeavors, a Deep Neural Network (DNN) model was constructed using TensorFlow's Keras API to explore the capabilities of deep learning in our classification task. The dataset presented to the DNN comprised 95,034 instances, each with 64 features, signifying a high-dimensional space well-suited for deep learning techniques.

The architecture of the DNN consisted of a sequential model with an input layer designed to accept the 64 features. It was followed by three hidden layers with 32, 64, and 32 neurons, respectively, all utilizing the ReLU (Rectified Linear Unit) activation function, known for its efficiency and effectiveness in non-linear transformations. The output layer was a single neuron employing the sigmoid activation function, apt for binary classification as it outputs a probability between 0 and 1.

The model was compiled with the Adam optimizer, a popular choice for deep learning applications due to its adaptive learning rate capabilities. The loss function used was Binary Crossentropy, which is suitable for binary classification problems. The primary metric for model performance evaluation was set as accuracy.

Training of the DNN was guided by an early stopping mechanism to prevent overfitting. This callback monitored the validation loss and would stop the training process if no improvement was observed for 10 consecutive epochs. The model was trained for a maximum of 1000 epochs with a batch size of 100, ensuring that the model had ample opportunity to learn from the data without overfitting to the training set.

During training, the model's performance was validated against a separate validation set to monitor its generalization to new data. The use of the validation set is crucial in deep learning to ensure that the model's performance is not merely a reflection of its memorization of the training data but its ability to make predictions on data it has not seen before.

Results:

This model was specifically tuned to minimize the financial impact of misclassifications, with costs of \$100 for false positives and \$40 for false negatives.

The DNN model's probabilities were converted to binary predictions over a range of thresholds to determine the most cost-effective threshold. The optimal threshold was calculated to be approximately 0.878, which is notably different from the default threshold of 0.5. This indicates that the model's threshold required significant adjustment to align with the cost considerations of the classification task.

Utilizing this cost-optimized threshold, the DNN model achieved impressive results, as evidenced by the generated confusion matrix and classification report. The confusion matrix

exhibited a significant reduction in false positives to 244, compared to the Random Forest model, which had 977 false positives. Similarly, the number of false negatives also decreased to 1507.

The classification report revealed high precision and recall across both classes, with class 0 achieving a precision of 0.93 and recall of 0.99, and class 1 achieving a precision of 0.98 and recall of 0.88. These metrics resulted in an F1-score of 0.96 for class 0 and 0.93 for class 1, contributing to an overall accuracy of 0.94, and macro and weighted averages of precision, recall, and the F1-score at 0.95 and 0.94, respectively.

The results demonstrate the effectiveness of the DNN model when incorporating a financial perspective into the performance optimization process. The DNN model not only maintained high accuracy but also significantly reduced the total cost of misclassifications by effectively balancing the trade-off between false positives and false negatives. This cost-optimized threshold approach is critical in practical scenarios where the financial stakes of prediction errors are high, showcasing the DNN model's ability to adapt to different cost structures while maintaining robust predictive performance.

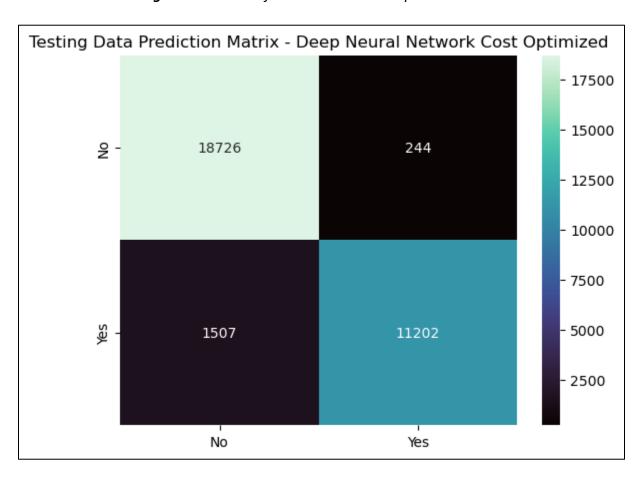


Figure 8: A visual of the Neural Network prediction matrix

Description: The plot above illustrates the confusion matrix for the predictions made by the Neural Network Model with threshold optimized for business cost savings. On the x-axis, we have the predicted labels, and on the y-axis, we have the true labels.

Table 8: Classification Report for Neural Network Classification Model

Neural Network Classification Report							
Precision Recall F1- Score Support							
No	0.93	0.99	0.96	18970			
Yes	0.98	0.88	0.93	12709			
Accuracy			0.94	31679			
Macro Avg	0.95	0.93	0.94	31679			
Weighted Avg	0.95	0.94	0.94	31679			

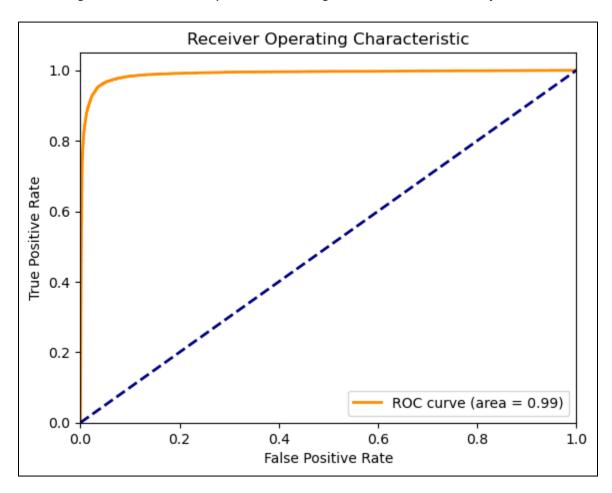
Description: The classification report indicates that the model achieved a precision of 0.93 for class No and 0.98 for class Yes, a recall of 0.99 for class No and 0.88 for class Yes, and an overall accuracy of 94%

Table 9: Misclassification Cost Report for Neural Network Model

Neural Network – Cost of Misclassification Report								
	Cost Per Number of Total Cost Total Cost Misclassification Misclassifications Combined							
False Positive	\$100	244	\$24,400	¢04 600				
False Negative	\$40	1507	\$60,280	\$84,680				

Description: Table 9 provides a breakdown of the costs associated with misclassifications for the Neural Network model optimized for the best business savings, detailing the financial impact of false positives and false negatives, leading to a total combined misclassification cost of \$84,680.

Figure 9: ROC Curve Analysis Demonstrating Model's Discriminative Performance



Description: The plot above illustrates the Receiver Operating Characteristic (ROC) curve, highlighting the model's excellent capability in distinguishing between the classes with a high area under the curve (AUC) of 0.99.

Train and Validation Loss Curves 0.40 Train Loss Validation Loss 0.35 0.30 0.25 0.20 0.15 0.10 15 25 10 20 30 35 Epochs

Figure 10: Cross validation Log-Loss Curve

Description: This plot illustrates the model's cross validation log loss per epoch, demonstrating how the losses decrease and stabilize over time, indicating the model's learning and stabilization, with minimal overfitting as evidenced by the parallel trajectories of both curves.

Cross Val Prediction Results

In this section, we delve into the results achieved by our binary classification model, emphasizing the use of cross-validation predict (cross_val_predict) to assess performance. This method is pivotal in approximating real-world results, as it allows for the evaluation of the model across nearly the entirety of the dataset.

Final Best Threshold: 0.88

The adoption of a threshold of approximately 0.889 plays a crucial role in balancing false positives and false negatives, especially under our cost structure. This higher threshold ensures the model is judicious in predicting a positive ('Yes') outcome, aligning with our objective to minimize expensive false positives.

Confusion Matrix: Comprehensive Data Coverage

This matrix is particularly valuable because it encapsulates the model's behavior over a comprehensive range of data scenarios, offering a closer approximation to real-world application.

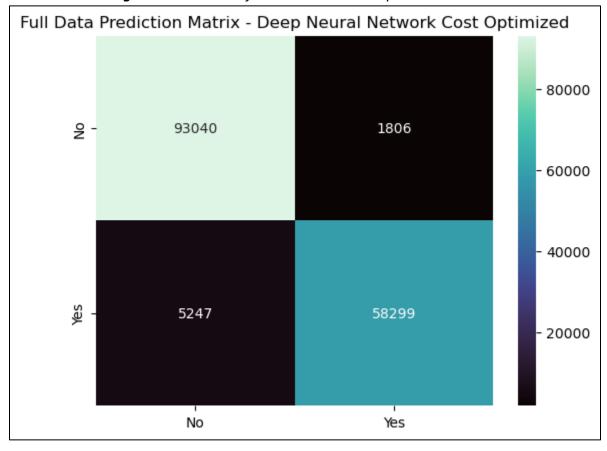


Figure 11: A visual of the Neural Network prediction matrix

Description: The plot above illustrates the confusion matrix for the predictions made by the Neural Network Model with threshold optimized for business cost savings. On the x-axis, we have the predicted labels, and on the y-axis, we have the true labels.

Table 10 : Classification Report for Neural Network Classification Model

Neural Network Classification Report – Cross Val Predict								
	Precision	Precision Recall F1- Score Support						
No	0.95	0.98	0.96	94846				
Yes	0.97	0.92	0.94	63546				
Accuracy			0.96	158392				
Macro Avg	0.96	0.95	0.95	158392				
Weighted Avg	eighted Avg 0.96 0.96 0.96		158392					

Description: The classification report indicates that the model achieved a precision of 0.95 for class No and 0.97 for class Yes, a recall of 0.98 for class No and 0.92 for class Yes, and an overall accuracy of 96%

Precision:

Class 0 (Negative): 95%

Class 1 (Positive): 97%

The high precision scores for both classes, evaluated over the entire dataset, reinforce the model's accuracy in its predictions.

Recall:

Class 0: 98%

Class 1: 92%

The recall metrics, especially for Class 0, highlight the model's efficacy in identifying true negatives, an insight gained by examining performance over the full data spread.

F1-Score:

Class 0: 96%

Class 1: 94%

These scores, representing a balance between precision and recall, are indicative of the model's overall robustness, validated through comprehensive data evaluation.

Accuracy:

Overall: 96%

This high accuracy rate, achieved through cross-validation, reflects the model's effectiveness in classifying outcomes over a wide array of data points.

Macro and Weighted Averages:

Macro Average: 95%

Weighted Average: 96%

These averages consider class imbalance and are significant as they underscore the model's consistent performance across diverse data segments.

Table 11: Misclassification Cost Report for Neural Network Model

Neural Network – Cost of Misclassification Report							
	Cost Per Number of Total Cost Total Cost Misclassification Misclassifications Combined						
False Positive	\$100	1806	\$180,600	¢207.690			
False Negative	\$40	5247	\$217,080	\$397,680			

Description: Table 11 provides a breakdown of the costs associated with misclassifications for the Neural Network model optimized for the best business savings, detailing the financial impact of false positives and false negatives, leading to a total combined misclassification cost of \$397,680.

Conclusion

In the final part of our case study, we pivot to a crucial aspect of model evaluation: the cost of misclassification. This is a key consideration, as our primary objective is to mitigate financial losses arising from incorrect predictions. We compare the cost implications of four distinct models: the Random Forest base model, the XGBoost base model, the XGBoost cost-optimized model, and the Neural Network model.

Random Forest Base Model

The Random Forest base model presented a total combined cost of \$173,940. This figure was the highest among all models tested, indicating a relatively less effective approach in managing the cost impact of misclassifications under our specific cost structure.

XGBoost Base Model

The XGBoost base model showed a slight improvement over the Random Forest model, with a total combined cost of \$147,180. This reduction suggests that the XGBoost model inherently possesses some efficiency in handling misclassifications, although not to an optimal extent.

XGBoost Cost-Optimized Model

Significant improvements were observed with the XGBoost cost-optimized model, which brought down the total combined cost to \$132,760. This reduction underscores the effectiveness of the cost optimization strategies applied to the XGBoost model. By fine-tuning the model parameters with a focus on cost reduction, it demonstrates a better alignment with our financial objectives.

Neural Network Model

The Neural Network model emerged as the clear leader in terms of cost savings, achieving the lowest total combined cost of \$84,680. This model's success can be largely attributed to its minimal number of false positives, which are the most heavily penalized misclassification according to our cost structure. The lower occurrence of false positives directly translates into considerable cost savings, making the Neural Network model the most economically viable option among those tested.

After assessing various models, we implemented a cross-validation approach on the Neural Network model, identified as the most effective in terms of cost efficiency. This step was crucial to understand its performance across a majority of the dataset, ensuring a robust and comprehensive evaluation.

Cost Analysis of the Cross-Validated Neural Network Model

The application of cross-validation on the Neural Network model led to a total combined cost of \$397,680. This figure is essential for understanding the model's performance in a more realistic, varied dataset scenario, as opposed to more controlled or specific data segments.

Finally, the comparative analysis of these models from a cost perspective highlights the importance of selecting and optimizing models not just for accuracy but also for their economic impact. The Neural Network model, with its significant reduction in costly misclassifications, stands out as the most effective option in minimizing financial loss due to prediction errors. This insight reinforces the value of integrating cost considerations into the model selection and optimization process, ensuring that predictive models align closely with business objectives.

The cross-validation of the Neural Network model, resulting in a total cost of \$397,680, provides a more nuanced understanding of the model's performance across a wider data spectrum. While the cost is higher in this comprehensive testing scenario, it offers invaluable insights into the model's real-world effectiveness and reliability. This extensive evaluation reaffirms the Neural Network model's suitability for deployment, balancing accuracy, and cost-efficiency, and highlighting its capability to handle diverse and extensive data in practical applications.

Appendix

```
import numpy as np
In [ ]:
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
In [ ]: df = pd.read_csv('final_project(5).csv')
          df.head()
                                                                                                                                            x42
Out[]:
          0 -0.166563 -3.961588
                                   4.621113 2.481908 -1.800135
                                                                  0.804684
                                                                              6.718751
                                                                                       -14.789997 -1.040673
                                                                                                            -4.204950 ...
                                                                                                                            -1.497117
                                                                                                                                       5.414063 -2
          1 -0.149894 -0.585676
                                 27.839856 4.152333 6.426802
                                                                  -2.426943
                                                                             40.477058
                                                                                        -6.725709
                                                                                                   0.896421
                                                                                                              0.330165 ...
                                                                                                                            36.292790
                                                                                                                                       4.490915
          2 -0.321707 -1.429819
                                  12.251561 6.586874 -5.304647 -11.311090
                                                                             17.812850
                                                                                        11.060572
                                                                                                   5.325880
                                                                                                             -2.632984
                                                                                                                            -0.368491
          3 -0.245594 5.076677 -24.149632 3.637307
                                                                  2.290224
                                                                            -35.111751 -18.913592 -0.337041
                                                       6.505811
                                                                                                            -5.568076 ...
                                                                                                                           15.691546 -7.467775
          4 -0.273366  0.306326  -11.352593  1.676758  2.928441
                                                                  -0.616824 \quad -16.505817 \quad 27.532281 \quad 1.199715 \quad -4.309105 \quad \dots \quad -13.911297 \quad -5.229937
         5 rows × 51 columns
```

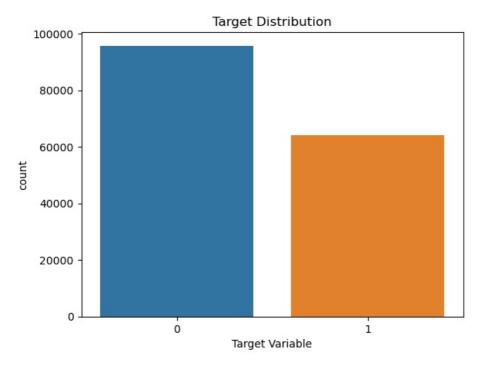
Goal

- Last Column is Target Variable
- · Enter into production we lose money.
 - class one prediction that is not actually class one = 100 loss
 - class 0 prediction that is not class zero = 40 loss

Accurately predict the class that minimizes the financial losses.

I HATE LOSING MONEY

Data Inspection

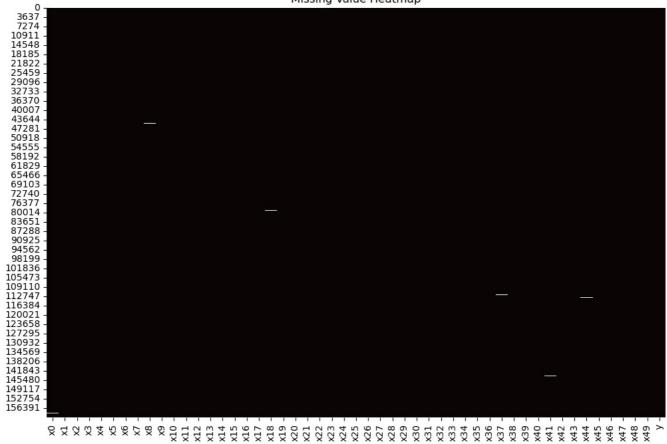


2 classes to predict, slight imbalance. 59% are 0

In []: df.isna().sum()

```
Out[]: x0
x1
                 25
         х2
                 38
         хЗ
                 37
         x4
                 26
         х5
                 37
         х6
                 26
         x7
                 27
         x8
                 21
         х9
                 30
         x10
                 43
         x11
                 30
         x12
                 36
         x13
                 31
         x14
                 34
         x15
                 35
                 26
         x16
         x17
                 27
         x18
                 40
         x19
                 35
         x20
         x21
                 29
         x22
                 27
         x23
                 47
         x24
                 28
         x25
                 22
         x26
                 36
                 30
         x27
         x28
                 35
         x29
                 30
         x30
                 30
         x31
         x32
                 31
         x33
                 41
         x34
                 41
         x35
                 30
                 27
         x36
         x37
                 23
         x38
                 31
         x39
                 23
         x40
                 36
         x41
                 40
         x42
                 26
         x43
                 37
         x44
                 40
         x45
                 29
         x46
                 31
         x47
                 37
         x48
                 32
         x49
                 32
                 0
         dtype: int64
In [ ]: plt.figure(figsize=(12,8))
    sns.heatmap(df.isnull(),
                      cmap = 'mako',
cbar=False)
         plt.title('Missing Value Heatmap')
         plt.show()
```





```
In [ ]: def missing_val_percentage(df):
    total = len(df)
    percentage = (df.isna().sum()/total) * 100
    print(percentage)

missing_val_percentage(df)
```

```
x0
      0.016250
       0.015625
x1
x2
      0.023750
x3
      0.023125
x4
      0.016250
x5
      0.023125
x6
      0.016250
      0.016875
x7
x8
      0.013125
x9
      0.018750
x10
      0.026875
      0.018750
x11
x12
      0.022500
x13
       0.019375
x14
      0.021250
      0.021875
x15
x16
       0.016250
x17
      0.016875
x18
      0.025000
x19
       0.021875
x20
      0.023750
x21
      0.018125
      0 016875
x22
x23
      0.029375
x24
       0.017500
x25
      0.013750
x26
      0.022500
x27
       0.018750
x28
      0.021875
x29
      0.018750
x30
       0.018750
x31
      0.024375
x32
      0.019375
x33
      0.025625
x34
      0.025625
x35
       0.018750
x36
      0.016875
x37
      0.014375
x38
       0.019375
      0.014375
x39
x40
      0.022500
x41
       0.025000
x42
      0.016250
x43
      0.023125
x44
       0.025000
x45
       0.018125
x46
       0.019375
x47
       0.023125
x48
       0.020000
x49
       0.020000
       0.000000
```

dtype: float64

Such as small amount of data is missing, additionally there appears to be no patterns to explain the missingness in the data. we will proceed with removal of the missing values. effectively this means removing 1608 values from our data.

```
In []: import pandas as pd
        # Create a new DataFrame to store missing value indicators
        missing indicators = pd.DataFrame()
        # For each column in the DataFrame, create a corresponding indicator column
        for column in df.columns:
            missing_indicators[column + '_missing'] = df[column].isna().astype(int)
        # This allows you to see the correlation between features and missingness
        df with indicators = pd.concat([df, missing indicators], axis=1)
        correlation_matrix = df_with_indicators.corr()
        # Extract correlations of missing indicators with other features
        missing value correlations = correlation matrix[missing indicators.columns].drop(missing indicators.columns)
        # Sort by absolute value to see the highest correlations first
        sorted correlations = missing value correlations.abs().unstack().sort values(ascending=False)
        # Filter out self-correlations (correlation of indicators with themselves)
        non self correlations = sorted correlations[sorted correlations < 1]</pre>
        # Print out the highest absolute correlations
        print(non_self_correlations * 100)
```

C:\Users\Joey\AppData\Local\Temp\ipykernel_23452\2860011729.py:13: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns

or specify the value of numeric only to silence this warning.

correlation matrix = df with indicators.corr()

Out[]:		count	mean	std	min	25%	50%	75%	max
	x0	158392.0	-0.000808	0.371064	-1.592635	-0.251246	-0.001818	0.248622	1.600849
	x 1	158392.0	0.003705	6.340297	-26.278302	-4.259016	0.010023	4.286606	27.988178
	x2	158392.0	-1.148314	13.274738	-59.394048	-10.166609	-1.342199	7.878130	63.545653
	х3	158392.0	-0.023012	8.066624	-33.864827	-5.453044	-0.028470	5.448332	38.906025
	x4	158392.0	-0.000266	6.383306	-28.467536	-4.313987	-0.001138	4.308644	26.247812
	х5	158392.0	0.013282	7.672102	-33.822988	-5.152419	0.015135	5.191172	35.550110
	х6	158392.0	-1.669562	19.300472	-86.354483	-14.781485	-1.951457	11.454209	92.390605
	х7	158392.0	-7.697877	30.541562	-181.506976	-27.315875	-6.959275	12.215119	149.150634
	x8	158392.0	-0.028853	8.904048	-37.691045	-6.034094	-0.016173	5.978646	39.049831
	х9	158392.0	0.004320	6.354359	-27.980659	-4.260304	0.003098	4.303807	27.377842
	x10	158392.0	0.000816	7.870963	-36.306571	-5.286455	-0.019074	5.327598	37.945583
	x11	158392.0	0.030692	8.767797	-38.092869	-5.902750	0.013579	5.933786	36.360443
	x12	158392.0	-1.337022	14.752763	-64.197967	-11.383333	-1.627464	8.375380	73.279354
	x13	158392.0	0.005699	8.952626	-38.723514	-6.030792	-0.004343	6.039018	42.392177
	x14	158392.0	0.008887	6.964429	-30.905214	-4.695374	0.003644	4.702776	32.546340
	x15	158392.0	0.002436	3.271402	-17.002359	-2.207028	0.005473	2.212473	13.782559
	x16	158392.0	0.006746	4.982869	-26.042983	-3.343254	0.012754	3.366107	21.961123
	x17	158392.0	0.012607	7.570453	-34.395898	-5.070818	0.024699	5.102171	37.057048
	x18	158392.0	0.014051	4.540760	-20.198686	-3.054185	0.017192	3.073832	19.652986
	x19	158392.0	0.021573	7.594895	-35.633396	-5.105826	0.040295	5.158919	33.515550
	x20	158392.0	0.298973	5.803957	-26.677396	-3.605254	0.432127	4.303770	27.814560
	x21	158392.0	-0.027341	9.410971	-43.501854	-6.360632	-0.016830	6.318381	46.237503
	x22	158392.0	0.007413	5.412217	-23.644193	-3.649892	0.009153	3.672444	24.863012
	x23	158392.0	0.726195	14.908566	-66.640341	-9.260850	1.035878	11.031540	58.490500
	x25	158392.0	-0.001621	1.263860	-6.364653	-0.853516	-0.004934	0.850890	5.314169
	x26	158392.0	-0.001013	0.843154	-3.857484	-0.566752	-0.001314	0.567379	3.951652
	x27	158392.0	-0.003656	6.773700	-32.003555	-4.596859	0.035506	4.647103	28.645074
	x28	158392.0	0.030159	14.437525	-72.896705	-9.700474	0.244454	9.934612	67.753845
	x31	158392.0	-0.007546		-12.289364				11.247163
	x33	158392.0	-0.007019	1.747829	-7.451454	-1.184854	-0.006598	1.179054	7.787120
	x34	158392.0	-0.001261	8.012550	-36.116606	-5.403326	-0.015421	5.411490	34.841428
	x35	158392.0	0.000049	2.379169	-10.008149	-1.610630	-0.003761	1.602599	9.892426
	x36	158392.0	0.006182	1.592854	-6.866024	-1.068702	0.004384	1.079242	6.999544
	x38	158392.0	6.063752	16.886960	-74.297559	-5.246467	6.192058	17.424261	90.467981
	x39	158392.0	0.003466	5.134009	-22.101647	-3.458830	0.017274	3.462758	21.545591
	x40	158392.0	-2.318750	17.040216	-74.059196	-13.952620	-2.709284	8.972837	88.824477
	x41	158392.0	6.706030	18.675642	-82.167224	-5.802178	6.847926	19.269855	100.050432
	x42	158392.0	-1.832959	5.110079	-27.933750	-5.159340	-1.922935	1.452018	22.668041
	x43	158392.0	-0.002174	1.535282	-6.876234	-1.039992	-0.004279	1.033870	6.680922
	x44	158392.0	-0.007254	4.163766	-17.983487	-2.814168	-0.012278	2.781096	19.069759
	x45	158392.0	0.000996	0.396604	-1.753221	-0.266369	0.001841	0.269194	1.669205
	x46	158392.0	-12.751993	36.608634	-201.826828	-36.432779	-12.975088	11.445524	150.859415
	x47	158392.0	0.028262	4.787974	-21.086333	-3.216974	0.036234	3.269134	20.836854
	x48	158392.0	0.000160	1.935087	-8.490155 -65.791191	-1.320800	-0.011800	1.318161	8.226552
	x49	158392.0	-0.672052	15.033134	-65.791191	-10.929046	-0.569139	9.649839	1,00000
	У	158392.0	0.401195	0.490142	0.000000	0.000000	0.000000	1.000000	1.000000

We have data in various ranges/scales. this will need to be normalized

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 158392 entries, 0 to 159999
Data columns (total 51 columns):
    Column Non-Null Count
                            Dtvpe
0
    x0
            158392 non-null float64
    x1
            158392 non-null float64
 2
            158392 non-null
    x2
                              float64
 3
    х3
            158392 non-null
                              float64
 4
            158392 non-null
                              float64
 5
    x5
            158392 non-null
                              float64
            158392 non-null
 6
    x6
                              float64
 7
     x7
            158392 non-null float64
 8
     x8
             158392 non-null
                              float64
 9
    x9
            158392 non-null
                              float64
 10
    x10
            158392 non-null
                              float64
 11
            158392 non-null
    x11
                              float64
 12
    x12
            158392 non-null
                              float64
 13
            158392 non-null
    x13
                              float64
 14
    x14
            158392 non-null
                              float64
            158392 non-null
 15
   x15
                              float64
            158392 non-null
 16
    x16
                              float64
 17
    x17
            158392 non-null
                              float64
 18 x18
            158392 non-null
                              float64
 19
    x19
            158392 non-null
                              float64
 20 x20
            158392 non-null
                              float64
 21
    x21
            158392 non-null
                             float64
 22
    x22
             158392 non-null
 23
    x23
            158392 non-null
                              float64
 24
    x24
            158392 non-null
                              object
 25
    x25
            158392 non-null
                              float64
 26
    x26
            158392 non-null
                              float64
            158392 non-null
 27
    x27
                              float64
 28
    x28
            158392 non-null
                              float64
 29
    x29
            158392 non-null
                              obiect
 30
    x30
            158392 non-null
                              object
 31
    x31
            158392 non-null
                              float64
 32
    x32
            158392 non-null
 33
    x33
             158392 non-null
                              float64
 34
            158392 non-null
    x34
                              float64
 35
    x35
            158392 non-null
                              float64
             158392 non-null
 36
     x36
 37
    x37
            158392 non-null
                              object
 38
    x38
            158392 non-null
                              float64
 39
    x39
            158392 non-null
                              float64
 40
   x40
            158392 non-null
                              float64
 41
    x41
            158392 non-null
                              float64
 42
    x42
            158392 non-null
                              float64
 43
            158392 non-null
    x43
                              float64
 44
    x44
            158392 non-null
                              float64
 45
    x45
            158392 non-null
                              float64
 46
    x46
            158392 non-null float64
 47
    x47
             158392 non-null
                              float64
 48
    x48
             158392 non-null
                              float64
 49
    x49
             158392 non-null
                             float64
             158392 non-null
 50
                             int64
dtypes: float64(45), int64(1), object(5)
memory usage: 62.8+ MB
```

Data seems to have a few columns which are not numerical. (or they are but need to be processed)

x24 = country (asia, europe, america) with counts respectively 137596, 16378, 4418 - one hot encoding

x29 = months(july, jun, aug, may, sept, apr, oct, mar, nov, feb, dev, jan) - one hot encoding

Data Standardization and Cleaning

```
df['decimal'] = df['x32'].replace('[\%]', '',regex=True).astype(float) / 100
        df.drop('x32', axis=1, inplace=True)
In [ ]: df = pd.get dummies(df, columns=['x29','x24','x30'], drop first=True).astype('int')
        df.head()
           x0 x1 x2 x3 x4 x5 x6 x7 x8 x9 ... x29_May x29_Nov x29_Oct x29_Sept x24_asia x24_euorpe x30_monday x30 thurday x
                              0
                                  6 -14
                                                         0
                                                                 0
                                                                         0
                                                                                  0
                                                                                           0
                                                                                                                 0
                                                                                                                            0
                          6
                              -2
                                 40
                                      -6
                                                                                                                            0
            0 -1 12
                       6 -5 -11 17
                                          5 -2 ...
                                                         0
                                                                 0
                                                                         0
                                                                                  n
                                                                                           1
                                                                                                     0
                                                                                                                 O
                                                                                                                            0
                                     11
            0
                5 -24
                       3
                          6
                              2 -35
                                     -18
                                          0
                                                         0
                                                                 0
                                                                         0
                                                                                  0
                                                                                                     0
                                                                                                                 0
                                                                                                                            0
                                             -5 ...
               0 -11
                              0 -16
                                    27
                                                                                           1
                                                                                                                            0
        5 rows × 65 columns
In []: df['y'] = df['y'].astype('category')
```

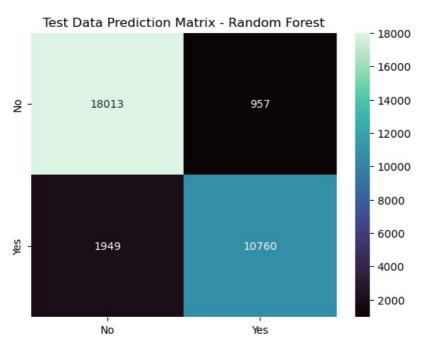
Data Preprocessing

scaling features we want to not scale hot encoded features, and also not scale

Base Model - Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion matrix, classification report
rf = RandomForestClassifier(class weight='balanced')
# Fit the model on the training set
rf.fit(X train, y train)
# predict on validation set
y_validation_pred = rf.predict(X_validation)
# Evaluate predictions using the validation set
cm_validation = confusion_matrix(y_validation, y_validation_pred)
cr validation = classification report(y validation, y validation pred)
print("Validation Confusion Matrix:")
print(cm_validation)
print("\nValidation Classification Report:")
print(cr_validation)
y_test_pred = rf.predict(X_test)
cm_test = confusion_matrix(y_test, y_test_pred)
cr_test = classification_report(y_test, y_test_pred)
```

```
print("Test Confusion Matrix:")
print(cm_test)
print("\nTest Classification Report:")
print(cr_test)
# print out test metrics
sns.heatmap(cm_test, annot=True, fmt='.0f', cmap = 'mako')
plt.title('Test Data Prediction Matrix - Random Forest')
plt.xticks(ticks = [.5,1.5], labels = ['No','Yes'])
plt.yticks(ticks = [.5,1.5], labels = ['No','Yes'])
plt.show()
Validation Confusion Matrix:
[[18033 936]
 [ 1986 10724]]
Validation Classification Report:
                precision recall f1-score support
             0
                       0.90
                                   0.95
                                               0.93
                                                          18969
             1
                       0.92
                                   0.84
                                               0.88
                                                          12710
    accuracy
                                               0.91
                                                          31679
                       0.91
                                   0.90
   macro avg
                                               0.90
                                                          31679
                                   0.91
                                               0.91
weighted avg
                       0.91
                                                          31679
Test Confusion Matrix:
[[18013 957]
 [ 1949 10760]]
Test Classification Report:
                               recall f1-score support
                 precision
                       0.90
                                   0.95
                                               0.93
                                                          18970
                       0.92
                                   0.85
                                               0.88
                                                          12709
    accuracy
                                               0.91
                                                          31679
   macro avg
                       0.91
                                   0.90
                                               0.90
                                                          31679
                                               0.91
                       0.91
                                   0.91
                                                          31679
weighted avg
```



Model Predictions Cost us: \$128,720

XGBoost

```
import xgboost as xgb

# Create the DMatrix for train, validation, and test sets
dtrain = xgb.DMatrix(X_train, label = y_train)
dvalidation = xgb.DMatrix(X_validation, label = y_validation)
dtest = xgb.DMatrix(X_test, label = y_test)

evallist = [(dtrain, 'train'), (dvalidation, 'validation')]
```

Param Search

```
In []: params = {
               'booster':'gbtree',
               'objective': 'binary:logistic',
               'eta':0.1,
               'subsample':.5,
               'colsample_bytree':.5,
'max_depth':3,
          }
          max_depth = [3,5,10,15,20,40]
          sub_s = np.random.random(10)
          cols = np.random.random(10)
          md = np.random.randint(0,6,10)
          for i in range(10):
              params['subsample'] = sub_s[i]
params['colsample_bytree']=cols[i]
params['max_depth'] = max_depth[md[i]]
               tmp = xgb.cv(
                    params, dtrain, num_boost_round=2000,
nfold = 5, metrics=(['logloss']),
                    early_stopping_rounds=5,
               as_pandas=True,verbose_eval=False,show_stdv=True,seed=0,shuffle=False)
print('_____DONE_____')
print(params)
               print(tmp.loc[tmp.shape[0]-1:,:])
               print("======"")
               tmp = 0
```

```
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.6933070768191619, 'colsample_b
ytree': 0.6279204295635943, 'max_depth': 5}
    train-logloss-mean train-logloss-std test-logloss-mean \
              0.100261
                               0.000693
1172
                                                 0.199277
     test-logloss-std
1172 0.00181
_____
         __DONE
{'booster': 'qbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.580548360415606, 'colsample by
tree': 0.859240211480657, 'max_depth': 3}
    train-logloss-mean train-logloss-std test-logloss-mean \
                               0.000856
              0.183943
                                                 0.233424
     test-logloss-std
1921
           0.002292
_____
          _DONE
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.675930885212629, 'colsample_by
tree': 0.06109841873546429, 'max depth': 20}
    train-logloss-mean train-logloss-std test-logloss-mean \
454
                              0.004981
             0.116175
                                                0 489914
    test-logloss-std
         0.009597
454
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.45274285610781184, 'colsample_
bytree': 0.283589353932732, 'max_depth': 20}
    train-logloss-mean train-logloss-std test-logloss-mean \
                              0.00012
            0.01393
    test-logloss-std
343
          0.001459
         DONE
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.9884180027352296, 'colsample_b
ytree': 0.47251993841361806, 'max_depth': 40}
    222
            0.006406
                               0.00004
                                                0.187276
    test-logloss-std
222
          0.002746
_____
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.9986339615338715, 'colsample_b
ytree': 0.7428389415716817, 'max depth': 40}
   train-logloss-mean train-logloss-std test-logloss-mean \
            0.008816
                              0.000026
                                               0.177299
    test-logloss-std
141
          0.001832
_____
          _DONE
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.3588629369997731, 'colsample_b
ytree': 0.9870155597890307, 'max_depth': 10}
    train-logloss-mean train-logloss-std test-logloss-mean
                                                0.193058
199
             0.074017
                              0.001154
    test-logloss-std
199
          0.001039
          DONE
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.007156569211485997, 'colsample
_bytree': 0.8175418589656883, 'max_depth': 20}
   train-logloss-mean train-logloss-std test-logloss-mean test-logloss-std
   0.39967 0.011066
81
                                              0.412169
                                                               0.010581
_____
          DONE
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.8015913573609416, 'colsample_b
ytree': 0.6361358572992668, 'max_depth': 20}
    train-logloss-mean train-logloss-std test-logloss-mean \
                              0.000095
            0.010911
    test-logloss-std
172
          0.002111
_____
{'booster': 'gbtree', 'objective': 'binary:logistic', 'eta': 0.1, 'subsample': 0.12082773328660013, 'colsample_
bytree': 0.07067883629885074, 'max depth': 40}
    train-logloss-mean train-logloss-std test-logloss-mean \
166
            0.368466
                              0.007235
                                                0.535744
    test-logloss-std
           0.00605
166
```

O----- \ /-!!-|---!!-

Cross validation

```
In [ ]: num_round = 1000
        'colsample bytree': 0.9236039374528398, 'max depth': 20}
        xgb_cv_results = xgb.cv(params = params,dtrain = dtrain,
In [ ]:
                                 num boost round=1000, nfold=5,
                                 verbose_eval=True, early_stopping_rounds=5)
                train-logloss:0.62844+0.00058
                                                 test-logloss:0.63971+0.00081
        [0]
        [1]
                train-logloss:0.57367+0.00096
                                                 test-logloss:0.59376+0.00116
        [2]
                                                 test-logloss:0.55291+0.00114
                train-logloss:0.52517+0.00110
        [3]
                train-logloss:0.48270+0.00121
                                                 test-logloss:0.51741+0.00137
        [4]
                train-logloss:0.44602+0.00149
                                                 test-logloss:0.48740+0.00184
        [5]
                train-logloss:0.41299+0.00094
                                                 test-logloss:0.46075+0.00158
        [6]
                train-logloss:0.38294+0.00077
                                                 test-logloss:0.43629+0.00129
        [7]
                train-logloss:0.35650+0.00067
                                                 test-logloss:0.41510+0.00128
        [8]
                train-logloss:0.33273+0.00057
                                                 test-logloss:0.39646+0.00175
        [9]
                                                 test-logloss:0.37988+0.00209
                train-logloss:0.31137+0.00043
        [10]
                train-logloss:0.29176+0.00054
                                                 test-logloss:0.36451+0.00187
        [11]
                train-logloss:0.27378+0.00036
                                                 test-logloss:0.35034+0.00201
        [12]
                train-logloss:0.25743+0.00029
                                                 test-logloss:0.33749+0.00248
        [13]
                train-logloss:0.24232+0.00032
                                                 test-logloss:0.32584+0.00247
        [14]
                train-logloss:0.22846+0.00046
                                                 test-logloss:0.31513+0.00260
        [15]
                                                 test-logloss:0.30549+0.00258
                train-logloss:0.21577+0.00039
        [16]
                train-logloss:0.20423+0.00031
                                                 test-logloss:0.29687+0.00269
        [17]
                train-logloss:0.19362+0.00044
                                                 test-logloss:0.28887+0.00276
        [18]
                train-logloss:0.18379+0.00036
                                                 test-logloss:0.28156+0.00254
                                                 test-logloss:0.27473+0.00268
        [19]
                train-logloss:0.17464+0.00034
        [20]
                train-logloss:0.16612+0.00049
                                                 test-logloss:0.26839+0.00309
        [21]
                train-logloss:0.15813+0.00044
                                                 test-logloss:0.26227+0.00301
        [22]
                train-logloss:0.15080+0.00049
                                                 test-logloss:0.25694+0.00308
        [23]
                train-logloss:0.14429+0.00062
                                                 test-logloss:0.25216+0.00335
        [24]
                train-logloss:0.13810+0.00053
                                                 test-logloss:0.24769+0.00337
        [25]
                train-logloss:0.13223+0.00055
                                                 test-logloss:0.24351+0.00339
        [26]
                                                 test-logloss:0.23933+0.00338
                train-logloss:0.12658+0.00055
        [27]
                train-logloss:0.12155+0.00023
                                                 test-logloss:0.23568+0.00320
        [28]
                                                 test-logloss:0.23241+0.00325
                train-logloss:0.11682+0.00030
        [29]
                train-logloss:0.11237+0.00029
                                                 test-logloss:0.22912+0.00314
        [30]
                train-logloss:0.10796+0.00038
                                                 test-logloss:0.22596+0.00326
        [31]
                train-logloss:0.10400+0.00043
                                                 test-logloss:0.22304+0.00350
        [32]
                train-logloss:0.10034+0.00039
                                                 test-logloss:0.22049+0.00352
                                                 test-logloss:0.21806+0.00372
        [33]
                train-logloss:0.09688+0.00064
        [34]
                train-logloss:0.09381+0.00047
                                                 test-logloss:0.21592+0.00365
        [35]
                train-logloss:0.09088+0.00046
                                                 test-logloss:0.21377+0.00367
        [36]
                train-logloss:0.08811+0.00052
                                                 test-logloss:0.21182+0.00368
        [37]
                train-logloss:0.08539+0.00059
                                                 test-logloss:0.21001+0.00372
        [38]
                train-logloss:0.08310+0.00067
                                                 test-logloss:0.20847+0.00386
        [39]
                train-logloss:0.08084+0.00075
                                                 test-logloss:0.20690+0.00377
        [40]
                train-logloss:0.07867+0.00052
                                                 test-logloss:0.20537+0.00382
        [41]
                train-logloss:0.07659+0.00071
                                                 test-logloss:0.20399+0.00396
        [42]
                train-logloss:0.07464+0.00051
                                                 test-logloss:0.20253+0.00367
                                                 test-logloss:0.20141+0.00364
        [43]
                train-logloss:0.07285+0.00051
        [44]
                train-logloss:0.07108+0.00032
                                                 test-logloss:0.20025+0.00355
        [45]
                train-logloss:0.06942+0.00039
                                                 test-logloss:0.19910+0.00359
        [46]
                train-logloss:0.06772+0.00033
                                                 test-logloss:0.19777+0.00372
        [47]
                train-logloss:0.06621+0.00031
                                                 test-logloss:0.19676+0.00368
        [48]
                train-logloss:0.06503+0.00033
                                                 test-logloss:0.19600+0.00355
        [49]
                train-logloss:0.06378+0.00050
                                                 test-logloss:0.19523+0.00343
        [50]
                                                 test-logloss:0.19432+0.00341
                train-logloss:0.06246+0.00043
        [51]
                train-logloss:0.06109+0.00026
                                                 test-logloss:0.19345+0.00351
        [52]
                train-logloss:0.05995+0.00023
                                                 test-logloss:0.19271+0.00359
        [53]
                train-logloss:0.05867+0.00032
                                                 test-logloss:0.19204+0.00344
        [54]
                train-logloss:0.05755+0.00031
                                                 test-logloss:0.19137+0.00348
        [55]
                train-logloss:0.05641+0.00055
                                                 test-logloss:0.19067+0.00331
        [56]
                                                 test-logloss:0.19005+0.00344
                train-logloss:0.05524+0.00067
        [57]
                train-logloss:0.05413+0.00057
                                                 test-logloss:0.18951+0.00361
        [58]
                train-logloss:0.05318+0.00057
                                                 test-logloss:0.18904+0.00387
        [59]
                train-logloss:0.05234+0.00081
                                                 test-logloss:0.18845+0.00392
        [60]
                train-logloss:0.05142+0.00073
                                                 test-logloss:0.18801+0.00386
        [61]
                                                 test-logloss:0.18742+0.00389
                train-logloss:0.05051+0.00067
        [62]
                train-logloss:0.04958+0.00058
                                                 test-logloss:0.18698+0.00372
        [63]
                train-logloss:0.04877+0.00045
                                                 test-logloss:0.18664+0.00363
                train-logloss:0.04794+0.00044
        [64]
                                                 test-logloss: 0.18632+0.00349
        [65]
                train-logloss:0.04729+0.00044
                                                 test-logloss:0.18597+0.00348
        [66]
                train-logloss:0.04656+0.00046
                                                 test-logloss:0.18578+0.00346
        [67]
                train-logloss:0.04587+0.00060
                                                 test-logloss:0.18541+0.00345
        [68]
                train-logloss:0.04518+0.00063
                                                 test-logloss:0.18524+0.00347
        [69]
                train-logloss:0.04434+0.00059
                                                 test-logloss:0.18488+0.00342
        [70]
                train-logloss:0.04367+0.00055
                                                 test-logloss:0.18462+0.00337
        [71]
                train-logloss:0.04304+0.00050
                                                 test-logloss:0.18441+0.00334
        [72]
                train-logloss:0.04234+0.00044
                                                 test-logloss:0.18422+0.00337
        [73]
                train-logloss:0.04179+0.00039
                                                 test-logloss:0.18407+0.00337
        [74]
                train-logloss:0.04111+0.00049
                                                 test-logloss:0.18391+0.00345
```

[75]	train-logloss:0.04043+0.00046	test-logloss:0.18368+0.00358
[76]	train-logloss:0.03979+0.00033	test-logloss:0.18348+0.00355
[77]	train-logloss:0.03916+0.00041	test-logloss:0.18317+0.00346
[78]	train-logloss:0.03869+0.00037	test-logloss:0.18311+0.00348
[79]	train-logloss:0.03813+0.00033	test-logloss:0.18300+0.00357
[80]	train-logloss:0.03764+0.00038	test-logloss:0.18293+0.00362
[81]	train-logloss:0.03712+0.00030	test-logloss:0.18278+0.00373
	3	
[82]	train-logloss:0.03650+0.00023	test-logloss:0.18255+0.00376
[83]	train-logloss:0.03603+0.00023	test-logloss:0.18251+0.00375
[84]	train-logloss:0.03549+0.00029	test-logloss:0.18243+0.00387
[85]	train-logloss:0.03500+0.00026	test-logloss:0.18231+0.00395
[86]	train-logloss:0.03456+0.00027	test-logloss:0.18224+0.00397
[87]	train-logloss:0.03410+0.00022	test-logloss:0.18212+0.00399
[88]	train-logloss:0.03369+0.00026	test-logloss:0.18200+0.00387
[89]	train-logloss:0.03324+0.00024	test-logloss:0.18188+0.00386
[90]	train-logloss:0.03275+0.00026	test-logloss:0.18171+0.00386
[91]	train-logloss:0.03225+0.00030	test-logloss:0.18151+0.00389
	train-logloss:0.03178+0.00030	test-logloss:0.18145+0.00405
[92]		_
[93]	train-logloss:0.03128+0.00032	test-logloss:0.18126+0.00412
[94]	train-logloss:0.03082+0.00030	test-logloss:0.18107+0.00407
[95]	train-logloss:0.03036+0.00031	test-logloss:0.18098+0.00393
[96]	train-logloss:0.02997+0.00029	test-logloss:0.18090+0.00392
[97]	train-logloss:0.02955+0.00025	test-logloss:0.18091+0.00384
[98]	train-logloss:0.02917+0.00023	test-logloss:0.18087+0.00386
[99]	train-logloss:0.02880+0.00023	test-logloss:0.18072+0.00380
[100]	train-logloss:0.02840+0.00027	test-logloss:0.18060+0.00373
[101]	train-logloss:0.02805+0.00028	test-logloss:0.18054+0.00381
[102]	train-logloss:0.02770+0.00029	test-logloss:0.18049+0.00375
	train-logloss:0.02733+0.00024	test-logloss:0.18026+0.00366
[103]		
[104]	train-logloss:0.02699+0.00020	test-logloss:0.18021+0.00375
[105]	train-logloss:0.02667+0.00014	test-logloss:0.18016+0.00379
[106]	train-logloss:0.02635+0.00013	test-logloss:0.18010+0.00382
[107]	train-logloss:0.02605+0.00017	test-logloss:0.18010+0.00378
[108]	train-logloss:0.02574+0.00018	test-logloss:0.18009+0.00373
[109]	train-logloss:0.02542+0.00025	test-logloss:0.17992+0.00361
[110]	train-logloss:0.02512+0.00024	test-logloss:0.17979+0.00363
[111]	train-logloss:0.02486+0.00022	test-logloss:0.17974+0.00370
[112]	train-logloss:0.02457+0.00025	test-logloss:0.17973+0.00373
[113]	train-logloss:0.02428+0.00026	test-logloss:0.17968+0.00372
[114]	train-logloss:0.02398+0.00025	test-logloss:0.17964+0.00373
[115]	train-logloss:0.02374+0.00026	test-logloss:0.17962+0.00376
[116]	train-logloss:0.02348+0.00026	test-logloss:0.17953+0.00371
[117]	train-logloss:0.02323+0.00031	test-logloss:0.17953+0.00364
[118]	train-logloss:0.02293+0.00028	test-logloss:0.17943+0.00373
[119]	train-logloss:0.02264+0.00026	test-logloss:0.17932+0.00383
[120]	train-logloss:0.02239+0.00025	test-logloss:0.17929+0.00378
[121]	train-logloss:0.02217+0.00028	test-logloss:0.17926+0.00378
[122]	train-logloss:0.02194+0.00026	test-logloss:0.17919+0.00375
[123]	train-logloss:0.02168+0.00026	test-logloss:0.17918+0.00379
[124]	train-logloss:0.02144+0.00024	test-logloss:0.17914+0.00384
[125]	train-logloss:0.02120+0.00024	test-logloss:0.17904+0.00385
[126]	train-logloss:0.02098+0.00024	test-logloss:0.17909+0.00385
		test-logloss:0.17903+0.00383
[127]	train-logloss:0.02072+0.00022	5
[128]	train-logloss:0.02051+0.00024	test-logloss:0.17895+0.00376
[129]	train-logloss:0.02031+0.00025	test-logloss:0.17893+0.00373
[130]	train-logloss:0.02007+0.00025	test-logloss:0.17886+0.00378
[131]	train-logloss:0.01985+0.00027	test-logloss:0.17889+0.00378
[132]	train-logloss:0.01965+0.00024	test-logloss:0.17888+0.00381
[133]	train-logloss:0.01946+0.00026	test-logloss:0.17878+0.00389
[134]	train-logloss:0.01927+0.00026	test-logloss:0.17877+0.00378
[135]	train-logloss:0.01911+0.00025	test-logloss:0.17877+0.00378
[136]	train-logloss:0.01892+0.00024	test-logloss:0.17873+0.00381
[137]	train-logloss:0.01872+0.00025	test-logloss:0.17864+0.00377
[138]	train-logloss:0.01855+0.00022	test-logloss:0.17863+0.00376
	train-logloss:0.01837+0.00022	
[139]		test-logloss:0.17857+0.00380
[140]	train-logloss:0.01820+0.00022	test-logloss:0.17853+0.00379
[141]	train-logloss:0.01803+0.00020	test-logloss:0.17850+0.00382
[142]	train-logloss:0.01786+0.00021	test-logloss:0.17847+0.00380
[143]	train-logloss:0.01769+0.00021	test-logloss:0.17851+0.00379
[144]	train-logloss:0.01752+0.00022	test-logloss:0.17852+0.00377
	train-logloss:0.01732+0.00022	test-logloss:0.17853+0.00377
[145]		
[146]	train-logloss:0.01720+0.00019	test-logloss:0.17856+0.00382
[147]	train-logloss:0.01703+0.00019	test-logloss:0.17852+0.00380

```
train-logloss-mean train-logloss-std test-logloss-mean test-logloss-std
Out[]:
             0
                         0.628445
                                           0.000582
                                                              0.639706
                                                                               0.000813
                         0.573671
                                           0.000957
                                                              0.593762
                                                                               0.001159
             2
                                           0.001097
                                                              0.552911
                                                                               0.001138
                         0.525169
             3
                         0.482704
                                           0.001210
                                                              0.517407
                                                                               0.001375
                                                                               0.001837
                         0.446016
                                           0.001488
                                                              0.487401
          138
                         0.018547
                                           0.000225
                                                              0.178626
                                                                               0.003756
                         0.018369
                                           0.000241
                                                              0.178573
                                                                               0.003801
          139
          140
                         0.018203
                                           0.000221
                                                              0.178535
                                                                               0.003794
           141
                         0.018029
                                           0.000195
                                                              0.178498
                                                                               0.003819
                                                                               0.003798
          142
                         0.017863
                                           0.000213
                                                              0.178470
```

143 rows × 4 columns

```
In []: plt.plot(xgb_cv_results['test-logloss-mean'], label='test')
   plt.plot(xgb_cv_results['train-logloss-mean'], label = 'train')
   plt.title('Cross Validatoin Log-Loss Curve - XGBoost')
   plt.xlabel('Number of Rounds')
   plt.ylabel('Log-Loss')
   plt.legend()
   plt.show()
```

Cross Validatoin Log-Loss Curve - XGBoost test 0.6 train 0.5 0.4 0.3 0.2 0.1 0.0 20 40 100 120 0 60 80 140 Number of Rounds

Training Model

```
param = {'booster': 'gbtree',
In [ ]:
                                                        'objective': 'binary:logistic',
'eta': 0.1, 'subsample': 0.6297428583724649,
                                                        'colsample_bytree': 0.9236039374528398, 'max_depth': 20}
                           num round =1000
                            evallist = [(dtrain, 'train'), (dvalidation, 'validation')]
                           xgb_model = xgb.train(param, dtrain,
                                                                                               num_round, evallist,
                                                                                               early stopping rounds=2)
                           \verb|c:\Users\Joey\anaconda3\envs\ML\lib\site-packages\xgboost\core.py:617: Future Warning: Pass `evals` as keyword a line of the packages in the packages of t
                           rgs.
                                 warnings.warn(msg, FutureWarning)
                           [0]
                                                                                                                                      validation-logloss:0.63926
                                                      train-logloss:0.62821
                            [1]
                                                      train-logloss:0.57066
                                                                                                                                      validation-logloss:0.59002
                            [2]
                                                      train-logloss:0.52315
                                                                                                                                      validation-logloss:0.55145
                                                      train-logloss:0.48036
                                                                                                                                      validation-logloss:0.51506
                           [3]
                            [4]
                                                      train-logloss:0.44276
                                                                                                                                      validation-logloss:0.48370
                            [5]
                                                      train-logloss:0.41049
                                                                                                                                       validation-logloss:0.45770
                                                                                                                                      validation-logloss:0.43468
                           [6]
                                                      train-logloss:0.38150
                           [7]
                                                      train-logloss:0.35494
                                                                                                                                      validation-logloss:0.41319
```

[8]	train-logloss:0.33111	validation-logloss:0.39426
[9]	train-logloss:0.30959	validation-logloss:0.37696
[10]	train-logloss:0.28944	validation-logloss:0.36067
[11]	train-logloss:0.27181	validation-logloss:0.34714
[12]	train-logloss:0.25506	validation-logloss:0.33358
[13]	train-logloss:0.24006	validation-logloss:0.32174
		validation-logloss:0.31174
[14]	train-logloss:0.22654	
[15]	train-logloss:0.21390	validation-logloss:0.30220
[16]	train-logloss:0.20242	validation-logloss:0.29350
[17]	train-logloss:0.19206	validation-logloss:0.28571
[18]	train-logloss:0.18215	validation-logloss:0.27841
[19]	train-logloss:0.17274	validation-logloss:0.27117
[20]	train-logloss:0.16426	validation-logloss:0.26477
[21]	train-logloss:0.15623	validation-logloss:0.25875
[22]	train-logloss:0.14897	validation-logloss:0.25344
[23]	train-logloss:0.14231	validation-logloss:0.24871
[24]	train-logloss:0.13603	validation-logloss:0.24414
[25]	train-logloss:0.13015	validation-logloss:0.24006
[26]	train-logloss:0.12467	validation-logloss:0.23624
[27]	train-logloss:0.11959	validation-logloss:0.23290
[28]	train-logloss:0.11530	validation-logloss:0.22984
[29]	train-logloss:0.11076	validation-logloss:0.22684
[30]	train-logloss:0.10641	validation-logloss:0.22358
[31]	train-logloss:0.10258	validation-logloss:0.22081
[32]	train-logloss:0.09890	validation-logloss:0.21842
[33]	train-logloss:0.09555	validation-logloss:0.21616
[34]	train-logloss:0.09259	validation-logloss:0.21391
[35]	train-logloss:0.08949	validation-logloss:0.21356
[36]	train-logloss:0.08686	validation-logloss:0.20929
[37]	train-logloss:0.08456	validation-logloss:0.20778
[38]	train-logloss:0.08182	validation-logloss:0.20563
[39]	train-logloss:0.08003	validation-logloss:0.20467
[40]	train-logloss:0.07742	validation-logloss:0.20274
[41]	train-logloss:0.07522	validation-logloss:0.20111
[42]	train-logloss:0.07337	validation-logloss:0.19976
[43]		validation-logloss:0.19834
[44]	train-logloss:0.07145 train-logloss:0.06970	validation-logloss:0.19834
[45]	train-logloss:0.06753	validation-logloss:0.19560 validation-logloss:0.19428
[46] [47]	train-logloss:0.06547 train-logloss:0.06445	validation-logloss:0.19428
[48]	train-logloss:0.06301	validation-logloss:0.19225
[49]	train-logloss:0.06139	validation-logloss:0.19118
[50]	train-logloss:0.06043	validation-logloss:0.19036
[51]	train-logloss:0.05956	validation-logloss:0.18982
[52]	train-logloss:0.05854	validation-logloss:0.18914
[53]	train-logloss:0.05741	validation-logloss:0.18838
[54]	train-logloss:0.05620	validation-logloss:0.18751
[55]	train-logloss:0.05549	validation-logloss:0.18699
[56]	train-logloss:0.05432	validation-logloss:0.18624
[57]	train-logloss:0.05336	validation-logloss:0.18565
[58]	train-logloss:0.05236	validation-logloss:0.18493
[59]	train-logloss:0.05141	validation-logloss:0.18441
[60]	train-logloss:0.05083	validation-logloss:0.18422
[61]	train-logloss:0.05011	validation-logloss:0.18387
[62]	train-logloss:0.04919	validation-logloss:0.18367
[63]	train-logloss:0.04858	validation-logloss:0.18318
[64]	train-logloss:0.04783	validation-logloss:0.18297
[65]	train-logloss:0.04706	validation-logloss:0.18284
[66]	train-logloss:0.04598	validation-logloss:0.18234
[67]	train-logloss:0.04521	validation-logloss:0.18222
[68]	train-logloss:0.04455	validation-logloss:0.18211
[69]	train-logloss:0.04416	validation-logloss:0.18196
[70]	train-logloss:0.04336	validation-logloss:0.18156
[71]	train-logloss:0.04293	validation-logloss:0.18123
[72]	train-logloss:0.04250	validation-logloss:0.18109
[73]	train-logloss:0.04212	validation-logloss:0.18069
[74]	train-logloss:0.04149	validation-logloss:0.18067
[75]	train-logloss:0.04071	validation-logloss:0.18026
[76]	train-logloss:0.04008	validation-logloss:0.18016
[77]	train-logloss:0.03927	validation-logloss:0.17977
[78]	train-logloss:0.03856	validation-logloss:0.17931
[79]	train-logloss:0.03792	validation-logloss:0.17908
[80]	train-logloss:0.03738	validation-logloss:0.17891
[81]	train-logloss:0.03701	validation-logloss:0.17884
[82]	train-logloss:0.03647	validation-logloss:0.17893
[83]	train-logloss:0.03598	validation-logloss:0.17877
[84]	train-logloss:0.03570	validation-logloss:0.17876
[85]	train-logloss:0.03503	validation-logloss:0.17851
[86]	train-logloss:0.03459	validation-logloss:0.17851
[87]	train-logloss:0.03432	validation-logloss:0.17839
[88]	train-logloss:0.03364	validation-logloss:0.17791
[89]	train-logloss:0.03325	validation-logloss:0.17787
[90]	train-logloss:0.03303	validation-logloss:0.17776
[91]	train-logloss:0.03257	validation-logloss:0.17756
[92]	train-logloss:0.03216	validation-logloss:0.17757
[93]	train-logloss:0.03164	validation-logloss:0.17724
[94]	train-logloss:0.03123	validation-logloss:0.17721
[95]	train-logloss:0.03083	validation-logloss:0.17715
[96]	train-logloss:0.03037	validation-logloss:0.17720

Validating Model

```
In [ ]: import xgboost as xgb
        import numpy as np
        from sklearn.metrics import f1_score
        # Make predictions on the test data
        y_test_pred = xgb_model.predict(dtest)
        best_threshold = 0.5
        best_f1 = 0
        thresholds = np.linspace(0, 1, 100)
        for threshold in thresholds:
             # Convert probabilities to binary output based on current threshold
            y_pred_binary = (y_test_pred > threshold).astype(int)
            # Calculate the F1 score
            current f1 = f1 score(y test, y pred binary)
            # If the current F1 score is better than the best so far, update the best threshold
            if current_f1 > best_f1:
                best f1 = current f1
                 best_threshold = Threshold
        # Print the best threshold and the corresponding F1 score
        print(f"Best Threshold: {best_threshold}")
print(f"Best F1 Score: {best_f1}")
        y_test_pred_binary = (y_test_pred > best_threshold).astype(int)
        Best Threshold: 0.44444444444445
        Best F1 Score: 0.9169783096484666
```

Tuned XGBoost Test Results

0.93

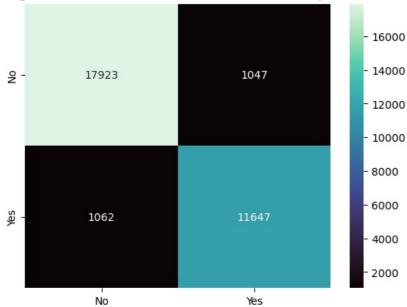
0.93

0.93

```
In [ ]: from sklearn.metrics import confusion_matrix, classification_report
        # Generate the confusion matrix
        cm = confusion_matrix(y_test, y_test_pred_binary)
        # Generate the classification report
        cr = classification_report(y_test, y_test_pred_binary)
        # Print the confusion matrix
        print("Confusion Matrix:")
        print(cm)
         # Print the classification report
        print("\nClassification Report:")
        print(cr)
        sns.heatmap(cm, annot=True, fmt='.0f', cmap = 'mako')
        plt.title('Testing Data Prediction Matrix - XGBoost Model F1 Optimized')
        plt.xticks(ticks = [.5,1.5], labels = ['No','Yes'])
plt.yticks(ticks = [.5,1.5], labels = ['No','Yes'])
        plt.show()
        Confusion Matrix:
        [[17923 1047]
          [ 1062 11647]]
        Classification Report:
                                     recall f1-score support
                       precision
                    0
                             0.94
                                       0.94
                                                  0.94
                                                            18970
                             0.92
                                       0.92
                                                  0.92
                                                            12709
                    1
             accuracy
                                                  0.93
                                                            31679
                             0.93
                                       0.93
                                                  0.93
                                                            31679
            macro avg
        weighted avg
```

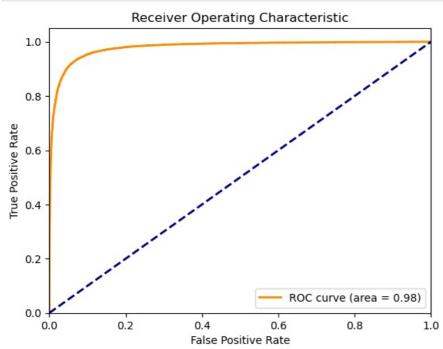
31679

Testing Data Prediction Matrix - XGBoost Model F1 Optimized



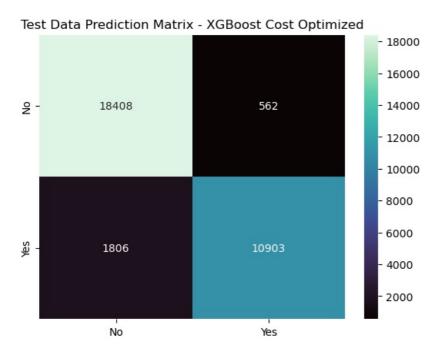
```
In []: from sklearn.metrics import roc_curve, auc
# Compute ROC curve and ROC area
fpr, tpr, thresholds = roc_curve(y_test, y_test_pred)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```



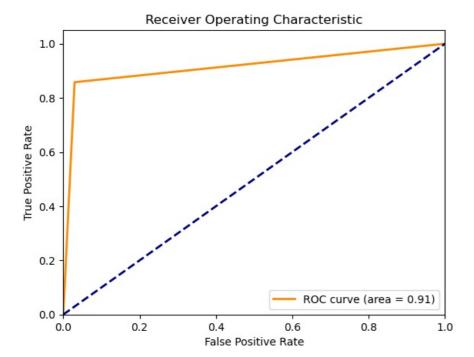
Cost Optimized Threshold

```
In [ ]: import numpy as np
         from sklearn.metrics import confusion matrix
        # Define costs
        cost_fp = 100
         cost_fn = 40
         # Assume y_test_pred contains the predicted probabilities for the positive class
        thresholds = np.linspace(0, 1, 1000)
        min cost = np.inf
        best threshold = None
         for threshold in thresholds:
             # Convert probabilities to binary output based on the current threshold
             y_pred_binary = (y_test_pred > threshold).astype(int)
             # Calculate the confusion matrix for the current threshold
             tn, fp, fn, tp = confusion_matrix(y_test, y_pred_binary).ravel()
             # Calculate the total cost for the current threshold
             total_cost = (fp * cost_fp) + (fn * cost_fn)
             # Update the minimum cost and the best threshold
             if total_cost < min_cost:</pre>
                 min cost = total_cost
                 best_threshold = threshold
        # Use the best threshold to update the binary predictions
        y_test_pred_binary = (y_test_pred > best_threshold).astype(int)
        # Recalculate the confusion matrix and classification report using the best threshold
        cm = confusion_matrix(y_test, y_test_pred_binary)
cr = classification_report(y_test, y_test_pred_binary)
        # Print the best threshold, the new confusion matrix, and the classification report
        print(f"Best Threshold: {best threshold}")
         print("Updated Confusion Matrix:")
        print(cm)
        print("\nUpdated Classification Report:")
        print(cr)
         sns.heatmap(cm, annot=True, fmt='.0f', cmap = 'mako')
        plt.title('Test Data Prediction Matrix - XGBoost Cost Optimized')
        plt.xticks(ticks = [.5,1.5], labels = ['No', 'Yes'])
plt.yticks(ticks = [.5,1.5], labels = ['No', 'Yes'])
        plt.show()
        Best Threshold: 0.6726726726726726
        Updated Confusion Matrix:
        [[18408
                  5621
         [ 1806 10903]]
        Updated Classification Report:
                                    recall f1-score support
                       precision
                    0
                             0.91
                                       0.97
                                                  0.94
                                                            18970
                                       0.86
                                                  0.90
                                                            12709
                             0.95
                    1
             accuracy
                                                  0.93
                                                            31679
                             0.93
                                       0.91
                                                  0.92
                                                            31679
            macro avq
                                       0.93
                                                  0.92
                                                            31679
        weighted avg
                             0.93
```



```
In [ ]: # Compute ROC curve and ROC area
fpr, tpr, thresholds = roc_curve(y_test, y_test_pred_binary)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```



Deep Neural Network

Epoch 3/1000

```
In [ ]: import tensorflow as tf
       df['y'] = df['y'].astype(int)
       X = df.drop('y', axis=1)
       y = df['y']
'x46', 'x47', 'x48', 'x49', 'money', 'decimal']
       scaled data = scaler.fit transform(df[col to scale])
       X[col_to_scale] = scaled_data
In [ ]: # Split the data into main training set and test set (80% - 20%)
       X_train_main, X_test, y_train_main, y_test = train_test_split(
          X, y, test size=0.2, random state=12, stratify=y)
       # Further split the main training set into training and validation sets (75% - 25% of main training)
       X_train, X_validation, y_train, y_validation = train_test_split(
          X train main, y train main, test size=0.25, random state=12, stratify=y train main)
In [ ]: X train.shape
Out[]: (95034, 64)
In []: dnn = tf.keras.Sequential()
       dnn.add(tf.keras.Input(shape = (64,)))
       dnn.add(tf.keras.layers.Dense(32, activation = 'relu'))
       dnn.add(tf.keras.layers.Dense(64, activation = 'relu'))
       dnn.add(tf.keras.layers.Dense(32, activation = 'relu'))
dnn.add(tf.keras.layers.Dense(1, activation = 'sigmoid'))
       opt = tf.keras.optimizers.Adam(learning rate=.001)
       dnn.compile(loss= 'BinaryCrossentropy',metrics = ['accuracy'], optimizer=opt)
In []: from tensorflow.keras.callbacks import EarlyStopping
       saftey = EarlyStopping(monitor = 'val_loss', patience = 10)
       history = dnn.fit(X_train, y_train, epochs=1000,
                     batch_size=100, callbacks=[saftey]
                     validation data=(X validation,y validation))
       Epoch 1/1000
       al accuracy: 0.8775
       Epoch 2/1000
       al_accuracy: 0.9052
```

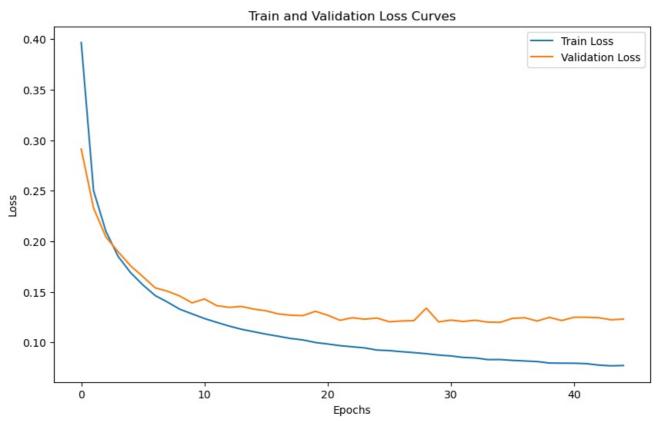
```
al_accuracy: 0.9203
Epoch 4/1000
951/951 [=======
            :===============] - 1s 1ms/step - loss: 0.1850 - accuracy: 0.9302 - val loss: 0.1896 - v
al_accuracy: 0.9266
Epoch 5/1000
951/951 [=====
         al accuracy: 0.9338
Epoch 6/1000
951/951 [=
                  =======] - 1s 1ms/step - loss: 0.1569 - accuracy: 0.9427 - val loss: 0.1651 - v
al accuracy: 0.9386
Epoch 7/1000
951/951 [===
             :=========] - 1s 1ms/step - loss: 0.1464 - accuracy: 0.9461 - val_loss: 0.1540 - v
al accuracy: 0.9438
Epoch 8/1000
951/951 [===
                ========] - 1s 1ms/step - loss: 0.1399 - accuracy: 0.9493 - val_loss: 0.1507 - v
al accuracy: 0.9449
Epoch 9/1000
al_accuracy: 0.9466
Epoch 10/1000
951/951 [==
                    =====] - 1s 1ms/step - loss: 0.1282 - accuracy: 0.9550 - val loss: 0.1391 - v
al_accuracy: 0.9513
Epoch 11/1000
951/951 [=====
           al accuracy: 0.9495
Epoch 12/1000
951/951 [=====
             ==========] - 1s 1ms/step - loss: 0.1199 - accuracy: 0.9576 - val loss: 0.1364 - v
al accuracy: 0.9518
Epoch 13/1000
al accuracy: 0.9532
Epoch 14/1000
al accuracy: 0.9522
Epoch 15/1000
951/951 [=====
            ==========] - 1s 1ms/step - loss: 0.1106 - accuracy: 0.9624 - val loss: 0.1330 - v
al accuracy: 0.9537
Epoch 16/1000
951/951 [==
                ========] - 1s 1ms/step - loss: 0.1082 - accuracy: 0.9636 - val_loss: 0.1313 - v
al accuracy: 0.9543
Epoch 17/1000
951/951 [==
                   =====] - 1s 1ms/step - loss: 0.1061 - accuracy: 0.9643 - val loss: 0.1282 - v
al accuracy: 0.9564
Epoch 18/1000
951/951 [=====
               :========] - 1s 1ms/step - loss: 0.1039 - accuracy: 0.9653 - val loss: 0.1269 - v
al_accuracy: 0.9569
Epoch 19/1000
951/951 [==
                  =======] - 1s 1ms/step - loss: 0.1025 - accuracy: 0.9661 - val loss: 0.1266 - v
al accuracy: 0.9558
Epoch 20/1000
al accuracy: 0.9552
Epoch 21/1000
al accuracy: 0.9573
Epoch 22/1000
al_accuracy: 0.9600
Epoch 23/1000
al accuracy: 0.9583
Epoch 24/1000
al accuracy: 0.9590
Epoch 25/1000
951/951 [===
                ========] - 1s 1ms/step - loss: 0.0925 - accuracy: 0.9696 - val loss: 0.1242 - v
al_accuracy: 0.9587
Epoch 26/1000
951/951 [=====
              :=========] - 1s 1ms/step - loss: 0.0919 - accuracy: 0.9698 - val_loss: 0.1205 - v
al accuracy: 0.9597
Epoch 27/1000
951/951 [==
                 :=======] - 1s 1ms/step - loss: 0.0909 - accuracy: 0.9698 - val loss: 0.1213 - v
al accuracy: 0.9600
Epoch 28/1000
951/951 [=====
              :=========] - 1s 1ms/step - loss: 0.0900 - accuracy: 0.9708 - val loss: 0.1216 - v
al_accuracy: 0.9605
Epoch 29/1000
al accuracy: 0.9560
Epoch 30/1000
al_accuracy: 0.9603
Epoch 31/1000
al accuracy: 0.9600
Epoch 32/1000
951/951 [=====
```

al accuracy: 0.9598

```
Epoch 33/1000
                 :=======] - 1s 1ms/step - loss: 0.0847 - accuracy: 0.9721 - val_loss: 0.1219 - v
951/951 [==
al accuracy: 0.9607
Epoch 34/1000
al_accuracy: 0.9614
Epoch 35/1000
al_accuracy: 0.9619
Epoch 36/1000
        951/951 [=====
al accuracy: 0.9618
Epoch 37/1000
951/951 [=====
             ==========] - 1s 1ms/step - loss: 0.0817 - accuracy: 0.9736 - val loss: 0.1244 - v
al accuracy: 0.9595
Epoch 38/1000
al accuracy: 0.9611
Epoch 39/1000
                 :======] - 1s 1ms/step - loss: 0.0797 - accuracy: 0.9742 - val_loss: 0.1248 - v
951/951 [=====
al accuracy: 0.9603
Epoch 40/1000
951/951 [=====
                =======] - 1s 1ms/step - loss: 0.0795 - accuracy: 0.9744 - val loss: 0.1217 - v
al accuracy: 0.9616
Epoch 41/1000
951/951 [=======
               ========] - 1s 1ms/step - loss: 0.0795 - accuracy: 0.9742 - val_loss: 0.1249 - v
al_accuracy: 0.9606
Epoch 42/1000
951/951 [==
                    =====] - 1s 1ms/step - loss: 0.0790 - accuracy: 0.9745 - val loss: 0.1249 - v
al_accuracy: 0.9598
Epoch 43/1000
951/951 [=======
             al accuracy: 0.9611
Epoch 44/1000
951/951 [=====
        al accuracy: 0.9613
Epoch 45/1000
al accuracy: 0.9610
```

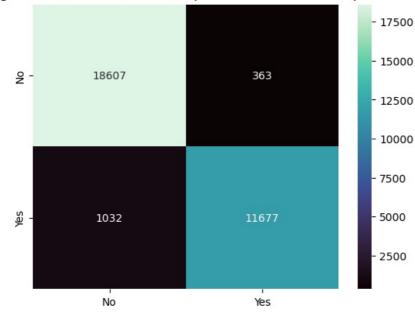
CV Loss Curve

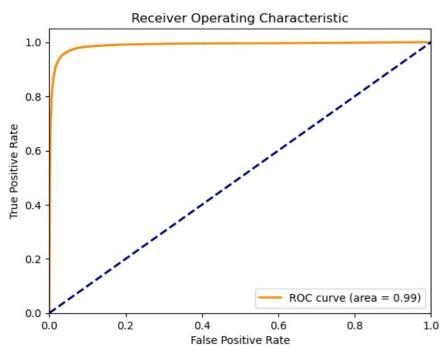
```
In []: plt.figure(figsize=(10, 6))
   plt.plot(history.history['loss'], label='Train Loss')
   plt.plot(history.history['val_loss'], label='Validation Loss')
   plt.title('Train and Validation Loss Curves')
   plt.xlabel('Epochs')
   plt.ylabel('Loss')
   plt.legend()
   plt.show()
```



```
cost fp = 100
cost_fn = 40
# Predict probabilities on the test set
y_pred_prob = dnn.predict(X_test).flatten()
# Initialize the list to store costs for each threshold
costs = []
thresholds = np.linspace(0, 1, 100)
# Loop over thresholds to calculate the total cost
for t in thresholds:
    y_pred = (y_pred_prob > t).astype(int)
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
total_cost = (fp * cost_fp) + (fn * cost_fn)
    costs.append(total_cost)
# Find the threshold that minimizes the total cost
min cost index = np.argmin(costs)
min_cost_thres = thresholds[min_cost_index]
print(f'Threshold that minimizes the total cost: {min cost thres}')
# Generate predictions using the threshold that minimizes the total cost
y pred min cost = (y pred prob > min cost thres).astype(int)
# Compute the confusion matrix
cm = confusion_matrix(y_test, y_pred_min_cost)
print("Confusion Matrix:")
print(cm)
# Generate the classification report
cr = classification_report(y_test, y_pred_min_cost)
print("\nClassification Report:")
print(cr)
sns.heatmap(cm, annot=True, fmt='.0f', cmap = 'mako')
plt.title('Testing Data Prediction Matrix - Deep Neural Network Cost Optimized')
plt.xticks(ticks = [.5,1.5], labels = ['No','Yes'])
plt.yticks(ticks = [.5,1.5], labels = ['No','Yes'])
plt.show()
# Compute ROC curve and ROC area
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
roc auc = auc(fpr, tpr)
# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
990/990 [=======] - 1s 626us/step
Threshold that minimizes the total cost: 0.737373737373737
Confusion Matrix:
[[18607
          363]
 [ 1032 11677]]
Classification Report:
                            recall f1-score support
              precision
                    0.95
                               0.98
                                         0.96
           0
                                                   18970
                    0.97
                               0.92
                                         0.94
                                                   12709
                                         0.96
                                                   31679
    accuracy
                    0.96
                               0.95
   macro avg
                                         0.95
                                                   31679
                               0.96
                                         0.96
                                                   31679
weighted avg
                    0.96
```







Entire Prediction Results - Cross Val Predict

```
In [ ]: from sklearn.model_selection import cross_val_predict

In [ ]: import tensorflow as tf
    from sklearn.model_selection import StratifiedKFold
    from sklearn.metrics import confusion_matrix, classification_report
    import numpy as np

    cost_fp = 100
    cost_fn = 40

    kfold = StratifiedKFold(n_splits=5, shuffle=True)

    best_threshold = []
```

```
all true labels = []
all_pred_labels = []
for train, test in kfold.split(X, y):
    dnn = tf.keras.Sequential([
        tf.keras.Input(shape=(64,))
        tf.keras.layers.Dense(32, activation='relu'),
        tf.keras.layers.Dense(64, activation='relu'),
        tf.keras.layers.Dense(32, activation='relu')
        tf.keras.layers.Dense(1, activation='sigmoid')
    dnn.compile(loss='binary_crossentropy', metrics=['accuracy'], optimizer='adam')
    X np = X.values
    y_np = y.values
    # Fit the model
    dnn.fit(X_np[train], y_np[train], epochs=600, batch_size=100, verbose=2)
    # Predict probabilities on the validation set
    y_pred_prob = dnn.predict(X_np[test]).flatten()
    # Initialize the list to store costs for each threshold
    costs = []
    thresholds = np.linspace(0, 1, 100)
    # Loop over thresholds to calculate the total cost
    for t in thresholds:
        y_pred = (y_pred_prob > t).astype(int)
tn, fp, fn, tp = confusion_matrix(y_np[test], y_pred).ravel()
total_cost = (fp * cost_fp) + (fn * cost_fn)
        costs.append(total_cost)
    # Find the threshold that minimizes the total cost for the fold
    min cost index = np.argmin(costs)
    min cost thres = thresholds[min cost index]
    best_threshold.append(min_cost_thres)
    y_pred = (y_pred_prob > min_cost_thres).astype(int)
    all_true_labels.extend(y_np[test])
    all pred labels.extend(y pred)
conf matrix = confusion matrix(all true labels,all pred labels)
class report = classification report(all true labels,all pred labels)
# Aggregate the best thresholds (e.g., by averaging)
final_best_threshold = np.mean(best_threshold)
print(f'Final Best Threshold: {final_best_threshold}')
print(conf matrix)
print(class_report)
Epoch 1/600
1268/1268 - 2s - loss: 0.3645 - accuracy: 0.8345 - 2s/epoch - 1ms/step
Epoch 2/600
1268/1268 - 1s - loss: 0.2324 - accuracy: 0.9062 - 1s/epoch - 984us/step
Epoch 3/600
1268/1268 - 1s - loss: 0.1888 - accuracy: 0.9282 - 1s/epoch - 962us/step
Epoch 4/600
1268/1268 - 1s - loss: 0.1625 - accuracy: 0.9398 - 1s/epoch - 982us/step
Epoch 5/600
1268/1268 - 1s - loss: 0.1470 - accuracy: 0.9470 - 1s/epoch - 964us/step
Epoch 6/600
1268/1268 - 1s - loss: 0.1365 - accuracy: 0.9516 - 1s/epoch - 960us/step
Epoch 7/600
1268/1268 - 1s - loss: 0.1296 - accuracy: 0.9543 - 1s/epoch - 978us/step
Epoch 8/600
1268/1268 - 1s - loss: 0.1234 - accuracy: 0.9574 - 1s/epoch - 961us/step
Epoch 9/600
1268/1268 - 1s - loss: 0.1192 - accuracy: 0.9590 - 1s/epoch - 980us/step
Epoch 10/600
1268/1268 - 1s - loss: 0.1157 - accuracy: 0.9602 - 1s/epoch - 984us/step
Epoch 11/600
1268/1268 - 1s - loss: 0.1120 - accuracy: 0.9621 - 1s/epoch - 971us/step
Epoch 12/600
1268/1268 - 1s - loss: 0.1097 - accuracy: 0.9629 - 1s/epoch - 965us/step
Epoch 13/600
1268/1268 - 1s - loss: 0.1078 - accuracy: 0.9638 - 1s/epoch - 982us/step
Epoch 14/600
1268/1268 - 1s - loss: 0.1055 - accuracy: 0.9645 - 1s/epoch - 967us/step
Epoch 15/600
1268/1268 - 1s - loss: 0.1031 - accuracy: 0.9655 - 1s/epoch - 985us/step
Epoch 16/600
1268/1268 - 1s - loss: 0.1019 - accuracy: 0.9660 - 1s/epoch - 972us/step
Epoch 17/600
1268/1268 - 1s - loss: 0.1002 - accuracy: 0.9668 - 1s/epoch - 961us/step
Epoch 18/600
1268/1268 - 1s - loss: 0.0988 - accuracy: 0.9673 - 1s/epoch - 960us/step
Epoch 19/600
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1268/1268 - 1s - loss: 0.0982 - accuracy: 0.9675 - 1s/epoch - 978us/step
Epoch 20/600
1268/1268 - 1s - loss: 0.0959 - accuracy: 0.9685 - 1s/epoch - 967us/step
Epoch 21/600
1268/1268 - 1s - loss: 0.0951 - accuracy: 0.9687 - 1s/epoch - 971us/step
Epoch 22/600
1268/1268 - 1s - loss: 0.0941 - accuracy: 0.9691 - 1s/epoch - 984us/step
Epoch 23/600
1268/1268 - 1s - loss: 0.0932 - accuracy: 0.9692 - 1s/epoch - 971us/step
Epoch 24/600
1268/1268 - 1s - loss: 0.0922 - accuracy: 0.9696 - 1s/epoch - 988us/step
Epoch 25/600
1268/1268 - 1s - loss: 0.0914 - accuracy: 0.9701 - 1s/epoch - 984us/step
Epoch 26/600
1268/1268 - 1s - loss: 0.0901 - accuracy: 0.9705 - 1s/epoch - 981us/step
Epoch 27/600
1268/1268 - 1s - loss: 0.0895 - accuracy: 0.9710 - 1s/epoch - 965us/step
Epoch 28/600
1268/1268 - 1s - loss: 0.0886 - accuracy: 0.9713 - 1s/epoch - 963us/step
Epoch 29/600
1268/1268 - 1s - loss: 0.0878 - accuracy: 0.9714 - 1s/epoch - 981us/step
Epoch 30/600
1268/1268 - 1s - loss: 0.0868 - accuracy: 0.9716 - 1s/epoch - 980us/step
Epoch 31/600
1268/1268 - 1s - loss: 0.0864 - accuracy: 0.9718 - 1s/epoch - 959us/step
Epoch 32/600
1268/1268 - 1s - loss: 0.0860 - accuracy: 0.9722 - 1s/epoch - 962us/step
Epoch 33/600
1268/1268 - 1s - loss: 0.0852 - accuracy: 0.9722 - 1s/epoch - 983us/step
Epoch 34/600
1268/1268 - 1s - loss: 0.0842 - accuracy: 0.9725 - 1s/epoch - 982us/step
Epoch 35/600
1268/1268 - 1s - loss: 0.0838 - accuracy: 0.9731 - 1s/epoch - 966us/step
Epoch 36/600
1268/1268 - 1s - loss: 0.0830 - accuracy: 0.9732 - 1s/epoch - 958us/step
Epoch 37/600
1268/1268 - 1s - loss: 0.0825 - accuracy: 0.9731 - 1s/epoch - 980us/step
Epoch 38/600
1268/1268 - 1s - loss: 0.0817 - accuracy: 0.9733 - 1s/epoch - 966us/step
Epoch 39/600
1268/1268 - 1s - loss: 0.0810 - accuracy: 0.9739 - 1s/epoch - 985us/step
Epoch 40/600
1268/1268 - 1s - loss: 0.0805 - accuracy: 0.9737 - 1s/epoch - 983us/step
Epoch 41/600
1268/1268 - 1s - loss: 0.0798 - accuracy: 0.9740 - 1s/epoch - 961us/step
Epoch 42/600
1268/1268 - 1s - loss: 0.0794 - accuracy: 0.9741 - 1s/epoch - 982us/step
Epoch 43/600
1268/1268 - 1s - loss: 0.0793 - accuracy: 0.9743 - 1s/epoch - 962us/step
Epoch 44/600
1268/1268 - 1s - loss: 0.0782 - accuracy: 0.9751 - 1s/epoch - 967us/step
Epoch 45/600
1268/1268 - 1s - loss: 0.0780 - accuracy: 0.9752 - 1s/epoch - 985us/step
Epoch 46/600
1268/1268 - 1s - loss: 0.0776 - accuracy: 0.9751 - 1s/epoch - 958us/step
Epoch 47/600
1268/1268 - 1s - loss: 0.0769 - accuracy: 0.9749 - 1s/epoch - 962us/step
Epoch 48/600
1268/1268 - 1s - loss: 0.0767 - accuracy: 0.9753 - 1s/epoch - 982us/step
Epoch 49/600
1268/1268 - 1s - loss: 0.0764 - accuracy: 0.9752 - 1s/epoch - 981us/step
Epoch 50/600
1268/1268 - 1s - loss: 0.0756 - accuracy: 0.9752 - 1s/epoch - 966us/step
Epoch 51/600
1268/1268 - 1s - loss: 0.0755 - accuracy: 0.9759 - 1s/epoch - 978us/step
Epoch 52/600
1268/1268 - 1s - loss: 0.0752 - accuracy: 0.9754 - 1s/epoch - 964us/step
Fnoch 53/600
1268/1268 - 1s - loss: 0.0748 - accuracy: 0.9759 - 1s/epoch - 980us/step
Epoch 54/600
1268/1268 - 1s - loss: 0.0742 - accuracy: 0.9758 - 1s/epoch - 961us/step
Epoch 55/600
1268/1268 - 1s - loss: 0.0737 - accuracy: 0.9764 - 1s/epoch - 1ms/step
Epoch 56/600
1268/1268 - 1s - loss: 0.0736 - accuracy: 0.9760 - 1s/epoch - 990us/step
Epoch 57/600
1268/1268 - 1s - loss: 0.0730 - accuracy: 0.9766 - 1s/epoch - 987us/step
Epoch 58/600
1268/1268 - 1s - loss: 0.0723 - accuracy: 0.9767 - 1s/epoch - 965us/step
Epoch 59/600
1268/1268 - 1s - loss: 0.0726 - accuracy: 0.9765 - 1s/epoch - 971us/step
Epoch 60/600
1268/1268 - 1s - loss: 0.0723 - accuracy: 0.9765 - 1s/epoch - 995us/step
Epoch 61/600
1268/1268 - 1s - loss: 0.0720 - accuracy: 0.9768 - 1s/epoch - 960us/step
Epoch 62/600
1268/1268 - 1s - loss: 0.0718 - accuracy: 0.9765 - 1s/epoch - 979us/step
Epoch 63/600
1268/1268 - 1s - loss: 0.0709 - accuracy: 0.9772 - 1s/epoch - 965us/step
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Epoch 64/600
1268/1268 - 1s - loss: 0.0712 - accuracy: 0.9770 - 1s/epoch - 985us/step
Epoch 65/600
1268/1268 - 1s - loss: 0.0703 - accuracy: 0.9773 - 1s/epoch - 972us/step
Epoch 66/600
1268/1268 - 1s - loss: 0.0706 - accuracy: 0.9772 - 1s/epoch - 962us/step
Epoch 67/600
1268/1268 - 1s - loss: 0.0700 - accuracy: 0.9774 - 1s/epoch - 977us/step
Epoch 68/600
1268/1268 - 1s - loss: 0.0695 - accuracy: 0.9775 - 1s/epoch - 951us/step
Epoch 69/600
1268/1268 - 1s - loss: 0.0701 - accuracy: 0.9773 - 1s/epoch - 978us/step
Epoch 70/600
1268/1268 - 1s - loss: 0.0694 - accuracy: 0.9778 - 1s/epoch - 966us/step
Epoch 71/600
1268/1268 - 1s - loss: 0.0687 - accuracy: 0.9780 - 1s/epoch - 958us/step
Epoch 72/600
1268/1268 - 1s - loss: 0.0689 - accuracy: 0.9776 - 1s/epoch - 981us/step
Epoch 73/600
1268/1268 - 1s - loss: 0.0686 - accuracy: 0.9780 - 1s/epoch - 980us/step
Epoch 74/600
1268/1268 - 1s - loss: 0.0678 - accuracy: 0.9784 - 1s/epoch - 962us/step
Epoch 75/600
1268/1268 - 1s - loss: 0.0682 - accuracy: 0.9783 - 1s/epoch - 964us/step
Epoch 76/600
1268/1268 - 1s - loss: 0.0677 - accuracy: 0.9785 - 1s/epoch - 963us/step
Epoch 77/600
1268/1268 - 1s - loss: 0.0675 - accuracy: 0.9779 - 1s/epoch - 973us/step
Epoch 78/600
1268/1268 - 1s - loss: 0.0678 - accuracy: 0.9782 - 1s/epoch - 968us/step
Epoch 79/600
1268/1268 - 1s - loss: 0.0671 - accuracy: 0.9785 - 1s/epoch - 980us/step
Epoch 80/600
1268/1268 - 1s - loss: 0.0668 - accuracy: 0.9785 - 1s/epoch - 964us/step
Epoch 81/600
1268/1268 - 1s - loss: 0.0670 - accuracy: 0.9782 - 1s/epoch - 976us/step
Epoch 82/600
1268/1268 - 1s - loss: 0.0660 - accuracy: 0.9788 - 1s/epoch - 972us/step
Epoch 83/600
1268/1268 - 1s - loss: 0.0660 - accuracy: 0.9786 - 1s/epoch - 974us/step
Epoch 84/600
1268/1268 - 1s - loss: 0.0661 - accuracy: 0.9786 - 1s/epoch - 965us/step
Epoch 85/600
1268/1268 - 1s - loss: 0.0657 - accuracy: 0.9790 - 1s/epoch - 978us/step
Epoch 86/600
1268/1268 - 1s - loss: 0.0655 - accuracy: 0.9787 - 1s/epoch - 965us/step
Epoch 87/600
1268/1268 - 1s - loss: 0.0650 - accuracy: 0.9791 - 1s/epoch - 982us/step
Epoch 88/600
1268/1268 - 1s - loss: 0.0650 - accuracy: 0.9788 - 1s/epoch - 970us/step
Epoch 89/600
1268/1268 - 1s - loss: 0.0647 - accuracy: 0.9787 - 1s/epoch - 980us/step
Epoch 90/600
1268/1268 - 1s - loss: 0.0648 - accuracy: 0.9792 - 1s/epoch - 964us/step
Epoch 91/600
1268/1268 - 1s - loss: 0.0648 - accuracy: 0.9791 - 1s/epoch - 984us/step
Epoch 92/600
1268/1268 - 1s - loss: 0.0644 - accuracy: 0.9792 - 1s/epoch - 965us/step
Epoch 93/600
1268/1268 - 1s - loss: 0.0641 - accuracy: 0.9794 - 1s/epoch - 961us/step
Fnoch 94/600
1268/1268 - 1s - loss: 0.0637 - accuracy: 0.9794 - 1s/epoch - 987us/step
Epoch 95/600
1268/1268 - 1s - loss: 0.0636 - accuracy: 0.9795 - 1s/epoch - 960us/step
Epoch 96/600
1268/1268 - 1s - loss: 0.0634 - accuracy: 0.9793 - 1s/epoch - 976us/step
Epoch 97/600
1268/1268 - 1s - loss: 0.0632 - accuracy: 0.9794 - 1s/epoch - 957us/step
Epoch 98/600
1268/1268 - 1s - loss: 0.0630 - accuracy: 0.9791 - 1s/epoch - 976us/step
Epoch 99/600
1268/1268 - 1s - loss: 0.0628 - accuracy: 0.9793 - 1s/epoch - 962us/step
Epoch 100/600
1268/1268 - 1s - loss: 0.0632 - accuracy: 0.9794 - 1s/epoch - 976us/step
Epoch 101/600
1268/1268 - 1s - loss: 0.0621 - accuracy: 0.9798 - 1s/epoch - 959us/step
Epoch 102/600
1268/1268 - 1s - loss: 0.0624 - accuracy: 0.9798 - 1s/epoch - 962us/step
Epoch 103/600
1268/1268 - 1s - loss: 0.0622 - accuracy: 0.9799 - 1s/epoch - 985us/step
Epoch 104/600
1268/1268 - 1s - loss: 0.0621 - accuracy: 0.9798 - 1s/epoch - 959us/step
Epoch 105/600
1268/1268 - 1s - loss: 0.0619 - accuracy: 0.9797 - 1s/epoch - 973us/step
Epoch 106/600
1268/1268 - 1s - loss: 0.0620 - accuracy: 0.9800 - 1s/epoch - 982us/step
Epoch 107/600
1268/1268 - 1s - loss: 0.0612 - accuracy: 0.9801 - 1s/epoch - 961us/step
Epoch 108/600
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1268/1268 - 1s - loss: 0.0616 - accuracy: 0.9801 - 1s/epoch - 977us/step
Epoch 109/600
1268/1268 - 1s - loss: 0.0613 - accuracy: 0.9799 - 1s/epoch - 1ms/step
Epoch 110/600
1268/1268 - 1s - loss: 0.0609 - accuracy: 0.9805 - 1s/epoch - 973us/step
Epoch 111/600
1268/1268 - 1s - loss: 0.0611 - accuracy: 0.9802 - 1s/epoch - 979us/step
Epoch 112/600
1268/1268 - 1s - loss: 0.0604 - accuracy: 0.9802 - 1s/epoch - 984us/step
Epoch 113/600
1268/1268 - 1s - loss: 0.0601 - accuracy: 0.9803 - 1s/epoch - 963us/step
Epoch 114/600
1268/1268 - 1s - loss: 0.0605 - accuracy: 0.9805 - 1s/epoch - 967us/step
Epoch 115/600
1268/1268 - 1s - loss: 0.0603 - accuracy: 0.9802 - 1s/epoch - 956us/step
Epoch 116/600
1268/1268 - 1s - loss: 0.0603 - accuracy: 0.9803 - 1s/epoch - 973us/step
Epoch 117/600
1268/1268 - 1s - loss: 0.0599 - accuracy: 0.9808 - 1s/epoch - 959us/step
Epoch 118/600
1268/1268 - 1s - loss: 0.0596 - accuracy: 0.9807 - 1s/epoch - 975us/step
Epoch 119/600
1268/1268 - 1s - loss: 0.0599 - accuracy: 0.9803 - 1s/epoch - 960us/step
Epoch 120/600
1268/1268 - 1s - loss: 0.0596 - accuracy: 0.9806 - 1s/epoch - 980us/step
Epoch 121/600
1268/1268 - 1s - loss: 0.0592 - accuracy: 0.9807 - 1s/epoch - 964us/step
Epoch 122/600
1268/1268 - 1s - loss: 0.0598 - accuracy: 0.9808 - 1s/epoch - 977us/step
Epoch 123/600
1268/1268 - 1s - loss: 0.0589 - accuracy: 0.9807 - 1s/epoch - 963us/step
Epoch 124/600
1268/1268 - 1s - loss: 0.0585 - accuracy: 0.9811 - 1s/epoch - 978us/step
Epoch 125/600
1268/1268 - 1s - loss: 0.0593 - accuracy: 0.9807 - 1s/epoch - 958us/step
Epoch 126/600
1268/1268 - 1s - loss: 0.0589 - accuracy: 0.9809 - 1s/epoch - 975us/step
Epoch 127/600
1268/1268 - 1s - loss: 0.0584 - accuracy: 0.9809 - 1s/epoch - 958us/step
Epoch 128/600
1268/1268 - 1s - loss: 0.0581 - accuracy: 0.9809 - 1s/epoch - 976us/step
Epoch 129/600
1268/1268 - 1s - loss: 0.0587 - accuracy: 0.9808 - 1s/epoch - 953us/step
Epoch 130/600
1268/1268 - 1s - loss: 0.0580 - accuracy: 0.9811 - 1s/epoch - 960us/step
Epoch 131/600
1268/1268 - 1s - loss: 0.0582 - accuracy: 0.9810 - 1s/epoch - 979us/step
Epoch 132/600
1268/1268 - 1s - loss: 0.0583 - accuracy: 0.9811 - 1s/epoch - 976us/step
Epoch 133/600
1268/1268 - 1s - loss: 0.0577 - accuracy: 0.9811 - 1s/epoch - 958us/step
Epoch 134/600
1268/1268 - 1s - loss: 0.0577 - accuracy: 0.9813 - 1s/epoch - 974us/step
Epoch 135/600
1268/1268 - 1s - loss: 0.0574 - accuracy: 0.9814 - 1s/epoch - 963us/step
Epoch 136/600
1268/1268 - 1s - loss: 0.0569 - accuracy: 0.9813 - 1s/epoch - 982us/step
Epoch 137/600
1268/1268 - 1s - loss: 0.0577 - accuracy: 0.9813 - 1s/epoch - 962us/step
Epoch 138/600
1268/1268 - 1s - loss: 0.0577 - accuracy: 0.9809 - 1s/epoch - 974us/step
Epoch 139/600
1268/1268 - 1s - loss: 0.0570 - accuracy: 0.9813 - 1s/epoch - 958us/step
Epoch 140/600
1268/1268 - 1s - loss: 0.0572 - accuracy: 0.9813 - 1s/epoch - 960us/step
Epoch 141/600
1268/1268 - 1s - loss: 0.0567 - accuracy: 0.9812 - 1s/epoch - 983us/step
Epoch 142/600
1268/1268 - 1s - loss: 0.0571 - accuracy: 0.9815 - 1s/epoch - 957us/step
Epoch 143/600
1268/1268 - 1s - loss: 0.0567 - accuracy: 0.9814 - 1s/epoch - 975us/step
Epoch 144/600
1268/1268 - 1s - loss: 0.0572 - accuracy: 0.9812 - 1s/epoch - 974us/step
Epoch 145/600
1268/1268 - 1s - loss: 0.0565 - accuracy: 0.9815 - 1s/epoch - 982us/step
Epoch 146/600
1268/1268 - 1s - loss: 0.0568 - accuracy: 0.9814 - 1s/epoch - 959us/step
Epoch 147/600
1268/1268 - 1s - loss: 0.0560 - accuracy: 0.9817 - 1s/epoch - 982us/step
Epoch 148/600
1268/1268 - 1s - loss: 0.0561 - accuracy: 0.9814 - 1s/epoch - 960us/step
Epoch 149/600
1268/1268 - 1s - loss: 0.0562 - accuracy: 0.9813 - 1s/epoch - 959us/step
Epoch 150/600
1268/1268 - 1s - loss: 0.0559 - accuracy: 0.9816 - 1s/epoch - 979us/step
Epoch 151/600
1268/1268 - 1s - loss: 0.0561 - accuracy: 0.9817 - 1s/epoch - 977us/step
Epoch 152/600
1268/1268 - 1s - loss: 0.0554 - accuracy: 0.9819 - 1s/epoch - 959us/step
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Epoch 153/600
1268/1268 - 1s - loss: 0.0556 - accuracy: 0.9819 - 1s/epoch - 992us/step
Epoch 154/600
1268/1268 - 1s - loss: 0.0557 - accuracy: 0.9818 - 1s/epoch - 961us/step
Epoch 155/600
1268/1268 - 1s - loss: 0.0562 - accuracy: 0.9815 - 1s/epoch - 979us/step
Epoch 156/600
1268/1268 - 1s - loss: 0.0552 - accuracy: 0.9818 - 1s/epoch - 961us/step
Epoch 157/600
1268/1268 - 1s - loss: 0.0549 - accuracy: 0.9817 - 1s/epoch - 978us/step
Epoch 158/600
1268/1268 - 1s - loss: 0.0556 - accuracy: 0.9819 - 1s/epoch - 974us/step
Epoch 159/600
1268/1268 - 1s - loss: 0.0551 - accuracy: 0.9817 - 1s/epoch - 980us/step
Epoch 160/600
1268/1268 - 1s - loss: 0.0554 - accuracy: 0.9818 - 1s/epoch - 965us/step
Epoch 161/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9819 - 1s/epoch - 986us/step
Epoch 162/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9822 - 1s/epoch - 963us/step
Epoch 163/600
1268/1268 - 1s - loss: 0.0549 - accuracy: 0.9819 - 1s/epoch - 981us/step
Epoch 164/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9822 - 1s/epoch - 963us/step
Epoch 165/600
1268/1268 - 1s - loss: 0.0548 - accuracy: 0.9819 - 1s/epoch - 959us/step
Epoch 166/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9819 - 1s/epoch - 987us/step
Epoch 167/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9817 - 1s/epoch - 974us/step
Epoch 168/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9823 - 1s/epoch - 966us/step
Epoch 169/600
1268/1268 - 1s - loss: 0.0539 - accuracy: 0.9823 - 1s/epoch - 997us/step
Epoch 170/600
1268/1268 - 1s - loss: 0.0538 - accuracy: 0.9821 - 1s/epoch - 970us/step
Epoch 171/600
1268/1268 - 1s - loss: 0.0537 - accuracy: 0.9824 - 1s/epoch - 978us/step
Epoch 172/600
1268/1268 - 1s - loss: 0.0540 - accuracy: 0.9824 - 1s/epoch - 963us/step
Epoch 173/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9822 - 1s/epoch - 973us/step
Epoch 174/600
1268/1268 - 1s - loss: 0.0538 - accuracy: 0.9821 - 1s/epoch - 963us/step
Epoch 175/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9818 - 1s/epoch - 979us/step
Epoch 176/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9819 - 1s/epoch - 963us/step
Epoch 177/600
1268/1268 - 1s - loss: 0.0535 - accuracy: 0.9822 - 1s/epoch - 960us/step
Epoch 178/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9826 - 1s/epoch - 979us/step
Epoch 179/600
1268/1268 - 1s - loss: 0.0537 - accuracy: 0.9824 - 1s/epoch - 979us/step
Epoch 180/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9824 - 1s/epoch - 962us/step
Epoch 181/600
1268/1268 - 1s - loss: 0.0532 - accuracy: 0.9824 - 1s/epoch - 973us/step
Epoch 182/600
1268/1268 - 1s - loss: 0.0531 - accuracy: 0.9823 - 1s/epoch - 959us/step
Epoch 183/600
1268/1268 - 1s - loss: 0.0534 - accuracy: 0.9822 - 1s/epoch - 980us/step
Epoch 184/600
1268/1268 - 1s - loss: 0.0532 - accuracy: 0.9825 - 1s/epoch - 962us/step
Epoch 185/600
1268/1268 - 1s - loss: 0.0531 - accuracy: 0.9827 - 1s/epoch - 983us/step
Epoch 186/600
1268/1268 - 1s - loss: 0.0532 - accuracy: 0.9822 - 1s/epoch - 963us/step
Epoch 187/600
1268/1268 - 1s - loss: 0.0522 - accuracy: 0.9830 - 1s/epoch - 980us/step
Epoch 188/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9824 - 1s/epoch - 966us/step
Epoch 189/600
1268/1268 - 1s - loss: 0.0525 - accuracy: 0.9826 - 1s/epoch - 964us/step
Epoch 190/600
1268/1268 - 1s - loss: 0.0524 - accuracy: 0.9826 - 1s/epoch - 991us/step
Epoch 191/600
1268/1268 - 1s - loss: 0.0521 - accuracy: 0.9827 - 1s/epoch - 980us/step
Epoch 192/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9822 - 1s/epoch - 961us/step
Epoch 193/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9826 - 1s/epoch - 980us/step
Epoch 194/600
1268/1268 - 1s - loss: 0.0523 - accuracy: 0.9828 - 1s/epoch - 962us/step
Epoch 195/600
1268/1268 - 1s - loss: 0.0521 - accuracy: 0.9829 - 1s/epoch - 984us/step
Epoch 196/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9828 - 1s/epoch - 1ms/step
Epoch 197/600
```

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1268/1268 - 1s - loss: 0.0526 - accuracy: 0.9826 - 1s/epoch - 960us/step
Epoch 198/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9830 - 1s/epoch - 978us/step
Epoch 199/600
1268/1268 - 1s - loss: 0.0514 - accuracy: 0.9831 - 1s/epoch - 987us/step
Epoch 200/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9828 - 1s/epoch - 961us/step
Epoch 201/600
1268/1268 - 1s - loss: 0.0515 - accuracy: 0.9827 - 1s/epoch - 962us/step
Epoch 202/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9832 - 1s/epoch - 974us/step
Epoch 203/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9829 - 1s/epoch - 981us/step
Epoch 204/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9829 - 1s/epoch - 965us/step
Epoch 205/600
1268/1268 - 1s - loss: 0.0512 - accuracy: 0.9831 - 1s/epoch - 961us/step
Epoch 206/600
1268/1268 - 1s - loss: 0.0515 - accuracy: 0.9827 - 1s/epoch - 984us/step
Epoch 207/600
1268/1268 - 1s - loss: 0.0512 - accuracy: 0.9834 - 1s/epoch - 990us/step
Epoch 208/600
1268/1268 - 1s - loss: 0.0514 - accuracy: 0.9830 - 1s/epoch - 959us/step
Epoch 209/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9833 - 1s/epoch - 977us/step
Epoch 210/600
1268/1268 - 1s - loss: 0.0513 - accuracy: 0.9832 - 1s/epoch - 957us/step
Epoch 211/600
1268/1268 - 1s - loss: 0.0515 - accuracy: 0.9831 - 1s/epoch - 970us/step
Epoch 212/600
1268/1268 - 1s - loss: 0.0510 - accuracy: 0.9830 - 1s/epoch - 968us/step
Epoch 213/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9831 - 1s/epoch - 982us/step
Epoch 214/600
1268/1268 - 1s - loss: 0.0510 - accuracy: 0.9830 - 1s/epoch - 962us/step
Epoch 215/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9832 - 1s/epoch - 958us/step
Epoch 216/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9827 - 1s/epoch - 976us/step
Epoch 217/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9835 - 1s/epoch - 975us/step
Epoch 218/600
1268/1268 - 1s - loss: 0.0505 - accuracy: 0.9830 - 1s/epoch - 982us/step
Epoch 219/600
1268/1268 - 1s - loss: 0.0504 - accuracy: 0.9830 - 1s/epoch - 965us/step
Epoch 220/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9832 - 1s/epoch - 980us/step
Epoch 221/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9835 - 1s/epoch - 965us/step
Epoch 222/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9835 - 1s/epoch - 980us/step
Epoch 223/600
1268/1268 - 1s - loss: 0.0506 - accuracy: 0.9834 - 1s/epoch - 963us/step
Epoch 224/600
1268/1268 - 1s - loss: 0.0505 - accuracy: 0.9830 - 1s/epoch - 985us/step
Epoch 225/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9833 - 1s/epoch - 965us/step
Epoch 226/600
1268/1268 - 1s - loss: 0.0499 - accuracy: 0.9834 - 1s/epoch - 981us/step
Epoch 227/600
1268/1268 - 1s - loss: 0.0506 - accuracy: 0.9833 - 1s/epoch - 960us/step
Epoch 228/600
1268/1268 - 1s - loss: 0.0494 - accuracy: 0.9839 - 1s/epoch - 981us/step
Epoch 229/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9835 - 1s/epoch - 957us/step
Epoch 230/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9836 - 1s/epoch - 967us/step
Fnoch 231/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9835 - 1s/epoch - 965us/step
Epoch 232/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9833 - 1s/epoch - 990us/step
Epoch 233/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9832 - 1s/epoch - 960us/step
Epoch 234/600
1268/1268 - 1s - loss: 0.0494 - accuracy: 0.9834 - 1s/epoch - 979us/step
Epoch 235/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9839 - 1s/epoch - 961us/step
Epoch 236/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9838 - 1s/epoch - 979us/step
Epoch 237/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9837 - 1s/epoch - 956us/step
Epoch 238/600
1268/1268 - 1s - loss: 0.0494 - accuracy: 0.9835 - 1s/epoch - 980us/step
Epoch 239/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9834 - 1s/epoch - 963us/step
Epoch 240/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9838 - 1s/epoch - 978us/step
Epoch 241/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9842 - 1s/epoch - 957us/step
```

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Epoch 242/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9840 - 1s/epoch - 968us/step
Epoch 243/600
1268/1268 - 1s - loss: 0.0488 - accuracy: 0.9841 - 1s/epoch - 972us/step
Epoch 244/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9837 - 1s/epoch - 972us/step
Epoch 245/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9840 - 1s/epoch - 961us/step
Epoch 246/600
1268/1268 - 1s - loss: 0.0485 - accuracy: 0.9837 - 1s/epoch - 978us/step
Epoch 247/600
1268/1268 - 1s - loss: 0.0488 - accuracy: 0.9831 - 1s/epoch - 972us/step
Epoch 248/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9839 - 1s/epoch - 980us/step
Epoch 249/600
1268/1268 - 1s - loss: 0.0487 - accuracy: 0.9839 - 1s/epoch - 957us/step
Epoch 250/600
1268/1268 - 1s - loss: 0.0482 - accuracy: 0.9838 - 1s/epoch - 977us/step
Epoch 251/600
1268/1268 - 1s - loss: 0.0482 - accuracy: 0.9841 - 1s/epoch - 962us/step
Epoch 252/600
1268/1268 - 1s - loss: 0.0484 - accuracy: 0.9841 - 1s/epoch - 976us/step
Epoch 253/600
1268/1268 - 1s - loss: 0.0485 - accuracy: 0.9837 - 1s/epoch - 959us/step
Epoch 254/600
1268/1268 - 1s - loss: 0.0485 - accuracy: 0.9836 - 1s/epoch - 978us/step
Epoch 255/600
1268/1268 - 1s - loss: 0.0487 - accuracy: 0.9839 - 1s/epoch - 963us/step
Epoch 256/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9842 - 1s/epoch - 991us/step
Epoch 257/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9837 - 1s/epoch - 961us/step
Epoch 258/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9842 - 1s/epoch - 990us/step
Epoch 259/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9839 - 1s/epoch - 958us/step
Epoch 260/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9841 - 1s/epoch - 980us/step
Epoch 261/600
1268/1268 - 1s - loss: 0.0483 - accuracy: 0.9840 - 1s/epoch - 963us/step
Epoch 262/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9840 - 1s/epoch - 978us/step
Epoch 263/600
1268/1268 - 1s - loss: 0.0479 - accuracy: 0.9838 - 1s/epoch - 964us/step
Epoch 264/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9839 - 1s/epoch - 979us/step
Epoch 265/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9841 - 1s/epoch - 961us/step
Epoch 266/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9840 - 1s/epoch - 976us/step
Epoch 267/600
1268/1268 - 1s - loss: 0.0476 - accuracy: 0.9841 - 1s/epoch - 959us/step
Epoch 268/600
1268/1268 - 1s - loss: 0.0473 - accuracy: 0.9841 - 1s/epoch - 971us/step
Epoch 269/600
1268/1268 - 1s - loss: 0.0482 - accuracy: 0.9838 - 1s/epoch - 957us/step
Epoch 270/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9842 - 1s/epoch - 975us/step
Epoch 271/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9841 - 1s/epoch - 966us/step
Epoch 272/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9839 - 1s/epoch - 974us/step
Epoch 273/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9844 - 1s/epoch - 961us/step
Epoch 274/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9844 - 1s/epoch - 977us/step
Epoch 275/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9842 - 1s/epoch - 963us/step
Epoch 276/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9840 - 1s/epoch - 977us/step
Epoch 277/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9843 - 1s/epoch - 960us/step
Epoch 278/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9844 - 1s/epoch - 984us/step
Epoch 279/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9840 - 1s/epoch - 961us/step
Epoch 280/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9844 - 1s/epoch - 986us/step
Epoch 281/600
1268/1268 - 1s - loss: 0.0468 - accuracy: 0.9845 - 1s/epoch - 959us/step
Epoch 282/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9839 - 1s/epoch - 976us/step
Epoch 283/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9845 - 1s/epoch - 961us/step
Epoch 284/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9845 - 1s/epoch - 974us/step
Epoch 285/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9845 - 1s/epoch - 963us/step
Epoch 286/600
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1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9847 - 1s/epoch - 980us/step
Epoch 287/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9844 - 1s/epoch - 963us/step
Epoch 288/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9841 - 1s/epoch - 967us/step
Epoch 289/600
1268/1268 - 1s - loss: 0.0462 - accuracy: 0.9847 - 1s/epoch - 982us/step
Epoch 290/600
1268/1268 - 1s - loss: 0.0462 - accuracy: 0.9845 - 1s/epoch - 958us/step
Epoch 291/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9845 - 1s/epoch - 981us/step
Epoch 292/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9848 - 1s/epoch - 961us/step
Epoch 293/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9844 - 1s/epoch - 977us/step
Epoch 294/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9846 - 1s/epoch - 962us/step
Epoch 295/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9846 - 1s/epoch - 978us/step
Epoch 296/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9846 - 1s/epoch - 963us/step
Epoch 297/600
1268/1268 - 1s - loss: 0.0462 - accuracy: 0.9841 - 1s/epoch - 976us/step
Epoch 298/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9846 - 1s/epoch - 960us/step
Epoch 299/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9846 - 1s/epoch - 954us/step
Epoch 300/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9848 - 1s/epoch - 976us/step
Epoch 301/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9848 - 1s/epoch - 974us/step
Epoch 302/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9849 - 1s/epoch - 957us/step
Epoch 303/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9849 - 1s/epoch - 982us/step
Epoch 304/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9845 - 1s/epoch - 969us/step
Epoch 305/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9850 - 1s/epoch - 991us/step
Epoch 306/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9847 - 1s/epoch - 961us/step
Epoch 307/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9846 - 1s/epoch - 991us/step
Epoch 308/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9849 - 1s/epoch - 971us/step
Epoch 309/600
1268/1268 - 1s - loss: 0.0462 - accuracy: 0.9844 - 1s/epoch - 977us/step
Epoch 310/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9847 - 1s/epoch - 961us/step
Epoch 311/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9845 - 1s/epoch - 977us/step
Epoch 312/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9843 - 1s/epoch - 972us/step
Epoch 313/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9847 - 1s/epoch - 985us/step
Epoch 314/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9854 - 1s/epoch - 961us/step
Epoch 315/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9843 - 1s/epoch - 1ms/step
Epoch 316/600
1268/1268 - 1s - loss: 0.0460 - accuracy: 0.9845 - 1s/epoch - 959us/step
Epoch 317/600
1268/1268 - 1s - loss: 0.0449 - accuracy: 0.9847 - 1s/epoch - 992us/step
Epoch 318/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9848 - 1s/epoch - 960us/step
Epoch 319/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9848 - 1s/epoch - 969us/step
Fnoch 320/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9848 - 1s/epoch - 961us/step
Epoch 321/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9846 - 1s/epoch - 983us/step
Epoch 322/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9847 - 1s/epoch - 962us/step
Epoch 323/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9849 - 1s/epoch - 980us/step
Epoch 324/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9850 - 1s/epoch - 961us/step
Epoch 325/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9846 - 1s/epoch - 984us/step
Epoch 326/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9847 - 1s/epoch - 961us/step
Epoch 327/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9853 - 1s/epoch - 975us/step
Epoch 328/600
1268/1268 - 1s - loss: 0.0449 - accuracy: 0.9847 - 1s/epoch - 963us/step
Epoch 329/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9847 - 1s/epoch - 976us/step
Epoch 330/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9847 - 1s/epoch - 959us/step
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Epoch 331/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9850 - 1s/epoch - 979us/step
Epoch 332/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9849 - 1s/epoch - 959us/step
Epoch 333/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9849 - 1s/epoch - 985us/step
Epoch 334/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9850 - 1s/epoch - 965us/step
Epoch 335/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9850 - 1s/epoch - 975us/step
Epoch 336/600
1268/1268 - 1s - loss: 0.0448 - accuracy: 0.9847 - 1s/epoch - 969us/step
Epoch 337/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9850 - 1s/epoch - 976us/step
Epoch 338/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9849 - 1s/epoch - 964us/step
Epoch 339/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9851 - 1s/epoch - 979us/step
Epoch 340/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9850 - 1s/epoch - 958us/step
Epoch 341/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9853 - 1s/epoch - 970us/step
Epoch 342/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9849 - 1s/epoch - 986us/step
Epoch 343/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 344/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9849 - 1s/epoch - 992us/step
Epoch 345/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 346/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9849 - 1s/epoch - 974us/step
Epoch 347/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9852 - 1s/epoch - 982us/step
Epoch 348/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9847 - 1s/epoch - 962us/step
Epoch 349/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9851 - 1s/epoch - 990us/step
Epoch 350/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9852 - 1s/epoch - 959us/step
Epoch 351/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9851 - 1s/epoch - 982us/step
Epoch 352/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9856 - 1s/epoch - 962us/step
Epoch 353/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9855 - 1s/epoch - 984us/step
Epoch 354/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9847 - 1s/epoch - 972us/step
Epoch 355/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9850 - 1s/epoch - 992us/step
Epoch 356/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9848 - 1s/epoch - 964us/step
Epoch 357/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9853 - 1s/epoch - 977us/step
Epoch 358/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 359/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9849 - 1s/epoch - 980us/step
Epoch 360/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9856 - 1s/epoch - 964us/step
Epoch 361/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9850 - 1s/epoch - 984us/step
Epoch 362/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9855 - 1s/epoch - 965us/step
Epoch 363/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9858 - 1s/epoch - 978us/step
Epoch 364/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9851 - 1s/epoch - 963us/step
Epoch 365/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9852 - 1s/epoch - 978us/step
Epoch 366/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9853 - 1s/epoch - 965us/step
Epoch 367/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9852 - 1s/epoch - 972us/step
Epoch 368/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9853 - 1s/epoch - 954us/step
Epoch 369/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9854 - 1s/epoch - 981us/step
Epoch 370/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9855 - 1s/epoch - 955us/step
Epoch 371/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9852 - 1s/epoch - 978us/step
Epoch 372/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9853 - 1s/epoch - 966us/step
Epoch 373/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9854 - 1s/epoch - 977us/step
Epoch 374/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9851 - 1s/epoch - 967us/step
Epoch 375/600
```

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1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9854 - 1s/epoch - 972us/step
Epoch 376/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9854 - 1s/epoch - 962us/step
Epoch 377/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9856 - 1s/epoch - 980us/step
Epoch 378/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9855 - 1s/epoch - 962us/step
Epoch 379/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9853 - 1s/epoch - 972us/step
Epoch 380/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9854 - 1s/epoch - 959us/step
Epoch 381/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9854 - 1s/epoch - 978us/step
Epoch 382/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9858 - 1s/epoch - 951us/step
Epoch 383/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9854 - 1s/epoch - 978us/step
Epoch 384/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9853 - 1s/epoch - 961us/step
Epoch 385/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9856 - 1s/epoch - 964us/step
Epoch 386/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9851 - 1s/epoch - 974us/step
Epoch 387/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9854 - 1s/epoch - 961us/step
Epoch 388/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9856 - 1s/epoch - 982us/step
Epoch 389/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9854 - 1s/epoch - 959us/step
Epoch 390/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9854 - 1s/epoch - 978us/step
Epoch 391/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9858 - 1s/epoch - 960us/step
Epoch 392/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9851 - 1s/epoch - 978us/step
Epoch 393/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9858 - 1s/epoch - 959us/step
Epoch 394/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9854 - 1s/epoch - 956us/step
Epoch 395/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9859 - 1s/epoch - 973us/step
Epoch 396/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9858 - 1s/epoch - 971us/step
Epoch 397/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9855 - 1s/epoch - 953us/step
Epoch 398/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9853 - 1s/epoch - 969us/step
Epoch 399/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9856 - 1s/epoch - 959us/step
Epoch 400/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9853 - 1s/epoch - 980us/step
Epoch 401/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9857 - 1s/epoch - 967us/step
Epoch 402/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9855 - 1s/epoch - 980us/step
Epoch 403/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9857 - 1s/epoch - 971us/step
Epoch 404/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9857 - 1s/epoch - 984us/step
Epoch 405/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9858 - 1s/epoch - 964us/step
Epoch 406/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9860 - 1s/epoch - 979us/step
Epoch 407/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9857 - 1s/epoch - 961us/step
Epoch 408/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9856 - 1s/epoch - 979us/step
Epoch 409/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9860 - 1s/epoch - 966us/step
Epoch 410/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9857 - 1s/epoch - 985us/step
Epoch 411/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9857 - 1s/epoch - 961us/step
Epoch 412/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9856 - 1s/epoch - 972us/step
Epoch 413/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9858 - 1s/epoch - 961us/step
Epoch 414/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9857 - 1s/epoch - 982us/step
Epoch 415/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9856 - 1s/epoch - 959us/step
Epoch 416/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9857 - 1s/epoch - 976us/step
Epoch 417/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9860 - 1s/epoch - 961us/step
Epoch 418/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9860 - 1s/epoch - 985us/step
Epoch 419/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9859 - 1s/epoch - 955us/step
```

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Epoch 420/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9853 - 1s/epoch - 982us/step
Epoch 421/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9863 - 1s/epoch - 961us/step
Epoch 422/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9854 - 1s/epoch - 979us/step
Epoch 423/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9862 - 1s/epoch - 956us/step
Epoch 424/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9855 - 1s/epoch - 979us/step
Epoch 425/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9861 - 1s/epoch - 958us/step
Epoch 426/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9856 - 1s/epoch - 982us/step
Epoch 427/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9863 - 1s/epoch - 961us/step
Epoch 428/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9860 - 1s/epoch - 980us/step
Epoch 429/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9860 - 1s/epoch - 960us/step
Epoch 430/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9859 - 1s/epoch - 973us/step
Epoch 431/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9862 - 1s/epoch - 964us/step
Epoch 432/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9861 - 1s/epoch - 975us/step
Epoch 433/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9859 - 1s/epoch - 958us/step
Epoch 434/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9861 - 1s/epoch - 984us/step
Epoch 435/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9854 - 1s/epoch - 963us/step
Epoch 436/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9860 - 1s/epoch - 981us/step
Epoch 437/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9856 - 1s/epoch - 966us/step
Epoch 438/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9860 - 1s/epoch - 979us/step
Epoch 439/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9861 - 1s/epoch - 961us/step
Epoch 440/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9859 - 1s/epoch - 978us/step
Epoch 441/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9859 - 1s/epoch - 963us/step
Epoch 442/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9858 - 1s/epoch - 983us/step
Epoch 443/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9860 - 1s/epoch - 964us/step
Epoch 444/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9862 - 1s/epoch - 985us/step
Epoch 445/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9854 - 1s/epoch - 960us/step
Epoch 446/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9861 - 1s/epoch - 978us/step
Epoch 447/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9861 - 1s/epoch - 965us/step
Epoch 448/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Epoch 449/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9858 - 1s/epoch - 965us/step
Epoch 450/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9860 - 1s/epoch - 967us/step
Epoch 451/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9860 - 1s/epoch - 988us/step
Epoch 452/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9864 - 1s/epoch - 981us/step
Epoch 453/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9858 - 1s/epoch - 961us/step
Epoch 454/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9862 - 1s/epoch - 980us/step
Epoch 455/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9863 - 1s/epoch - 963us/step
Epoch 456/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9858 - 1s/epoch - 978us/step
Epoch 457/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9862 - 1s/epoch - 958us/step
Epoch 458/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9863 - 1s/epoch - 980us/step
Epoch 459/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9859 - 1s/epoch - 958us/step
Epoch 460/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9863 - 1s/epoch - 972us/step
Epoch 461/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9861 - 1s/epoch - 973us/step
Epoch 462/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9865 - 1s/epoch - 974us/step
Epoch 463/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9862 - 1s/epoch - 961us/step
Epoch 464/600
```

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1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9860 - 1s/epoch - 986us/step
Epoch 465/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9859 - 1s/epoch - 955us/step
Epoch 466/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9863 - 1s/epoch - 976us/step
Epoch 467/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9864 - 1s/epoch - 965us/step
Epoch 468/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9859 - 1s/epoch - 981us/step
Epoch 469/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9862 - 1s/epoch - 960us/step
Epoch 470/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9860 - 1s/epoch - 956us/step
Epoch 471/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9862 - 1s/epoch - 973us/step
Epoch 472/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9863 - 1s/epoch - 978us/step
Epoch 473/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9867 - 1s/epoch - 956us/step
Epoch 474/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9863 - 1s/epoch - 980us/step
Epoch 475/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9859 - 1s/epoch - 963us/step
Epoch 476/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9862 - 1s/epoch - 975us/step
Epoch 477/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9860 - 1s/epoch - 958us/step
Epoch 478/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9865 - 1s/epoch - 976us/step
Epoch 479/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9865 - 1s/epoch - 954us/step
Epoch 480/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9863 - 1s/epoch - 968us/step
Epoch 481/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9862 - 1s/epoch - 959us/step
Epoch 482/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9863 - 1s/epoch - 980us/step
Epoch 483/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9864 - 1s/epoch - 964us/step
Epoch 484/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9867 - 1s/epoch - 973us/step
Epoch 485/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9865 - 1s/epoch - 959us/step
Epoch 486/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9860 - 1s/epoch - 979us/step
Epoch 487/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9864 - 1s/epoch - 960us/step
Epoch 488/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 978us/step
Epoch 489/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9868 - 1s/epoch - 961us/step
Epoch 490/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9863 - 1s/epoch - 982us/step
Epoch 491/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9862 - 1s/epoch - 963us/step
Epoch 492/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9867 - 1s/epoch - 984us/step
Epoch 493/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9864 - 1s/epoch - 964us/step
Epoch 494/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9861 - 1s/epoch - 982us/step
Epoch 495/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9864 - 1s/epoch - 963us/step
Epoch 496/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9862 - 1s/epoch - 984us/step
Epoch 497/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9863 - 1s/epoch - 964us/step
Fnoch 498/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9862 - 1s/epoch - 993us/step
Epoch 499/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9864 - 1s/epoch - 964us/step
Epoch 500/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9865 - 1s/epoch - 987us/step
Epoch 501/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9865 - 1s/epoch - 971us/step
Epoch 502/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9864 - 1s/epoch - 980us/step
Epoch 503/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9866 - 1s/epoch - 961us/step
Epoch 504/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9867 - 1s/epoch - 982us/step
Epoch 505/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9864 - 1s/epoch - 963us/step
Epoch 506/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9868 - 1s/epoch - 986us/step
Epoch 507/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9867 - 1s/epoch - 971us/step
Epoch 508/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9866 - 1s/epoch - 981us/step
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Epoch 509/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9866 - 1s/epoch - 964us/step
Epoch 510/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9866 - 1s/epoch - 981us/step
Epoch 511/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9862 - 1s/epoch - 962us/step
Epoch 512/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9869 - 1s/epoch - 979us/step
Epoch 513/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9864 - 1s/epoch - 961us/step
Epoch 514/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9858 - 1s/epoch - 981us/step
Epoch 515/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9867 - 1s/epoch - 960us/step
Epoch 516/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9863 - 1s/epoch - 985us/step
Epoch 517/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9862 - 1s/epoch - 960us/step
Epoch 518/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9870 - 1s/epoch - 983us/step
Epoch 519/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9863 - 1s/epoch - 964us/step
Epoch 520/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9866 - 1s/epoch - 982us/step
Epoch 521/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9867 - 1s/epoch - 958us/step
Epoch 522/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9866 - 1s/epoch - 978us/step
Epoch 523/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9860 - 1s/epoch - 959us/step
Epoch 524/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9866 - 1s/epoch - 982us/step
Epoch 525/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 959us/step
Epoch 526/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9865 - 1s/epoch - 978us/step
Epoch 527/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9866 - 1s/epoch - 966us/step
Epoch 528/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9869 - 1s/epoch - 982us/step
Epoch 529/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9867 - 1s/epoch - 962us/step
Epoch 530/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9863 - 1s/epoch - 985us/step
Epoch 531/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9867 - 1s/epoch - 962us/step
Epoch 532/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9865 - 1s/epoch - 987us/step
Epoch 533/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9871 - 1s/epoch - 967us/step
Epoch 534/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9863 - 1s/epoch - 983us/step
Epoch 535/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9865 - 1s/epoch - 960us/step
Epoch 536/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9865 - 1s/epoch - 986us/step
Epoch 537/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9871 - 1s/epoch - 963us/step
Epoch 538/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9867 - 1s/epoch - 980us/step
Epoch 539/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9866 - 1s/epoch - 960us/step
Epoch 540/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9866 - 1s/epoch - 986us/step
Epoch 541/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9870 - 1s/epoch - 961us/step
Epoch 542/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9865 - 1s/epoch - 984us/step
Epoch 543/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9867 - 1s/epoch - 963us/step
Epoch 544/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9872 - 1s/epoch - 984us/step
Epoch 545/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9867 - 1s/epoch - 963us/step
Epoch 546/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9869 - 1s/epoch - 984us/step
Epoch 547/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9866 - 1s/epoch - 959us/step
Epoch 548/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9864 - 1s/epoch - 979us/step
Epoch 549/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9868 - 1s/epoch - 980us/step
Epoch 550/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9869 - 1s/epoch - 984us/step
Epoch 551/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9868 - 1s/epoch - 960us/step
Epoch 552/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 980us/step
Epoch 553/600
```

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1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9870 - 1s/epoch - 961us/step
Epoch 554/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9867 - 1s/epoch - 971us/step
Epoch 555/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9869 - 1s/epoch - 968us/step
Epoch 556/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9864 - 1s/epoch - 985us/step
Epoch 557/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9872 - 1s/epoch - 962us/step
Epoch 558/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 973us/step
Epoch 559/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9866 - 1s/epoch - 962us/step
Epoch 560/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9865 - 1s/epoch - 982us/step
Epoch 561/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9868 - 1s/epoch - 962us/step
Epoch 562/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9871 - 1s/epoch - 982us/step
Epoch 563/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9866 - 1s/epoch - 963us/step
Epoch 564/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9870 - 1s/epoch - 985us/step
Epoch 565/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9869 - 1s/epoch - 965us/step
Epoch 566/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9871 - 1s/epoch - 972us/step
Epoch 567/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9870 - 1s/epoch - 959us/step
Epoch 568/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9866 - 1s/epoch - 979us/step
Epoch 569/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 570/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9872 - 1s/epoch - 988us/step
Epoch 571/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9871 - 1s/epoch - 970us/step
Epoch 572/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9868 - 1s/epoch - 984us/step
Epoch 573/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9873 - 1s/epoch - 968us/step
Epoch 574/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9872 - 1s/epoch - 981us/step
Epoch 575/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9867 - 1s/epoch - 964us/step
Epoch 576/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9872 - 1s/epoch - 981us/step
Epoch 577/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9868 - 1s/epoch - 967us/step
Epoch 578/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 985us/step
Epoch 579/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9865 - 1s/epoch - 961us/step
Epoch 580/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9870 - 1s/epoch - 981us/step
Epoch 581/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9868 - 1s/epoch - 964us/step
Epoch 582/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9868 - 1s/epoch - 987us/step
Epoch 583/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9873 - 1s/epoch - 960us/step
Epoch 584/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 963us/step
Epoch 585/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9871 - 1s/epoch - 984us/step
Epoch 586/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9873 - 1s/epoch - 984us/step
Fnoch 587/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9870 - 1s/epoch - 963us/step
Epoch 588/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9870 - 1s/epoch - 975us/step
Epoch 589/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9871 - 1s/epoch - 963us/step
Epoch 590/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9867 - 1s/epoch - 979us/step
Epoch 591/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9871 - 1s/epoch - 965us/step
Epoch 592/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9868 - 1s/epoch - 984us/step
Epoch 593/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9868 - 1s/epoch - 962us/step
Epoch 594/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9873 - 1s/epoch - 981us/step
Epoch 595/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9870 - 1s/epoch - 963us/step
Epoch 596/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9872 - 1s/epoch - 983us/step
Epoch 597/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9870 - 1s/epoch - 971us/step
```

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Epoch 598/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9875 - 1s/epoch - 997us/step
Epoch 599/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9871 - 1s/epoch - 964us/step
Epoch 600/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9872 - 1s/epoch - 982us/step
990/990 [========] - 1s 660us/step
Epoch 1/600
1268/1268 - 2s - loss: 0.3680 - accuracy: 0.8315 - 2s/epoch - 1ms/step
Epoch 2/600
1268/1268 - 1s - loss: 0.2239 - accuracy: 0.9107 - 1s/epoch - 969us/step
Epoch 3/600
1268/1268 - 1s - loss: 0.1842 - accuracy: 0.9295 - 1s/epoch - 969us/step
Epoch 4/600
1268/1268 - 1s - loss: 0.1631 - accuracy: 0.9390 - 1s/epoch - 983us/step
Epoch 5/600
1268/1268 - 1s - loss: 0.1496 - accuracy: 0.9451 - 1s/epoch - 968us/step
Epoch 6/600
1268/1268 - 1s - loss: 0.1402 - accuracy: 0.9502 - 1s/epoch - 978us/step
Epoch 7/600
1268/1268 - 1s - loss: 0.1327 - accuracy: 0.9537 - 1s/epoch - 968us/step
Epoch 8/600
1268/1268 - 1s - loss: 0.1280 - accuracy: 0.9555 - 1s/epoch - 966us/step
Epoch 9/600
1268/1268 - 1s - loss: 0.1218 - accuracy: 0.9578 - 1s/epoch - 979us/step
Epoch 10/600
1268/1268 - 1s - loss: 0.1179 - accuracy: 0.9595 - 1s/epoch - 987us/step
Epoch 11/600
1268/1268 - 1s - loss: 0.1151 - accuracy: 0.9612 - 1s/epoch - 967us/step
Epoch 12/600
1268/1268 - 1s - loss: 0.1115 - accuracy: 0.9620 - 1s/epoch - 981us/step
Epoch 13/600
1268/1268 - 1s - loss: 0.1087 - accuracy: 0.9636 - 1s/epoch - 966us/step
Epoch 14/600
1268/1268 - 1s - loss: 0.1058 - accuracy: 0.9645 - 1s/epoch - 985us/step
Epoch 15/600
1268/1268 - 1s - loss: 0.1038 - accuracy: 0.9661 - 1s/epoch - 968us/step
Epoch 16/600
1268/1268 - 1s - loss: 0.1016 - accuracy: 0.9667 - 1s/epoch - 982us/step
Epoch 17/600
1268/1268 - 1s - loss: 0.0998 - accuracy: 0.9673 - 1s/epoch - 967us/step
Epoch 18/600
1268/1268 - 1s - loss: 0.0985 - accuracy: 0.9676 - 1s/epoch - 982us/step
Epoch 19/600
1268/1268 - 1s - loss: 0.0969 - accuracy: 0.9687 - 1s/epoch - 966us/step
Epoch 20/600
1268/1268 - 1s - loss: 0.0952 - accuracy: 0.9688 - 1s/epoch - 986us/step
Fnoch 21/600
1268/1268 - 1s - loss: 0.0948 - accuracy: 0.9690 - 1s/epoch - 965us/step
Epoch 22/600
1268/1268 - 1s - loss: 0.0926 - accuracy: 0.9701 - 1s/epoch - 985us/step
Epoch 23/600
1268/1268 - 1s - loss: 0.0918 - accuracy: 0.9702 - 1s/epoch - 968us/step
Epoch 24/600
1268/1268 - 1s - loss: 0.0904 - accuracy: 0.9711 - 1s/epoch - 987us/step
Epoch 25/600
1268/1268 - 1s - loss: 0.0903 - accuracy: 0.9710 - 1s/epoch - 968us/step
Epoch 26/600
1268/1268 - 1s - loss: 0.0887 - accuracy: 0.9712 - 1s/epoch - 982us/step
Epoch 27/600
1268/1268 - 1s - loss: 0.0875 - accuracy: 0.9720 - 1s/epoch - 971us/step
Epoch 28/600
1268/1268 - 1s - loss: 0.0877 - accuracy: 0.9719 - 1s/epoch - 984us/step
Epoch 29/600
1268/1268 - 1s - loss: 0.0861 - accuracy: 0.9726 - 1s/epoch - 971us/step
Epoch 30/600
1268/1268 - 1s - loss: 0.0861 - accuracy: 0.9723 - 1s/epoch - 983us/step
Epoch 31/600
1268/1268 - 1s - loss: 0.0851 - accuracy: 0.9728 - 1s/epoch - 971us/step
Epoch 32/600
1268/1268 - 1s - loss: 0.0843 - accuracy: 0.9731 - 1s/epoch - 989us/step
Epoch 33/600
1268/1268 - 1s - loss: 0.0839 - accuracy: 0.9737 - 1s/epoch - 968us/step
Epoch 34/600
1268/1268 - 1s - loss: 0.0829 - accuracy: 0.9740 - 1s/epoch - 976us/step
Epoch 35/600
1268/1268 - 1s - loss: 0.0822 - accuracy: 0.9739 - 1s/epoch - 969us/step
Epoch 36/600
1268/1268 - 1s - loss: 0.0817 - accuracy: 0.9739 - 1s/epoch - 985us/step
Epoch 37/600
1268/1268 - 1s - loss: 0.0808 - accuracy: 0.9745 - 1s/epoch - 968us/step
Epoch 38/600
1268/1268 - 1s - loss: 0.0807 - accuracy: 0.9743 - 1s/epoch - 985us/step
Epoch 39/600
1268/1268 - 1s - loss: 0.0797 - accuracy: 0.9749 - 1s/epoch - 965us/step
Epoch 40/600
1268/1268 - 1s - loss: 0.0797 - accuracy: 0.9748 - 1s/epoch - 983us/step
Epoch 41/600
1268/1268 - 1s - loss: 0.0793 - accuracy: 0.9750 - 1s/epoch - 967us/step
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Epoch 42/600
1268/1268 - 1s - loss: 0.0785 - accuracy: 0.9751 - 1s/epoch - 984us/step
Epoch 43/600
1268/1268 - 1s - loss: 0.0779 - accuracy: 0.9756 - 1s/epoch - 972us/step
Epoch 44/600
1268/1268 - 1s - loss: 0.0776 - accuracy: 0.9756 - 1s/epoch - 982us/step
Epoch 45/600
1268/1268 - 1s - loss: 0.0775 - accuracy: 0.9753 - 1s/epoch - 982us/step
Epoch 46/600
1268/1268 - 1s - loss: 0.0770 - accuracy: 0.9760 - 1s/epoch - 987us/step
Epoch 47/600
1268/1268 - 1s - loss: 0.0762 - accuracy: 0.9762 - 1s/epoch - 968us/step
Epoch 48/600
1268/1268 - 1s - loss: 0.0757 - accuracy: 0.9761 - 1s/epoch - 984us/step
Epoch 49/600
1268/1268 - 1s - loss: 0.0754 - accuracy: 0.9762 - 1s/epoch - 969us/step
Epoch 50/600
1268/1268 - 1s - loss: 0.0748 - accuracy: 0.9766 - 1s/epoch - 979us/step
Epoch 51/600
1268/1268 - 1s - loss: 0.0745 - accuracy: 0.9763 - 1s/epoch - 971us/step
Epoch 52/600
1268/1268 - 1s - loss: 0.0739 - accuracy: 0.9768 - 1s/epoch - 995us/step
Epoch 53/600
1268/1268 - 1s - loss: 0.0742 - accuracy: 0.9763 - 1s/epoch - 970us/step
Epoch 54/600
1268/1268 - 1s - loss: 0.0737 - accuracy: 0.9767 - 1s/epoch - 996us/step
Epoch 55/600
1268/1268 - 1s - loss: 0.0732 - accuracy: 0.9768 - 1s/epoch - 967us/step
Epoch 56/600
1268/1268 - 1s - loss: 0.0723 - accuracy: 0.9774 - 1s/epoch - 983us/step
Epoch 57/600
1268/1268 - 1s - loss: 0.0721 - accuracy: 0.9772 - 1s/epoch - 969us/step
Epoch 58/600
1268/1268 - 1s - loss: 0.0723 - accuracy: 0.9771 - 1s/epoch - 990us/step
Epoch 59/600
1268/1268 - 1s - loss: 0.0717 - accuracy: 0.9774 - 1s/epoch - 974us/step
Epoch 60/600
1268/1268 - 1s - loss: 0.0715 - accuracy: 0.9772 - 1s/epoch - 987us/step
Epoch 61/600
1268/1268 - 1s - loss: 0.0714 - accuracy: 0.9775 - 1s/epoch - 968us/step
Epoch 62/600
1268/1268 - 1s - loss: 0.0703 - accuracy: 0.9776 - 1s/epoch - 981us/step
Epoch 63/600
1268/1268 - 1s - loss: 0.0704 - accuracy: 0.9777 - 1s/epoch - 973us/step
Epoch 64/600
1268/1268 - 1s - loss: 0.0697 - accuracy: 0.9781 - 1s/epoch - 990us/step
Epoch 65/600
1268/1268 - 1s - loss: 0.0701 - accuracy: 0.9775 - 1s/epoch - 968us/step
Epoch 66/600
1268/1268 - 1s - loss: 0.0695 - accuracy: 0.9775 - 1s/epoch - 984us/step
Epoch 67/600
1268/1268 - 1s - loss: 0.0688 - accuracy: 0.9787 - 1s/epoch - 968us/step
Epoch 68/600
1268/1268 - 1s - loss: 0.0684 - accuracy: 0.9784 - 1s/epoch - 989us/step
Epoch 69/600
1268/1268 - 1s - loss: 0.0683 - accuracy: 0.9784 - 1s/epoch - 971us/step
Epoch 70/600
1268/1268 - 1s - loss: 0.0679 - accuracy: 0.9785 - 1s/epoch - 968us/step
Epoch 71/600
1268/1268 - 1s - loss: 0.0678 - accuracy: 0.9786 - 1s/epoch - 984us/step
Epoch 72/600
1268/1268 - 1s - loss: 0.0676 - accuracy: 0.9788 - 1s/epoch - 985us/step
Epoch 73/600
1268/1268 - 1s - loss: 0.0675 - accuracy: 0.9786 - 1s/epoch - 968us/step
Epoch 74/600
1268/1268 - 1s - loss: 0.0671 - accuracy: 0.9789 - 1s/epoch - 966us/step
Epoch 75/600
1268/1268 - 1s - loss: 0.0671 - accuracy: 0.9786 - 1s/epoch - 992us/step
Epoch 76/600
1268/1268 - 1s - loss: 0.0665 - accuracy: 0.9788 - 1s/epoch - 987us/step
Epoch 77/600
1268/1268 - 1s - loss: 0.0663 - accuracy: 0.9788 - 1s/epoch - 967us/step
Epoch 78/600
1268/1268 - 1s - loss: 0.0658 - accuracy: 0.9787 - 1s/epoch - 984us/step
Epoch 79/600
1268/1268 - 1s - loss: 0.0663 - accuracy: 0.9793 - 1s/epoch - 984us/step
Epoch 80/600
1268/1268 - 1s - loss: 0.0654 - accuracy: 0.9790 - 1s/epoch - 967us/step
Epoch 81/600
1268/1268 - 1s - loss: 0.0649 - accuracy: 0.9798 - 1s/epoch - 989us/step
Epoch 82/600
1268/1268 - 1s - loss: 0.0646 - accuracy: 0.9792 - 1s/epoch - 982us/step
Epoch 83/600
1268/1268 - 1s - loss: 0.0649 - accuracy: 0.9792 - 1s/epoch - 969us/step
Epoch 84/600
1268/1268 - 1s - loss: 0.0644 - accuracy: 0.9794 - 1s/epoch - 972us/step
Epoch 85/600
1268/1268 - 1s - loss: 0.0639 - accuracy: 0.9796 - 1s/epoch - 984us/step
Epoch 86/600
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1268/1268 - 1s - loss: 0.0638 - accuracy: 0.9798 - 1s/epoch - 981us/step
Epoch 87/600
1268/1268 - 1s - loss: 0.0642 - accuracy: 0.9793 - 1s/epoch - 968us/step
Epoch 88/600
1268/1268 - 1s - loss: 0.0633 - accuracy: 0.9795 - 1s/epoch - 988us/step
Epoch 89/600
1268/1268 - 1s - loss: 0.0630 - accuracy: 0.9802 - 1s/epoch - 968us/step
Epoch 90/600
1268/1268 - 1s - loss: 0.0639 - accuracy: 0.9794 - 1s/epoch - 985us/step
Epoch 91/600
1268/1268 - 1s - loss: 0.0626 - accuracy: 0.9803 - 1s/epoch - 970us/step
Epoch 92/600
1268/1268 - 1s - loss: 0.0627 - accuracy: 0.9800 - 1s/epoch - 969us/step
Epoch 93/600
1268/1268 - 1s - loss: 0.0623 - accuracy: 0.9802 - 1s/epoch - 990us/step
Epoch 94/600
1268/1268 - 1s - loss: 0.0624 - accuracy: 0.9801 - 1s/epoch - 995us/step
Epoch 95/600
1268/1268 - 1s - loss: 0.0620 - accuracy: 0.9805 - 1s/epoch - 965us/step
Epoch 96/600
1268/1268 - 1s - loss: 0.0620 - accuracy: 0.9797 - 1s/epoch - 983us/step
Epoch 97/600
1268/1268 - 1s - loss: 0.0621 - accuracy: 0.9802 - 1s/epoch - 967us/step
Epoch 98/600
1268/1268 - 1s - loss: 0.0615 - accuracy: 0.9805 - 1s/epoch - 980us/step
Epoch 99/600
1268/1268 - 1s - loss: 0.0619 - accuracy: 0.9803 - 1s/epoch - 965us/step
Epoch 100/600
1268/1268 - 1s - loss: 0.0609 - accuracy: 0.9808 - 1s/epoch - 980us/step
Epoch 101/600
1268/1268 - 1s - loss: 0.0610 - accuracy: 0.9804 - 1s/epoch - 967us/step
Epoch 102/600
1268/1268 - 1s - loss: 0.0606 - accuracy: 0.9810 - 1s/epoch - 985us/step
Epoch 103/600
1268/1268 - 1s - loss: 0.0606 - accuracy: 0.9806 - 1s/epoch - 976us/step
Epoch 104/600
1268/1268 - 1s - loss: 0.0605 - accuracy: 0.9805 - 1s/epoch - 964us/step
Epoch 105/600
1268/1268 - 1s - loss: 0.0607 - accuracy: 0.9808 - 1s/epoch - 974us/step
Epoch 106/600
1268/1268 - 1s - loss: 0.0600 - accuracy: 0.9808 - 1s/epoch - 969us/step
Epoch 107/600
1268/1268 - 1s - loss: 0.0599 - accuracy: 0.9808 - 1s/epoch - 984us/step
Epoch 108/600
1268/1268 - 1s - loss: 0.0596 - accuracy: 0.9815 - 1s/epoch - 962us/step
Epoch 109/600
1268/1268 - 1s - loss: 0.0598 - accuracy: 0.9810 - 1s/epoch - 980us/step
Epoch 110/600
1268/1268 - 1s - loss: 0.0596 - accuracy: 0.9811 - 1s/epoch - 966us/step
Epoch 111/600
1268/1268 - 1s - loss: 0.0590 - accuracy: 0.9812 - 1s/epoch - 980us/step
Epoch 112/600
1268/1268 - 1s - loss: 0.0598 - accuracy: 0.9811 - 1s/epoch - 962us/step
Epoch 113/600
1268/1268 - 1s - loss: 0.0583 - accuracy: 0.9815 - 1s/epoch - 983us/step
Epoch 114/600
1268/1268 - 1s - loss: 0.0587 - accuracy: 0.9815 - 1s/epoch - 964us/step
Epoch 115/600
1268/1268 - 1s - loss: 0.0588 - accuracy: 0.9812 - 1s/epoch - 985us/step
Epoch 116/600
1268/1268 - 1s - loss: 0.0584 - accuracy: 0.9814 - 1s/epoch - 964us/step
Epoch 117/600
1268/1268 - 1s - loss: 0.0583 - accuracy: 0.9813 - 1s/epoch - 966us/step
Epoch 118/600
1268/1268 - 1s - loss: 0.0577 - accuracy: 0.9818 - 1s/epoch - 982us/step
Epoch 119/600
1268/1268 - 1s - loss: 0.0583 - accuracy: 0.9813 - 1s/epoch - 984us/step
Fnoch 120/600
1268/1268 - 1s - loss: 0.0575 - accuracy: 0.9815 - 1s/epoch - 963us/step
Epoch 121/600
1268/1268 - 1s - loss: 0.0580 - accuracy: 0.9815 - 1s/epoch - 987us/step
Epoch 122/600
1268/1268 - 1s - loss: 0.0569 - accuracy: 0.9819 - 1s/epoch - 964us/step
Epoch 123/600
1268/1268 - 1s - loss: 0.0575 - accuracy: 0.9816 - 1s/epoch - 967us/step
Epoch 124/600
1268/1268 - 1s - loss: 0.0571 - accuracy: 0.9816 - 1s/epoch - 989us/step
Epoch 125/600
1268/1268 - 1s - loss: 0.0564 - accuracy: 0.9823 - 1s/epoch - 976us/step
Epoch 126/600
1268/1268 - 1s - loss: 0.0566 - accuracy: 0.9819 - 1s/epoch - 988us/step
Epoch 127/600
1268/1268 - 1s - loss: 0.0569 - accuracy: 0.9814 - 1s/epoch - 969us/step
Epoch 128/600
1268/1268 - 1s - loss: 0.0564 - accuracy: 0.9819 - 1s/epoch - 974us/step
Epoch 129/600
1268/1268 - 1s - loss: 0.0562 - accuracy: 0.9823 - 1s/epoch - 988us/step
Epoch 130/600
1268/1268 - 1s - loss: 0.0570 - accuracy: 0.9815 - 1s/epoch - 993us/step
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Epoch 131/600
1268/1268 - 1s - loss: 0.0560 - accuracy: 0.9822 - 1s/epoch - 969us/step
Epoch 132/600
1268/1268 - 1s - loss: 0.0564 - accuracy: 0.9821 - 1s/epoch - 993us/step
Epoch 133/600
1268/1268 - 1s - loss: 0.0561 - accuracy: 0.9819 - 1s/epoch - 969us/step
Epoch 134/600
1268/1268 - 1s - loss: 0.0557 - accuracy: 0.9821 - 1s/epoch - 983us/step
Epoch 135/600
1268/1268 - 1s - loss: 0.0555 - accuracy: 0.9824 - 1s/epoch - 970us/step
Epoch 136/600
1268/1268 - 1s - loss: 0.0555 - accuracy: 0.9821 - 1s/epoch - 969us/step
Epoch 137/600
1268/1268 - 1s - loss: 0.0552 - accuracy: 0.9827 - 1s/epoch - 988us/step
Epoch 138/600
1268/1268 - 1s - loss: 0.0555 - accuracy: 0.9824 - 1s/epoch - 987us/step
Epoch 139/600
1268/1268 - 1s - loss: 0.0548 - accuracy: 0.9826 - 1s/epoch - 968us/step
Epoch 140/600
1268/1268 - 1s - loss: 0.0551 - accuracy: 0.9826 - 1s/epoch - 989us/step
Epoch 141/600
.
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9826 - 1s/epoch - 975us/step
Epoch 142/600
1268/1268 - 1s - loss: 0.0551 - accuracy: 0.9827 - 1s/epoch - 996us/step
Epoch 143/600
1268/1268 - 1s - loss: 0.0545 - accuracy: 0.9827 - 1s/epoch - 984us/step
Epoch 144/600
1268/1268 - 1s - loss: 0.0549 - accuracy: 0.9827 - 1s/epoch - 992us/step
Epoch 145/600
1268/1268 - 1s - loss: 0.0546 - accuracy: 0.9825 - 1s/epoch - 976us/step
Epoch 146/600
1268/1268 - 1s - loss: 0.0543 - accuracy: 0.9823 - 1s/epoch - 970us/step
Epoch 147/600
1268/1268 - 1s - loss: 0.0540 - accuracy: 0.9830 - 1s/epoch - 993us/step
Epoch 148/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9829 - 1s/epoch - 988us/step
Epoch 149/600
1268/1268 - 1s - loss: 0.0540 - accuracy: 0.9826 - 1s/epoch - 972us/step
Epoch 150/600
1268/1268 - 1s - loss: 0.0538 - accuracy: 0.9827 - 1s/epoch - 993us/step
Epoch 151/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9832 - 1s/epoch - 972us/step
Epoch 152/600
1268/1268 - 1s - loss: 0.0536 - accuracy: 0.9827 - 1s/epoch - 972us/step
Epoch 153/600
1268/1268 - 1s - loss: 0.0534 - accuracy: 0.9829 - 1s/epoch - 991us/step
Epoch 154/600
1268/1268 - 1s - loss: 0.0532 - accuracy: 0.9832 - 1s/epoch - 989us/step
Epoch 155/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9829 - 1s/epoch - 969us/step
Epoch 156/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9827 - 1s/epoch - 990us/step
Epoch 157/600
1268/1268 - 1s - loss: 0.0531 - accuracy: 0.9833 - 1s/epoch - 972us/step
Epoch 158/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9827 - 1s/epoch - 969us/step
Epoch 159/600
1268/1268 - 1s - loss: 0.0528 - accuracy: 0.9829 - 1s/epoch - 992us/step
Epoch 160/600
1268/1268 - 1s - loss: 0.0527 - accuracy: 0.9829 - 1s/epoch - 991us/step
Epoch 161/600
1268/1268 - 1s - loss: 0.0527 - accuracy: 0.9832 - 1s/epoch - 969us/step
Epoch 162/600
1268/1268 - 1s - loss: 0.0521 - accuracy: 0.9833 - 1s/epoch - 991us/step
Epoch 163/600
1268/1268 - 1s - loss: 0.0523 - accuracy: 0.9828 - 1s/epoch - 976us/step
Epoch 164/600
1268/1268 - 1s - loss: 0.0524 - accuracy: 0.9830 - 1s/epoch - 991us/step
Epoch 165/600
1268/1268 - 1s - loss: 0.0522 - accuracy: 0.9831 - 1s/epoch - 969us/step
Epoch 166/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9835 - 1s/epoch - 990us/step
Epoch 167/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9832 - 1s/epoch - 968us/step
Epoch 168/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9835 - 1s/epoch - 983us/step
Epoch 169/600
1268/1268 - 1s - loss: 0.0522 - accuracy: 0.9833 - 1s/epoch - 972us/step
Epoch 170/600
1268/1268 - 1s - loss: 0.0515 - accuracy: 0.9834 - 1s/epoch - 986us/step
Epoch 171/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 172/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9834 - 1s/epoch - 983us/step
Epoch 173/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9836 - 1s/epoch - 980us/step
Epoch 174/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9836 - 1s/epoch - 995us/step
Epoch 175/600
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1268/1268 - 1s - loss: 0.0518 - accuracy: 0.9833 - 1s/epoch - 974us/step
Epoch 176/600
1268/1268 - 1s - loss: 0.0506 - accuracy: 0.9840 - 1s/epoch - 989us/step
Epoch 177/600
1268/1268 - 1s - loss: 0.0509 - accuracy: 0.9836 - 1s/epoch - 968us/step
Epoch 178/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9835 - 1s/epoch - 984us/step
Epoch 179/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9832 - 1s/epoch - 972us/step
Epoch 180/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9839 - 1s/epoch - 989us/step
Epoch 181/600
1268/1268 - 1s - loss: 0.0507 - accuracy: 0.9837 - 1s/epoch - 971us/step
Epoch 182/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9836 - 1s/epoch - 972us/step
Epoch 183/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9833 - 1s/epoch - 987us/step
Epoch 184/600
1268/1268 - 1s - loss: 0.0506 - accuracy: 0.9837 - 1s/epoch - 969us/step
Epoch 185/600
1268/1268 - 1s - loss: 0.0505 - accuracy: 0.9834 - 1s/epoch - 978us/step
Epoch 186/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9839 - 1s/epoch - 980us/step
Epoch 187/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9838 - 1s/epoch - 972us/step
Epoch 188/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9840 - 1s/epoch - 994us/step
Epoch 189/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9836 - 1s/epoch - 971us/step
Epoch 190/600
1268/1268 - 1s - loss: 0.0497 - accuracy: 0.9842 - 1s/epoch - 989us/step
Epoch 191/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9841 - 1s/epoch - 978us/step
Epoch 192/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9839 - 1s/epoch - 993us/step
Epoch 193/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9838 - 1s/epoch - 972us/step
Epoch 194/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9838 - 1s/epoch - 990us/step
Epoch 195/600
1268/1268 - 1s - loss: 0.0496 - accuracy: 0.9842 - 1s/epoch - 968us/step
Epoch 196/600
1268/1268 - 1s - loss: 0.0494 - accuracy: 0.9841 - 1s/epoch - 991us/step
Epoch 197/600
1268/1268 - 1s - loss: 0.0494 - accuracy: 0.9840 - 1s/epoch - 971us/step
Epoch 198/600
1268/1268 - 1s - loss: 0.0491 - accuracy: 0.9839 - 1s/epoch - 987us/step
Epoch 199/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9837 - 1s/epoch - 967us/step
Epoch 200/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9842 - 1s/epoch - 990us/step
Epoch 201/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9842 - 1s/epoch - 974us/step
Epoch 202/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9841 - 1s/epoch - 991us/step
Epoch 203/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9842 - 1s/epoch - 971us/step
Epoch 204/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9843 - 1s/epoch - 991us/step
Epoch 205/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9843 - 1s/epoch - 972us/step
Epoch 206/600
1268/1268 - 1s - loss: 0.0487 - accuracy: 0.9844 - 1s/epoch - 994us/step
Epoch 207/600
1268/1268 - 1s - loss: 0.0487 - accuracy: 0.9841 - 1s/epoch - 972us/step
Epoch 208/600
1268/1268 - 1s - loss: 0.0482 - accuracy: 0.9846 - 1s/epoch - 993us/step
Fnoch 209/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9847 - 1s/epoch - 974us/step
Epoch 210/600
1268/1268 - 1s - loss: 0.0488 - accuracy: 0.9842 - 1s/epoch - 988us/step
Epoch 211/600
1268/1268 - 1s - loss: 0.0479 - accuracy: 0.9843 - 1s/epoch - 971us/step
Epoch 212/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9844 - 1s/epoch - 967us/step
Epoch 213/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9846 - 1s/epoch - 987us/step
Epoch 214/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9848 - 1s/epoch - 993us/step
Epoch 215/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9842 - 1s/epoch - 969us/step
Epoch 216/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9845 - 1s/epoch - 988us/step
Epoch 217/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9845 - 1s/epoch - 976us/step
Epoch 218/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9847 - 1s/epoch - 993us/step
Epoch 219/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9843 - 1s/epoch - 970us/step
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Epoch 220/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9846 - 1s/epoch - 973us/step
Epoch 221/600
1268/1268 - 1s - loss: 0.0476 - accuracy: 0.9844 - 1s/epoch - 989us/step
Epoch 222/600
1268/1268 - 1s - loss: 0.0476 - accuracy: 0.9845 - 1s/epoch - 975us/step
Epoch 223/600
1268/1268 - 1s - loss: 0.0476 - accuracy: 0.9844 - 1s/epoch - 987us/step
Epoch 224/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9846 - 1s/epoch - 971us/step
Epoch 225/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9849 - 1s/epoch - 984us/step
Epoch 226/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9847 - 1s/epoch - 971us/step
Epoch 227/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 228/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9850 - 1s/epoch - 971us/step
Epoch 229/600
1268/1268 - 1s - loss: 0.0468 - accuracy: 0.9847 - 1s/epoch - 994us/step
Epoch 230/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9843 - 1s/epoch - 971us/step
Fnoch 231/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9849 - 1s/epoch - 988us/step
Epoch 232/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9848 - 1s/epoch - 973us/step
Epoch 233/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9849 - 1s/epoch - 969us/step
Epoch 234/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9852 - 1s/epoch - 989us/step
Epoch 235/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9843 - 1s/epoch - 993us/step
Epoch 236/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9851 - 1s/epoch - 973us/step
Epoch 237/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9852 - 1s/epoch - 992us/step
Epoch 238/600
1268/1268 - 1s - loss: 0.0468 - accuracy: 0.9850 - 1s/epoch - 978us/step
Epoch 239/600
1268/1268 - 1s - loss: 0.0468 - accuracy: 0.9850 - 1s/epoch - 996us/step
Epoch 240/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9846 - 1s/epoch - 973us/step
Epoch 241/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9852 - 1s/epoch - 970us/step
Epoch 242/600
1268/1268 - 1s - loss: 0.0462 - accuracy: 0.9847 - 1s/epoch - 979us/step
Epoch 243/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9845 - 1s/epoch - 988us/step
Epoch 244/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9852 - 1s/epoch - 978us/step
Epoch 245/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9848 - 1s/epoch - 988us/step
Epoch 246/600
1268/1268 - 1s - loss: 0.0460 - accuracy: 0.9851 - 1s/epoch - 972us/step
Epoch 247/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9850 - 1s/epoch - 991us/step
Epoch 248/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9849 - 1s/epoch - 974us/step
Epoch 249/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9849 - 1s/epoch - 995us/step
Epoch 250/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9854 - 1s/epoch - 968us/step
Epoch 251/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9849 - 1s/epoch - 988us/step
Epoch 252/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9850 - 1s/epoch - 974us/step
Epoch 253/600
1268/1268 - 1s - loss: 0.0460 - accuracy: 0.9851 - 1s/epoch - 991us/step
Epoch 254/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9854 - 1s/epoch - 972us/step
Epoch 255/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9852 - 1s/epoch - 989us/step
Epoch 256/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9853 - 1s/epoch - 966us/step
Epoch 257/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9853 - 1s/epoch - 986us/step
Epoch 258/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9850 - 1s/epoch - 969us/step
Epoch 259/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9851 - 1s/epoch - 987us/step
Epoch 260/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9854 - 1s/epoch - 963us/step
Epoch 261/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9853 - 1s/epoch - 988us/step
Epoch 262/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9854 - 1s/epoch - 971us/step
Epoch 263/600
1268/1268 - 1s - loss: 0.0448 - accuracy: 0.9852 - 1s/epoch - 985us/step
Epoch 264/600
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1268/1268 - 1s - loss: 0.0449 - accuracy: 0.9853 - 1s/epoch - 966us/step
Epoch 265/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9855 - 1s/epoch - 965us/step
Epoch 266/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9849 - 1s/epoch - 990us/step
Epoch 267/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9852 - 1s/epoch - 989us/step
Epoch 268/600
1268/1268 - 1s - loss: 0.0449 - accuracy: 0.9849 - 1s/epoch - 972us/step
Epoch 269/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9855 - 1s/epoch - 989us/step
Epoch 270/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9856 - 1s/epoch - 980us/step
Epoch 271/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9853 - 1s/epoch - 985us/step
Epoch 272/600
1268/1268 - 1s - loss: 0.0449 - accuracy: 0.9851 - 1s/epoch - 967us/step
Epoch 273/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9854 - 1s/epoch - 989us/step
Epoch 274/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9851 - 1s/epoch - 973us/step
Epoch 275/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9855 - 1s/epoch - 991us/step
Epoch 276/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9853 - 1s/epoch - 974us/step
Epoch 277/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9857 - 1s/epoch - 994us/step
Epoch 278/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9853 - 1s/epoch - 977us/step
Epoch 279/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9855 - 1s/epoch - 989us/step
Epoch 280/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9857 - 1s/epoch - 971us/step
Epoch 281/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9860 - 1s/epoch - 987us/step
Epoch 282/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9849 - 1s/epoch - 970us/step
Epoch 283/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9856 - 1s/epoch - 991us/step
Epoch 284/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9855 - 1s/epoch - 971us/step
Epoch 285/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9857 - 1s/epoch - 993us/step
Epoch 286/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9858 - 1s/epoch - 975us/step
Epoch 287/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9855 - 1s/epoch - 995us/step
Epoch 288/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9856 - 1s/epoch - 983us/step
Epoch 289/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9851 - 1s/epoch - 973us/step
Epoch 290/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9859 - 1s/epoch - 992us/step
Epoch 291/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9855 - 1s/epoch - 993us/step
Epoch 292/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9859 - 1s/epoch - 969us/step
Epoch 293/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9855 - 1s/epoch - 994us/step
Epoch 294/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9857 - 1s/epoch - 972us/step
Epoch 295/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9860 - 1s/epoch - 993us/step
Epoch 296/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9859 - 1s/epoch - 972us/step
Epoch 297/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9857 - 1s/epoch - 988us/step
Fnoch 298/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9858 - 1s/epoch - 979us/step
Epoch 299/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9858 - 1s/epoch - 999us/step
Epoch 300/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9863 - 1s/epoch - 975us/step
Epoch 301/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9857 - 1s/epoch - 995us/step
Epoch 302/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9860 - 1s/epoch - 973us/step
Epoch 303/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9861 - 1s/epoch - 980us/step
Epoch 304/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9858 - 1s/epoch - 972us/step
Epoch 305/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9858 - 1s/epoch - 997us/step
Epoch 306/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9860 - 1s/epoch - 971us/step
Epoch 307/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9857 - 1s/epoch - 977us/step
Epoch 308/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9861 - 1s/epoch - 995us/step
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Epoch 309/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9856 - 1s/epoch - 995us/step
Epoch 310/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9863 - 1s/epoch - 973us/step
Epoch 311/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9862 - 1s/epoch - 988us/step
Epoch 312/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9856 - 1s/epoch - 971us/step
Epoch 313/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9861 - 1s/epoch - 995us/step
Epoch 314/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9855 - 1s/epoch - 969us/step
Epoch 315/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9859 - 1s/epoch - 991us/step
Epoch 316/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9858 - 1s/epoch - 975us/step
Epoch 317/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9863 - 1s/epoch - 993us/step
Epoch 318/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9862 - 1s/epoch - 983us/step
Epoch 319/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9856 - 1s/epoch - 969us/step
Epoch 320/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9867 - 1s/epoch - 987us/step
Epoch 321/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9857 - 1s/epoch - 993us/step
Epoch 322/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9861 - 1s/epoch - 976us/step
Epoch 323/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9864 - 1s/epoch - 990us/step
Epoch 324/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9859 - 1s/epoch - 981us/step
Epoch 325/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9862 - 1s/epoch - 991us/step
Epoch 326/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 327/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9861 - 1s/epoch - 989us/step
Epoch 328/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9864 - 1s/epoch - 974us/step
Epoch 329/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9862 - 1s/epoch - 992us/step
Epoch 330/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9864 - 1s/epoch - 974us/step
Epoch 331/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9860 - 1s/epoch - 993us/step
Epoch 332/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9866 - 1s/epoch - 966us/step
Epoch 333/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9854 - 1s/epoch - 990us/step
Epoch 334/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9861 - 1s/epoch - 979us/step
Epoch 335/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9861 - 1s/epoch - 990us/step
Epoch 336/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9862 - 1s/epoch - 975us/step
Epoch 337/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9860 - 1s/epoch - 995us/step
Epoch 338/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9861 - 1s/epoch - 968us/step
Epoch 339/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9865 - 1s/epoch - 984us/step
Epoch 340/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9862 - 1s/epoch - 972us/step
Epoch 341/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9866 - 1s/epoch - 995us/step
Epoch 342/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9859 - 1s/epoch - 977us/step
Epoch 343/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 344/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9864 - 1s/epoch - 970us/step
Epoch 345/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9865 - 1s/epoch - 969us/step
Epoch 346/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9861 - 1s/epoch - 996us/step
Epoch 347/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9859 - 1s/epoch - 992us/step
Epoch 348/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9864 - 1s/epoch - 971us/step
Epoch 349/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9866 - 1s/epoch - 992us/step
Epoch 350/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9863 - 1s/epoch - 973us/step
Epoch 351/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9863 - 1s/epoch - 986us/step
Epoch 352/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9862 - 1s/epoch - 968us/step
Epoch 353/600
```

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1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9870 - 1s/epoch - 995us/step
Epoch 354/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9869 - 1s/epoch - 976us/step
Epoch 355/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9863 - 1s/epoch - 990us/step
Epoch 356/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9868 - 1s/epoch - 971us/step
Epoch 357/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9863 - 1s/epoch - 986us/step
Epoch 358/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9864 - 1s/epoch - 972us/step
Epoch 359/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9860 - 1s/epoch - 987us/step
Epoch 360/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9866 - 1s/epoch - 976us/step
Epoch 361/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9865 - 1s/epoch - 993us/step
Epoch 362/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 973us/step
Epoch 363/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9866 - 1s/epoch - 994us/step
Epoch 364/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9862 - 1s/epoch - 971us/step
Epoch 365/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9865 - 1s/epoch - 996us/step
Epoch 366/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9866 - 1s/epoch - 974us/step
Epoch 367/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9866 - 1s/epoch - 991us/step
Epoch 368/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9864 - 1s/epoch - 975us/step
Epoch 369/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9866 - 1s/epoch - 993us/step
Epoch 370/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9866 - 1s/epoch - 970us/step
Epoch 371/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9866 - 1s/epoch - 999us/step
Epoch 372/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9865 - 1s/epoch - 976us/step
Epoch 373/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9866 - 1s/epoch - 994us/step
Epoch 374/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9868 - 1s/epoch - 978us/step
Epoch 375/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9866 - 1s/epoch - 994us/step
Epoch 376/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9866 - 1s/epoch - 971us/step
Epoch 377/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9868 - 1s/epoch - 994us/step
Epoch 378/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9867 - 1s/epoch - 973us/step
Epoch 379/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 989us/step
Epoch 380/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9868 - 1s/epoch - 977us/step
Epoch 381/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9869 - 1s/epoch - 970us/step
Epoch 382/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9865 - 1s/epoch - 997us/step
Epoch 383/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9865 - 1s/epoch - 975us/step
Epoch 384/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9865 - 1s/epoch - 993us/step
Epoch 385/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9869 - 1s/epoch - 977us/step
Epoch 386/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9862 - 1s/epoch - 985us/step
Fnoch 387/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9866 - 1s/epoch - 971us/step
Epoch 388/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9867 - 1s/epoch - 991us/step
Epoch 389/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9869 - 1s/epoch - 986us/step
Epoch 390/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9869 - 1s/epoch - 975us/step
Epoch 391/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9868 - 1s/epoch - 978us/step
Epoch 392/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9869 - 1s/epoch - 971us/step
Epoch 393/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9866 - 1s/epoch - 972us/step
Epoch 394/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9868 - 1s/epoch - 993us/step
Epoch 395/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9871 - 1s/epoch - 990us/step
Epoch 396/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9869 - 1s/epoch - 970us/step
Epoch 397/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9870 - 1s/epoch - 973us/step
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Epoch 398/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9871 - 1s/epoch - 991us/step
Epoch 399/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9868 - 1s/epoch - 977us/step
Epoch 400/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9868 - 1s/epoch - 992us/step
Epoch 401/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9867 - 1s/epoch - 989us/step
Epoch 402/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9868 - 1s/epoch - 970us/step
Epoch 403/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9872 - 1s/epoch - 975us/step
Epoch 404/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9869 - 1s/epoch - 976us/step
Epoch 405/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9873 - 1s/epoch - 970us/step
Epoch 406/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9867 - 1s/epoch - 989us/step
Epoch 407/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9870 - 1s/epoch - 989us/step
Epoch 408/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9870 - 1s/epoch - 965us/step
Epoch 409/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9867 - 1s/epoch - 969us/step
Epoch 410/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9869 - 1s/epoch - 987us/step
Epoch 411/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9869 - 1s/epoch - 973us/step
Epoch 412/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9864 - 1s/epoch - 989us/step
Epoch 413/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9869 - 1s/epoch - 970us/step
Epoch 414/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9871 - 1s/epoch - 991us/step
Epoch 415/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9868 - 1s/epoch - 990us/step
Epoch 416/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9870 - 1s/epoch - 973us/step
Epoch 417/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9869 - 1s/epoch - 971us/step
Epoch 418/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9869 - 1s/epoch - 990us/step
Epoch 419/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9872 - 1s/epoch - 968us/step
Epoch 420/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9870 - 1s/epoch - 987us/step
Epoch 421/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9867 - 1s/epoch - 991us/step
Epoch 422/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9869 - 1s/epoch - 972us/step
Epoch 423/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9873 - 1s/epoch - 969us/step
Epoch 424/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9868 - 1s/epoch - 987us/step
Epoch 425/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9866 - 1s/epoch - 993us/step
Epoch 426/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9872 - 1s/epoch - 971us/step
Epoch 427/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 972us/step
Epoch 428/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9870 - 1s/epoch - 988us/step
Epoch 429/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 969us/step
Epoch 430/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9870 - 1s/epoch - 991us/step
Epoch 431/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9874 - 1s/epoch - 981us/step
Epoch 432/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9870 - 1s/epoch - 983us/step
Epoch 433/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9870 - 1s/epoch - 999us/step
Epoch 434/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9872 - 1s/epoch - 974us/step
Epoch 435/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9867 - 1s/epoch - 990us/step
Epoch 436/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9871 - 1s/epoch - 971us/step
Epoch 437/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9871 - 1s/epoch - 969us/step
Epoch 438/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9870 - 1s/epoch - 991us/step
Epoch 439/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9872 - 1s/epoch - 987us/step
Epoch 440/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9873 - 1s/epoch - 970us/step
Epoch 441/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9870 - 1s/epoch - 969us/step
Epoch 442/600
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1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9874 - 1s/epoch - 989us/step
Epoch 443/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9874 - 1s/epoch - 991us/step
Epoch 444/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9871 - 1s/epoch - 972us/step
Epoch 445/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9871 - 1s/epoch - 987us/step
Epoch 446/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9870 - 1s/epoch - 973us/step
Epoch 447/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9872 - 1s/epoch - 973us/step
Epoch 448/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9872 - 1s/epoch - 991us/step
Epoch 449/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9873 - 1s/epoch - 989us/step
Epoch 450/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9873 - 1s/epoch - 971us/step
Epoch 451/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9871 - 1s/epoch - 987us/step
Epoch 452/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9870 - 1s/epoch - 974us/step
Epoch 453/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9869 - 1s/epoch - 991us/step
Epoch 454/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9872 - 1s/epoch - 972us/step
Epoch 455/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9872 - 1s/epoch - 993us/step
Epoch 456/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 972us/step
Epoch 457/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9872 - 1s/epoch - 991us/step
Epoch 458/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9873 - 1s/epoch - 969us/step
Epoch 459/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9875 - 1s/epoch - 975us/step
Epoch 460/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9873 - 1s/epoch - 970us/step
Epoch 461/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9872 - 1s/epoch - 992us/step
Epoch 462/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9877 - 1s/epoch - 974us/step
Epoch 463/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9873 - 1s/epoch - 997us/step
Epoch 464/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9873 - 1s/epoch - 976us/step
Epoch 465/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9875 - 1s/epoch - 973us/step
Epoch 466/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9876 - 1s/epoch - 997us/step
Epoch 467/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9869 - 1s/epoch - 991us/step
Epoch 468/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9873 - 1s/epoch - 972us/step
Epoch 469/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9874 - 1s/epoch - 990us/step
Epoch 470/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 471/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 472/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9872 - 1s/epoch - 983us/step
Epoch 473/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9880 - 1s/epoch - 981us/step
Epoch 474/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 475/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9874 - 1s/epoch - 984us/step
Fnoch 476/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9874 - 1s/epoch - 974us/step
Epoch 477/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 478/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9879 - 1s/epoch - 978us/step
Epoch 479/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9875 - 1s/epoch - 997us/step
Epoch 480/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9876 - 1s/epoch - 972us/step
Epoch 481/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9876 - 1s/epoch - 997us/step
Epoch 482/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9876 - 1s/epoch - 974us/step
Epoch 483/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9879 - 1s/epoch - 970us/step
Epoch 484/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9873 - 1s/epoch - 991us/step
Epoch 485/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9876 - 1s/epoch - 993us/step
Epoch 486/600
1268/1268 - 1s - loss: 0.0369 - accuracy: 0.9877 - 1s/epoch - 977us/step
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Epoch 487/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 488/600
1268/1268 - 1s - loss: 0.0369 - accuracy: 0.9877 - 1s/epoch - 969us/step
Epoch 489/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9878 - 1s/epoch - 986us/step
Epoch 490/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9871 - 1s/epoch - 974us/step
Epoch 491/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9875 - 1s/epoch - 993us/step
Epoch 492/600
1268/1268 - 1s - loss: 0.0369 - accuracy: 0.9875 - 1s/epoch - 974us/step
Epoch 493/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9881 - 1s/epoch - 991us/step
Epoch 494/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9878 - 1s/epoch - 969us/step
Epoch 495/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9879 - 1s/epoch - 971us/step
Epoch 496/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9878 - 1s/epoch - 993us/step
Epoch 497/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9880 - 1s/epoch - 991us/step
Fnoch 498/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9875 - 1s/epoch - 969us/step
Epoch 499/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9879 - 1s/epoch - 970us/step
Epoch 500/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9877 - 1s/epoch - 990us/step
Epoch 501/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9870 - 1s/epoch - 991us/step
Epoch 502/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9879 - 1s/epoch - 971us/step
Epoch 503/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9877 - 1s/epoch - 993us/step
Epoch 504/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9880 - 1s/epoch - 973us/step
Epoch 505/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9873 - 1s/epoch - 989us/step
Epoch 506/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9876 - 1s/epoch - 970us/step
Epoch 507/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9880 - 1s/epoch - 993us/step
Epoch 508/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9878 - 1s/epoch - 971us/step
Epoch 509/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9879 - 1s/epoch - 991us/step
Epoch 510/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9877 - 1s/epoch - 977us/step
Epoch 511/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9874 - 1s/epoch - 978us/step
Epoch 512/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9875 - 1s/epoch - 993us/step
Epoch 513/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9878 - 1s/epoch - 979us/step
Epoch 514/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9874 - 1s/epoch - 972us/step
Epoch 515/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9882 - 1s/epoch - 988us/step
Epoch 516/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9878 - 1s/epoch - 974us/step
Epoch 517/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9881 - 1s/epoch - 988us/step
Epoch 518/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9875 - 1s/epoch - 966us/step
Epoch 519/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9876 - 1s/epoch - 970us/step
Epoch 520/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9877 - 1s/epoch - 993us/step
Epoch 521/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9878 - 1s/epoch - 997us/step
Epoch 522/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9879 - 1s/epoch - 969us/step
Epoch 523/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9875 - 1s/epoch - 986us/step
Epoch 524/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9880 - 1s/epoch - 971us/step
Epoch 525/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9876 - 1s/epoch - 993us/step
Epoch 526/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9879 - 1s/epoch - 972us/step
Epoch 527/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9878 - 1s/epoch - 999us/step
Epoch 528/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9876 - 1s/epoch - 969us/step
Epoch 529/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9874 - 1s/epoch - 992us/step
Epoch 530/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9880 - 1s/epoch - 984us/step
Epoch 531/600
```

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1268/1268 - 1s - loss: 0.0355 - accuracy: 0.9882 - 1s/epoch - 989us/step
Epoch 532/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9880 - 1s/epoch - 970us/step
Epoch 533/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9878 - 1s/epoch - 987us/step
Epoch 534/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9881 - 1s/epoch - 974us/step
Epoch 535/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9876 - 1s/epoch - 997us/step
Epoch 536/600
1268/1268 - 1s - loss: 0.0356 - accuracy: 0.9880 - 1s/epoch - 974us/step
Epoch 537/600
1268/1268 - 1s - loss: 0.0355 - accuracy: 0.9879 - 1s/epoch - 992us/step
Epoch 538/600
1268/1268 - 1s - loss: 0.0356 - accuracy: 0.9876 - 1s/epoch - 973us/step
Epoch 539/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9877 - 1s/epoch - 991us/step
Epoch 540/600
1268/1268 - 1s - loss: 0.0356 - accuracy: 0.9881 - 1s/epoch - 971us/step
Epoch 541/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9882 - 1s/epoch - 986us/step
Epoch 542/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9876 - 1s/epoch - 971us/step
Epoch 543/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9877 - 1s/epoch - 967us/step
Epoch 544/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9878 - 1s/epoch - 993us/step
Epoch 545/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9883 - 1s/epoch - 981us/step
Epoch 546/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9881 - 1s/epoch - 971us/step
Epoch 547/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9878 - 1s/epoch - 994us/step
Epoch 548/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9883 - 1s/epoch - 972us/step
Epoch 549/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9875 - 1s/epoch - 991us/step
Epoch 550/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9879 - 1s/epoch - 972us/step
Epoch 551/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9879 - 1s/epoch - 990us/step
Epoch 552/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9881 - 1s/epoch - 974us/step
Epoch 553/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9881 - 1s/epoch - 990us/step
Epoch 554/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9883 - 1s/epoch - 974us/step
Epoch 555/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9879 - 1s/epoch - 993us/step
Epoch 556/600
1268/1268 - 1s - loss: 0.0355 - accuracy: 0.9879 - 1s/epoch - 970us/step
Epoch 557/600
1268/1268 - 1s - loss: 0.0349 - accuracy: 0.9881 - 1s/epoch - 973us/step
Epoch 558/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9880 - 1s/epoch - 988us/step
Epoch 559/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9880 - 1s/epoch - 970us/step
Epoch 560/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9880 - 1s/epoch - 984us/step
Epoch 561/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9880 - 1s/epoch - 971us/step
Epoch 562/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9879 - 1s/epoch - 995us/step
Epoch 563/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9881 - 1s/epoch - 971us/step
Epoch 564/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9879 - 1s/epoch - 986us/step
Fnoch 565/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9879 - 1s/epoch - 970us/step
Epoch 566/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9879 - 1s/epoch - 994us/step
Epoch 567/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9881 - 1s/epoch - 972us/step
Epoch 568/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9881 - 1s/epoch - 995us/step
Epoch 569/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9883 - 1s/epoch - 973us/step
Epoch 570/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9882 - 1s/epoch - 991us/step
Epoch 571/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9879 - 1s/epoch - 969us/step
Epoch 572/600
1268/1268 - 1s - loss: 0.0355 - accuracy: 0.9878 - 1s/epoch - 980us/step
Epoch 573/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9880 - 1s/epoch - 971us/step
Epoch 574/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9878 - 1s/epoch - 971us/step
Epoch 575/600
1268/1268 - 1s - loss: 0.0347 - accuracy: 0.9882 - 1s/epoch - 993us/step
```

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Epoch 576/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9881 - 1s/epoch - 997us/step
Epoch 577/600
1268/1268 - 1s - loss: 0.0346 - accuracy: 0.9886 - 1s/epoch - 974us/step
Epoch 578/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 579/600
1268/1268 - 1s - loss: 0.0347 - accuracy: 0.9882 - 1s/epoch - 973us/step
Epoch 580/600
1268/1268 - 1s - loss: 0.0346 - accuracy: 0.9886 - 1s/epoch - 971us/step
Epoch 581/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9883 - 1s/epoch - 990us/step
Epoch 582/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9881 - 1s/epoch - 973us/step
Epoch 583/600
1268/1268 - 1s - loss: 0.0348 - accuracy: 0.9881 - 1s/epoch - 990us/step
Epoch 584/600
1268/1268 - 1s - loss: 0.0344 - accuracy: 0.9884 - 1s/epoch - 993us/step
Epoch 585/600
1268/1268 - 1s - loss: 0.0348 - accuracy: 0.9881 - 1s/epoch - 991us/step
Epoch 586/600
1268/1268 - 1s - loss: 0.0344 - accuracy: 0.9885 - 1s/epoch - 974us/step
Epoch 587/600
1268/1268 - 1s - loss: 0.0349 - accuracy: 0.9879 - 1s/epoch - 993us/step
Epoch 588/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9880 - 1s/epoch - 971us/step
Epoch 589/600
1268/1268 - 1s - loss: 0.0345 - accuracy: 0.9883 - 1s/epoch - 976us/step
Epoch 590/600
1268/1268 - 1s - loss: 0.0345 - accuracy: 0.9882 - 1s/epoch - 986us/step
Epoch 591/600
1268/1268 - 1s - loss: 0.0348 - accuracy: 0.9882 - 1s/epoch - 994us/step
Epoch 592/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9879 - 1s/epoch - 971us/step
Epoch 593/600
1268/1268 - 1s - loss: 0.0343 - accuracy: 0.9882 - 1s/epoch - 992us/step
Epoch 594/600
1268/1268 - 1s - loss: 0.0344 - accuracy: 0.9884 - 1s/epoch - 976us/step
Epoch 595/600
1268/1268 - 1s - loss: 0.0347 - accuracy: 0.9882 - 1s/epoch - 984us/step
Epoch 596/600
1268/1268 - 1s - loss: 0.0349 - accuracy: 0.9884 - 1s/epoch - 986us/step
Epoch 597/600
1268/1268 - 1s - loss: 0.0341 - accuracy: 0.9883 - 1s/epoch - 988us/step
Epoch 598/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9880 - 1s/epoch - 971us/step
Epoch 599/600
1268/1268 - 1s - loss: 0.0347 - accuracy: 0.9882 - 1s/epoch - 989us/step
Epoch 600/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9878 - 1s/epoch - 973us/step
990/990 [========] - 1s 667us/step
Epoch 1/600
1268/1268 - 2s - loss: 0.3698 - accuracy: 0.8299 - 2s/epoch - 1ms/step
Epoch 2/600
1268/1268 - 1s - loss: 0.2342 - accuracy: 0.9061 - 1s/epoch - 967us/step
Epoch 3/600
1268/1268 - 1s - loss: 0.1943 - accuracy: 0.9242 - 1s/epoch - 1ms/step
Epoch 4/600
1268/1268 - 1s - loss: 0.1719 - accuracy: 0.9358 - 1s/epoch - 969us/step
Epoch 5/600
1268/1268 - 1s - loss: 0.1563 - accuracy: 0.9425 - 1s/epoch - 986us/step
Epoch 6/600
1268/1268 - 1s - loss: 0.1455 - accuracy: 0.9477 - 1s/epoch - 969us/step
Epoch 7/600
1268/1268 - 1s - loss: 0.1372 - accuracy: 0.9514 - 1s/epoch - 976us/step
Epoch 8/600
1268/1268 - 1s - loss: 0.1303 - accuracy: 0.9551 - 1s/epoch - 991us/step
Fnoch 9/600
1268/1268 - 1s - loss: 0.1259 - accuracy: 0.9567 - 1s/epoch - 971us/step
Epoch 10/600
1268/1268 - 1s - loss: 0.1205 - accuracy: 0.9592 - 1s/epoch - 977us/step
Epoch 11/600
1268/1268 - 1s - loss: 0.1174 - accuracy: 0.9602 - 1s/epoch - 972us/step
Epoch 12/600
1268/1268 - 1s - loss: 0.1140 - accuracy: 0.9617 - 1s/epoch - 988us/step
Epoch 13/600
1268/1268 - 1s - loss: 0.1112 - accuracy: 0.9630 - 1s/epoch - 991us/step
Epoch 14/600
1268/1268 - 1s - loss: 0.1096 - accuracy: 0.9637 - 1s/epoch - 970us/step
Epoch 15/600
1268/1268 - 1s - loss: 0.1072 - accuracy: 0.9645 - 1s/epoch - 988us/step
Epoch 16/600
1268/1268 - 1s - loss: 0.1048 - accuracy: 0.9657 - 1s/epoch - 970us/step
Epoch 17/600
1268/1268 - 1s - loss: 0.1032 - accuracy: 0.9660 - 1s/epoch - 986us/step
Epoch 18/600
1268/1268 - 1s - loss: 0.1016 - accuracy: 0.9668 - 1s/epoch - 965us/step
Epoch 19/600
1268/1268 - 1s - loss: 0.1007 - accuracy: 0.9668 - 1s/epoch - 991us/step
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Epoch 20/600
1268/1268 - 1s - loss: 0.0985 - accuracy: 0.9674 - 1s/epoch - 967us/step
Epoch 21/600
1268/1268 - 1s - loss: 0.0973 - accuracy: 0.9684 - 1s/epoch - 992us/step
Epoch 22/600
1268/1268 - 1s - loss: 0.0958 - accuracy: 0.9691 - 1s/epoch - 974us/step
Epoch 23/600
1268/1268 - 1s - loss: 0.0948 - accuracy: 0.9692 - 1s/epoch - 986us/step
Epoch 24/600
1268/1268 - 1s - loss: 0.0938 - accuracy: 0.9699 - 1s/epoch - 972us/step
Epoch 25/600
1268/1268 - 1s - loss: 0.0922 - accuracy: 0.9701 - 1s/epoch - 998us/step
Epoch 26/600
1268/1268 - 1s - loss: 0.0921 - accuracy: 0.9701 - 1s/epoch - 972us/step
Epoch 27/600
1268/1268 - 1s - loss: 0.0911 - accuracy: 0.9703 - 1s/epoch - 993us/step
Epoch 28/600
1268/1268 - 1s - loss: 0.0903 - accuracy: 0.9707 - 1s/epoch - 970us/step
Epoch 29/600
1268/1268 - 1s - loss: 0.0890 - accuracy: 0.9713 - 1s/epoch - 987us/step
Epoch 30/600
1268/1268 - 1s - loss: 0.0883 - accuracy: 0.9718 - 1s/epoch - 967us/step
Epoch 31/600
1268/1268 - 1s - loss: 0.0880 - accuracy: 0.9713 - 1s/epoch - 988us/step
Epoch 32/600
1268/1268 - 1s - loss: 0.0867 - accuracy: 0.9722 - 1s/epoch - 973us/step
Epoch 33/600
1268/1268 - 1s - loss: 0.0859 - accuracy: 0.9726 - 1s/epoch - 990us/step
Epoch 34/600
1268/1268 - 1s - loss: 0.0856 - accuracy: 0.9728 - 1s/epoch - 969us/step
Epoch 35/600
1268/1268 - 1s - loss: 0.0845 - accuracy: 0.9733 - 1s/epoch - 987us/step
Epoch 36/600
1268/1268 - 1s - loss: 0.0847 - accuracy: 0.9731 - 1s/epoch - 965us/step
Epoch 37/600
1268/1268 - 1s - loss: 0.0839 - accuracy: 0.9734 - 1s/epoch - 999us/step
Epoch 38/600
1268/1268 - 1s - loss: 0.0829 - accuracy: 0.9737 - 1s/epoch - 967us/step
Epoch 39/600
1268/1268 - 1s - loss: 0.0825 - accuracy: 0.9735 - 1s/epoch - 988us/step
Epoch 40/600
1268/1268 - 1s - loss: 0.0813 - accuracy: 0.9742 - 1s/epoch - 965us/step
Epoch 41/600
1268/1268 - 1s - loss: 0.0811 - accuracy: 0.9745 - 1s/epoch - 983us/step
Epoch 42/600
1268/1268 - 1s - loss: 0.0805 - accuracy: 0.9746 - 1s/epoch - 972us/step
Epoch 43/600
1268/1268 - 1s - loss: 0.0798 - accuracy: 0.9746 - 1s/epoch - 991us/step
Epoch 44/600
1268/1268 - 1s - loss: 0.0798 - accuracy: 0.9747 - 1s/epoch - 969us/step
Epoch 45/600
1268/1268 - 1s - loss: 0.0793 - accuracy: 0.9753 - 1s/epoch - 986us/step
Epoch 46/600
1268/1268 - 1s - loss: 0.0785 - accuracy: 0.9750 - 1s/epoch - 967us/step
Epoch 47/600
1268/1268 - 1s - loss: 0.0784 - accuracy: 0.9751 - 1s/epoch - 987us/step
Epoch 48/600
1268/1268 - 1s - loss: 0.0774 - accuracy: 0.9753 - 1s/epoch - 969us/step
Epoch 49/600
1268/1268 - 1s - loss: 0.0767 - accuracy: 0.9756 - 1s/epoch - 989us/step
Epoch 50/600
1268/1268 - 1s - loss: 0.0774 - accuracy: 0.9753 - 1s/epoch - 970us/step
Epoch 51/600
1268/1268 - 1s - loss: 0.0765 - accuracy: 0.9761 - 1s/epoch - 986us/step
Epoch 52/600
1268/1268 - 1s - loss: 0.0762 - accuracy: 0.9762 - 1s/epoch - 962us/step
Epoch 53/600
1268/1268 - 1s - loss: 0.0761 - accuracy: 0.9761 - 1s/epoch - 997us/step
Epoch 54/600
1268/1268 - 1s - loss: 0.0755 - accuracy: 0.9761 - 1s/epoch - 967us/step
Epoch 55/600
1268/1268 - 1s - loss: 0.0749 - accuracy: 0.9764 - 1s/epoch - 981us/step
Epoch 56/600
1268/1268 - 1s - loss: 0.0743 - accuracy: 0.9763 - 1s/epoch - 965us/step
Epoch 57/600
1268/1268 - 1s - loss: 0.0745 - accuracy: 0.9757 - 1s/epoch - 986us/step
Epoch 58/600
1268/1268 - 1s - loss: 0.0743 - accuracy: 0.9762 - 1s/epoch - 969us/step
Epoch 59/600
1268/1268 - 1s - loss: 0.0735 - accuracy: 0.9769 - 1s/epoch - 986us/step
Epoch 60/600
1268/1268 - 1s - loss: 0.0729 - accuracy: 0.9773 - 1s/epoch - 968us/step
Epoch 61/600
1268/1268 - 1s - loss: 0.0732 - accuracy: 0.9767 - 1s/epoch - 982us/step
Epoch 62/600
1268/1268 - 1s - loss: 0.0732 - accuracy: 0.9769 - 1s/epoch - 963us/step
Epoch 63/600
1268/1268 - 1s - loss: 0.0724 - accuracy: 0.9773 - 1s/epoch - 987us/step
Epoch 64/600
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1268/1268 - 1s - loss: 0.0724 - accuracy: 0.9771 - 1s/epoch - 967us/step
Epoch 65/600
1268/1268 - 1s - loss: 0.0715 - accuracy: 0.9774 - 1s/epoch - 987us/step
Epoch 66/600
1268/1268 - 1s - loss: 0.0719 - accuracy: 0.9775 - 1s/epoch - 964us/step
Epoch 67/600
1268/1268 - 1s - loss: 0.0713 - accuracy: 0.9775 - 1s/epoch - 980us/step
Epoch 68/600
1268/1268 - 1s - loss: 0.0711 - accuracy: 0.9779 - 1s/epoch - 963us/step
Epoch 69/600
1268/1268 - 1s - loss: 0.0709 - accuracy: 0.9774 - 1s/epoch - 982us/step
Epoch 70/600
1268/1268 - 1s - loss: 0.0704 - accuracy: 0.9774 - 1s/epoch - 969us/step
Epoch 71/600
1268/1268 - 1s - loss: 0.0698 - accuracy: 0.9783 - 1s/epoch - 989us/step
Epoch 72/600
1268/1268 - 1s - loss: 0.0697 - accuracy: 0.9777 - 1s/epoch - 984us/step
Epoch 73/600
1268/1268 - 1s - loss: 0.0692 - accuracy: 0.9782 - 1s/epoch - 989us/step
Epoch 74/600
1268/1268 - 1s - loss: 0.0692 - accuracy: 0.9781 - 1s/epoch - 974us/step
Epoch 75/600
1268/1268 - 1s - loss: 0.0691 - accuracy: 0.9784 - 1s/epoch - 991us/step
Epoch 76/600
1268/1268 - 1s - loss: 0.0689 - accuracy: 0.9780 - 1s/epoch - 967us/step
Epoch 77/600
1268/1268 - 1s - loss: 0.0685 - accuracy: 0.9784 - 1s/epoch - 982us/step
Epoch 78/600
1268/1268 - 1s - loss: 0.0685 - accuracy: 0.9787 - 1s/epoch - 965us/step
Epoch 79/600
1268/1268 - 1s - loss: 0.0674 - accuracy: 0.9787 - 1s/epoch - 992us/step
Epoch 80/600
1268/1268 - 1s - loss: 0.0677 - accuracy: 0.9785 - 1s/epoch - 969us/step
Epoch 81/600
1268/1268 - 1s - loss: 0.0673 - accuracy: 0.9786 - 1s/epoch - 981us/step
Epoch 82/600
1268/1268 - 1s - loss: 0.0674 - accuracy: 0.9783 - 1s/epoch - 962us/step
Epoch 83/600
1268/1268 - 1s - loss: 0.0666 - accuracy: 0.9789 - 1s/epoch - 990us/step
Epoch 84/600
1268/1268 - 1s - loss: 0.0666 - accuracy: 0.9788 - 1s/epoch - 967us/step
Epoch 85/600
1268/1268 - 1s - loss: 0.0666 - accuracy: 0.9787 - 1s/epoch - 991us/step
Epoch 86/600
1268/1268 - 1s - loss: 0.0664 - accuracy: 0.9787 - 1s/epoch - 967us/step
Epoch 87/600
1268/1268 - 1s - loss: 0.0666 - accuracy: 0.9788 - 1s/epoch - 987us/step
Epoch 88/600
1268/1268 - 1s - loss: 0.0660 - accuracy: 0.9793 - 1s/epoch - 963us/step
Epoch 89/600
1268/1268 - 1s - loss: 0.0656 - accuracy: 0.9791 - 1s/epoch - 987us/step
Epoch 90/600
1268/1268 - 1s - loss: 0.0656 - accuracy: 0.9791 - 1s/epoch - 964us/step
Epoch 91/600
1268/1268 - 1s - loss: 0.0658 - accuracy: 0.9789 - 1s/epoch - 990us/step
Epoch 92/600
1268/1268 - 1s - loss: 0.0650 - accuracy: 0.9793 - 1s/epoch - 970us/step
Epoch 93/600
1268/1268 - 1s - loss: 0.0643 - accuracy: 0.9799 - 1s/epoch - 988us/step
Epoch 94/600
1268/1268 - 1s - loss: 0.0645 - accuracy: 0.9799 - 1s/epoch - 969us/step
Epoch 95/600
1268/1268 - 1s - loss: 0.0649 - accuracy: 0.9794 - 1s/epoch - 993us/step
Epoch 96/600
1268/1268 - 1s - loss: 0.0639 - accuracy: 0.9799 - 1s/epoch - 967us/step
Epoch 97/600
1268/1268 - 1s - loss: 0.0646 - accuracy: 0.9794 - 1s/epoch - 988us/step
Fnoch 98/600
1268/1268 - 1s - loss: 0.0633 - accuracy: 0.9802 - 1s/epoch - 969us/step
Epoch 99/600
1268/1268 - 1s - loss: 0.0635 - accuracy: 0.9803 - 1s/epoch - 991us/step
Epoch 100/600
1268/1268 - 1s - loss: 0.0640 - accuracy: 0.9796 - 1s/epoch - 972us/step
Epoch 101/600
1268/1268 - 1s - loss: 0.0636 - accuracy: 0.9796 - 1s/epoch - 990us/step
Epoch 102/600
1268/1268 - 1s - loss: 0.0632 - accuracy: 0.9800 - 1s/epoch - 971us/step
Epoch 103/600
1268/1268 - 1s - loss: 0.0630 - accuracy: 0.9801 - 1s/epoch - 976us/step
Epoch 104/600
1268/1268 - 1s - loss: 0.0623 - accuracy: 0.9804 - 1s/epoch - 964us/step
Epoch 105/600
1268/1268 - 1s - loss: 0.0630 - accuracy: 0.9800 - 1s/epoch - 978us/step
Epoch 106/600
1268/1268 - 1s - loss: 0.0632 - accuracy: 0.9801 - 1s/epoch - 966us/step
Epoch 107/600
1268/1268 - 1s - loss: 0.0624 - accuracy: 0.9800 - 1s/epoch - 989us/step
Epoch 108/600
1268/1268 - 1s - loss: 0.0619 - accuracy: 0.9804 - 1s/epoch - 973us/step
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Epoch 109/600
1268/1268 - 1s - loss: 0.0622 - accuracy: 0.9799 - 1s/epoch - 995us/step
Epoch 110/600
1268/1268 - 1s - loss: 0.0614 - accuracy: 0.9805 - 1s/epoch - 967us/step
Epoch 111/600
1268/1268 - 1s - loss: 0.0621 - accuracy: 0.9803 - 1s/epoch - 993us/step
Epoch 112/600
1268/1268 - 1s - loss: 0.0613 - accuracy: 0.9806 - 1s/epoch - 972us/step
Epoch 113/600
1268/1268 - 1s - loss: 0.0610 - accuracy: 0.9803 - 1s/epoch - 985us/step
Epoch 114/600
1268/1268 - 1s - loss: 0.0606 - accuracy: 0.9809 - 1s/epoch - 966us/step
Epoch 115/600
1268/1268 - 1s - loss: 0.0616 - accuracy: 0.9805 - 1s/epoch - 991us/step
Epoch 116/600
1268/1268 - 1s - loss: 0.0609 - accuracy: 0.9811 - 1s/epoch - 970us/step
Epoch 117/600
1268/1268 - 1s - loss: 0.0610 - accuracy: 0.9804 - 1s/epoch - 985us/step
Epoch 118/600
1268/1268 - 1s - loss: 0.0601 - accuracy: 0.9810 - 1s/epoch - 977us/step
Epoch 119/600
1268/1268 - 1s - loss: 0.0609 - accuracy: 0.9805 - 1s/epoch - 991us/step
Fnoch 120/600
1268/1268 - 1s - loss: 0.0600 - accuracy: 0.9809 - 1s/epoch - 969us/step
Epoch 121/600
1268/1268 - 1s - loss: 0.0607 - accuracy: 0.9807 - 1s/epoch - 987us/step
Epoch 122/600
1268/1268 - 1s - loss: 0.0598 - accuracy: 0.9810 - 1s/epoch - 976us/step
Epoch 123/600
1268/1268 - 1s - loss: 0.0604 - accuracy: 0.9805 - 1s/epoch - 988us/step
Epoch 124/600
1268/1268 - 1s - loss: 0.0595 - accuracy: 0.9809 - 1s/epoch - 972us/step
Epoch 125/600
1268/1268 - 1s - loss: 0.0597 - accuracy: 0.9807 - 1s/epoch - 987us/step
Epoch 126/600
1268/1268 - 1s - loss: 0.0592 - accuracy: 0.9810 - 1s/epoch - 970us/step
Epoch 127/600
1268/1268 - 1s - loss: 0.0597 - accuracy: 0.9809 - 1s/epoch - 989us/step
Epoch 128/600
1268/1268 - 1s - loss: 0.0595 - accuracy: 0.9811 - 1s/epoch - 974us/step
Epoch 129/600
1268/1268 - 1s - loss: 0.0587 - accuracy: 0.9810 - 1s/epoch - 987us/step
Epoch 130/600
1268/1268 - 1s - loss: 0.0592 - accuracy: 0.9810 - 1s/epoch - 962us/step
Epoch 131/600
1268/1268 - 1s - loss: 0.0588 - accuracy: 0.9810 - 1s/epoch - 985us/step
Epoch 132/600
1268/1268 - 1s - loss: 0.0589 - accuracy: 0.9811 - 1s/epoch - 988us/step
Epoch 133/600
1268/1268 - 1s - loss: 0.0586 - accuracy: 0.9814 - 1s/epoch - 1ms/step
Epoch 134/600
1268/1268 - 1s - loss: 0.0581 - accuracy: 0.9814 - 1s/epoch - 969us/step
Epoch 135/600
1268/1268 - 1s - loss: 0.0590 - accuracy: 0.9812 - 1s/epoch - 990us/step
Epoch 136/600
1268/1268 - 1s - loss: 0.0582 - accuracy: 0.9812 - 1s/epoch - 978us/step
Epoch 137/600
1268/1268 - 1s - loss: 0.0581 - accuracy: 0.9815 - 1s/epoch - 985us/step
Epoch 138/600
1268/1268 - 1s - loss: 0.0580 - accuracy: 0.9816 - 1s/epoch - 968us/step
Epoch 139/600
1268/1268 - 1s - loss: 0.0581 - accuracy: 0.9814 - 1s/epoch - 986us/step
Epoch 140/600
1268/1268 - 1s - loss: 0.0583 - accuracy: 0.9810 - 1s/epoch - 969us/step
Epoch 141/600
1268/1268 - 1s - loss: 0.0581 - accuracy: 0.9815 - 1s/epoch - 993us/step
Epoch 142/600
1268/1268 - 1s - loss: 0.0578 - accuracy: 0.9814 - 1s/epoch - 968us/step
Epoch 143/600
1268/1268 - 1s - loss: 0.0577 - accuracy: 0.9813 - 1s/epoch - 965us/step
Epoch 144/600
1268/1268 - 1s - loss: 0.0574 - accuracy: 0.9817 - 1s/epoch - 989us/step
Epoch 145/600
1268/1268 - 1s - loss: 0.0576 - accuracy: 0.9814 - 1s/epoch - 964us/step
Epoch 146/600
1268/1268 - 1s - loss: 0.0569 - accuracy: 0.9815 - 1s/epoch - 987us/step
Epoch 147/600
1268/1268 - 1s - loss: 0.0569 - accuracy: 0.9819 - 1s/epoch - 988us/step
Epoch 148/600
1268/1268 - 1s - loss: 0.0570 - accuracy: 0.9818 - 1s/epoch - 971us/step
Epoch 149/600
1268/1268 - 1s - loss: 0.0563 - accuracy: 0.9817 - 1s/epoch - 988us/step
Epoch 150/600
1268/1268 - 1s - loss: 0.0572 - accuracy: 0.9818 - 1s/epoch - 963us/step
Epoch 151/600
1268/1268 - 1s - loss: 0.0566 - accuracy: 0.9819 - 1s/epoch - 988us/step
Epoch 152/600
1268/1268 - 1s - loss: 0.0568 - accuracy: 0.9819 - 1s/epoch - 969us/step
Epoch 153/600
```

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1268/1268 - 1s - loss: 0.0562 - accuracy: 0.9823 - 1s/epoch - 984us/step
Epoch 154/600
1268/1268 - 1s - loss: 0.0567 - accuracy: 0.9818 - 1s/epoch - 965us/step
Epoch 155/600
1268/1268 - 1s - loss: 0.0563 - accuracy: 0.9815 - 1s/epoch - 980us/step
Epoch 156/600
1268/1268 - 1s - loss: 0.0562 - accuracy: 0.9815 - 1s/epoch - 967us/step
Epoch 157/600
1268/1268 - 1s - loss: 0.0565 - accuracy: 0.9818 - 1s/epoch - 981us/step
Epoch 158/600
1268/1268 - 1s - loss: 0.0559 - accuracy: 0.9817 - 1s/epoch - 966us/step
Epoch 159/600
1268/1268 - 1s - loss: 0.0555 - accuracy: 0.9822 - 1s/epoch - 991us/step
Epoch 160/600
1268/1268 - 1s - loss: 0.0564 - accuracy: 0.9815 - 1s/epoch - 968us/step
Epoch 161/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9823 - 1s/epoch - 982us/step
Epoch 162/600
1268/1268 - 1s - loss: 0.0554 - accuracy: 0.9823 - 1s/epoch - 969us/step
Epoch 163/600
1268/1268 - 1s - loss: 0.0562 - accuracy: 0.9816 - 1s/epoch - 989us/step
Epoch 164/600
1268/1268 - 1s - loss: 0.0550 - accuracy: 0.9826 - 1s/epoch - 968us/step
Epoch 165/600
1268/1268 - 1s - loss: 0.0552 - accuracy: 0.9821 - 1s/epoch - 987us/step
Epoch 166/600
1268/1268 - 1s - loss: 0.0554 - accuracy: 0.9817 - 1s/epoch - 974us/step
Epoch 167/600
1268/1268 - 1s - loss: 0.0546 - accuracy: 0.9825 - 1s/epoch - 983us/step
Epoch 168/600
1268/1268 - 1s - loss: 0.0551 - accuracy: 0.9823 - 1s/epoch - 972us/step
Epoch 169/600
1268/1268 - 1s - loss: 0.0554 - accuracy: 0.9820 - 1s/epoch - 984us/step
Epoch 170/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9820 - 1s/epoch - 963us/step
Epoch 171/600
1268/1268 - 1s - loss: 0.0545 - accuracy: 0.9821 - 1s/epoch - 1ms/step
Epoch 172/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9820 - 1s/epoch - 971us/step
Epoch 173/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9825 - 1s/epoch - 990us/step
Epoch 174/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9823 - 1s/epoch - 969us/step
Epoch 175/600
1268/1268 - 1s - loss: 0.0548 - accuracy: 0.9821 - 1s/epoch - 990us/step
Epoch 176/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9825 - 1s/epoch - 971us/step
Epoch 177/600
1268/1268 - 1s - loss: 0.0540 - accuracy: 0.9825 - 1s/epoch - 987us/step
Epoch 178/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9826 - 1s/epoch - 966us/step
Epoch 179/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9822 - 1s/epoch - 985us/step
Epoch 180/600
1268/1268 - 1s - loss: 0.0545 - accuracy: 0.9824 - 1s/epoch - 970us/step
Epoch 181/600
1268/1268 - 1s - loss: 0.0536 - accuracy: 0.9829 - 1s/epoch - 995us/step
Epoch 182/600
1268/1268 - 1s - loss: 0.0535 - accuracy: 0.9829 - 1s/epoch - 983us/step
Epoch 183/600
1268/1268 - 1s - loss: 0.0539 - accuracy: 0.9829 - 1s/epoch - 1ms/step
Epoch 184/600
1268/1268 - 1s - loss: 0.0536 - accuracy: 0.9824 - 1s/epoch - 976us/step
Epoch 185/600
1268/1268 - 1s - loss: 0.0532 - accuracy: 0.9825 - 1s/epoch - 991us/step
Epoch 186/600
1268/1268 - 1s - loss: 0.0532 - accuracy: 0.9829 - 1s/epoch - 966us/step
Fnoch 187/600
1268/1268 - 1s - loss: 0.0538 - accuracy: 0.9823 - 1s/epoch - 981us/step
Epoch 188/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9828 - 1s/epoch - 968us/step
Epoch 189/600
1268/1268 - 1s - loss: 0.0536 - accuracy: 0.9823 - 1s/epoch - 985us/step
Epoch 190/600
1268/1268 - 1s - loss: 0.0527 - accuracy: 0.9827 - 1s/epoch - 963us/step
Epoch 191/600
1268/1268 - 1s - loss: 0.0529 - accuracy: 0.9831 - 1s/epoch - 985us/step
Epoch 192/600
1268/1268 - 1s - loss: 0.0526 - accuracy: 0.9829 - 1s/epoch - 970us/step
Epoch 193/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9824 - 1s/epoch - 991us/step
Epoch 194/600
1268/1268 - 1s - loss: 0.0525 - accuracy: 0.9831 - 1s/epoch - 965us/step
Epoch 195/600
1268/1268 - 1s - loss: 0.0524 - accuracy: 0.9831 - 1s/epoch - 982us/step
Epoch 196/600
1268/1268 - 1s - loss: 0.0524 - accuracy: 0.9827 - 1s/epoch - 969us/step
Epoch 197/600
1268/1268 - 1s - loss: 0.0521 - accuracy: 0.9829 - 1s/epoch - 969us/step
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Epoch 198/600
1268/1268 - 1s - loss: 0.0523 - accuracy: 0.9828 - 1s/epoch - 986us/step
Epoch 199/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9834 - 1s/epoch - 968us/step
Epoch 200/600
1268/1268 - 1s - loss: 0.0527 - accuracy: 0.9830 - 1s/epoch - 1ms/step
Epoch 201/600
1268/1268 - 1s - loss: 0.0527 - accuracy: 0.9829 - 1s/epoch - 964us/step
Epoch 202/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9828 - 1s/epoch - 989us/step
Epoch 203/600
1268/1268 - 1s - loss: 0.0522 - accuracy: 0.9830 - 1s/epoch - 963us/step
Epoch 204/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9831 - 1s/epoch - 980us/step
Epoch 205/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9831 - 1s/epoch - 965us/step
Epoch 206/600
1268/1268 - 1s - loss: 0.0515 - accuracy: 0.9834 - 1s/epoch - 988us/step
Epoch 207/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9831 - 1s/epoch - 965us/step
Epoch 208/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9831 - 1s/epoch - 989us/step
Epoch 209/600
1268/1268 - 1s - loss: 0.0512 - accuracy: 0.9832 - 1s/epoch - 963us/step
Epoch 210/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9830 - 1s/epoch - 988us/step
Epoch 211/600
1268/1268 - 1s - loss: 0.0515 - accuracy: 0.9830 - 1s/epoch - 965us/step
Epoch 212/600
1268/1268 - 1s - loss: 0.0509 - accuracy: 0.9836 - 1s/epoch - 987us/step
Epoch 213/600
1268/1268 - 1s - loss: 0.0510 - accuracy: 0.9834 - 1s/epoch - 965us/step
Epoch 214/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9832 - 1s/epoch - 983us/step
Epoch 215/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9830 - 1s/epoch - 968us/step
Epoch 216/600
1268/1268 - 1s - loss: 0.0514 - accuracy: 0.9833 - 1s/epoch - 980us/step
Epoch 217/600
1268/1268 - 1s - loss: 0.0503 - accuracy: 0.9835 - 1s/epoch - 969us/step
Epoch 218/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9835 - 1s/epoch - 983us/step
Epoch 219/600
1268/1268 - 1s - loss: 0.0504 - accuracy: 0.9831 - 1s/epoch - 973us/step
Epoch 220/600
1268/1268 - 1s - loss: 0.0502 - accuracy: 0.9838 - 1s/epoch - 980us/step
Epoch 221/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9835 - 1s/epoch - 964us/step
Epoch 222/600
1268/1268 - 1s - loss: 0.0502 - accuracy: 0.9836 - 1s/epoch - 963us/step
Epoch 223/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9832 - 1s/epoch - 986us/step
Epoch 224/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9835 - 1s/epoch - 970us/step
Epoch 225/600
1268/1268 - 1s - loss: 0.0503 - accuracy: 0.9837 - 1s/epoch - 996us/step
Epoch 226/600
1268/1268 - 1s - loss: 0.0503 - accuracy: 0.9833 - 1s/epoch - 960us/step
Epoch 227/600
1268/1268 - 1s - loss: 0.0502 - accuracy: 0.9834 - 1s/epoch - 985us/step
Epoch 228/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9835 - 1s/epoch - 968us/step
Epoch 229/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9835 - 1s/epoch - 993us/step
Epoch 230/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9836 - 1s/epoch - 966us/step
Epoch 231/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9836 - 1s/epoch - 984us/step
Epoch 232/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9839 - 1s/epoch - 969us/step
Epoch 233/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9839 - 1s/epoch - 971us/step
Epoch 234/600
1268/1268 - 1s - loss: 0.0496 - accuracy: 0.9838 - 1s/epoch - 988us/step
Epoch 235/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9832 - 1s/epoch - 972us/step
Epoch 236/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9837 - 1s/epoch - 964us/step
Epoch 237/600
1268/1268 - 1s - loss: 0.0497 - accuracy: 0.9841 - 1s/epoch - 989us/step
Epoch 238/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9837 - 1s/epoch - 974us/step
Epoch 239/600
1268/1268 - 1s - loss: 0.0496 - accuracy: 0.9838 - 1s/epoch - 980us/step
Epoch 240/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9839 - 1s/epoch - 964us/step
Epoch 241/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9840 - 1s/epoch - 995us/step
Epoch 242/600
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1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9839 - 1s/epoch - 973us/step
Epoch 243/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9835 - 1s/epoch - 982us/step
Epoch 244/600
1268/1268 - 1s - loss: 0.0487 - accuracy: 0.9840 - 1s/epoch - 967us/step
Epoch 245/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9835 - 1s/epoch - 966us/step
Epoch 246/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 247/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9838 - 1s/epoch - 970us/step
Epoch 248/600
1268/1268 - 1s - loss: 0.0485 - accuracy: 0.9840 - 1s/epoch - 990us/step
Epoch 249/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9837 - 1s/epoch - 971us/step
Epoch 250/600
1268/1268 - 1s - loss: 0.0488 - accuracy: 0.9842 - 1s/epoch - 986us/step
Epoch 251/600
1268/1268 - 1s - loss: 0.0487 - accuracy: 0.9839 - 1s/epoch - 970us/step
Epoch 252/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9839 - 1s/epoch - 986us/step
Epoch 253/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9840 - 1s/epoch - 967us/step
Epoch 254/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9840 - 1s/epoch - 989us/step
Epoch 255/600
1268/1268 - 1s - loss: 0.0483 - accuracy: 0.9840 - 1s/epoch - 961us/step
Epoch 256/600
1268/1268 - 1s - loss: 0.0487 - accuracy: 0.9840 - 1s/epoch - 984us/step
Epoch 257/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9839 - 1s/epoch - 973us/step
Epoch 258/600
1268/1268 - 1s - loss: 0.0479 - accuracy: 0.9841 - 1s/epoch - 989us/step
Epoch 259/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9840 - 1s/epoch - 969us/step
Epoch 260/600
1268/1268 - 1s - loss: 0.0484 - accuracy: 0.9842 - 1s/epoch - 971us/step
Epoch 261/600
1268/1268 - 1s - loss: 0.0482 - accuracy: 0.9842 - 1s/epoch - 982us/step
Epoch 262/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9842 - 1s/epoch - 987us/step
Epoch 263/600
1268/1268 - 1s - loss: 0.0482 - accuracy: 0.9840 - 1s/epoch - 973us/step
Epoch 264/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9842 - 1s/epoch - 986us/step
Epoch 265/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9841 - 1s/epoch - 971us/step
Epoch 266/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9839 - 1s/epoch - 986us/step
Epoch 267/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9844 - 1s/epoch - 969us/step
Epoch 268/600
1268/1268 - 1s - loss: 0.0485 - accuracy: 0.9838 - 1s/epoch - 999us/step
Epoch 269/600
1268/1268 - 1s - loss: 0.0476 - accuracy: 0.9845 - 1s/epoch - 967us/step
Epoch 270/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9846 - 1s/epoch - 982us/step
Epoch 271/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9840 - 1s/epoch - 964us/step
Epoch 272/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9846 - 1s/epoch - 983us/step
Epoch 273/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9845 - 1s/epoch - 975us/step
Epoch 274/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9843 - 1s/epoch - 986us/step
Epoch 275/600
1268/1268 - 1s - loss: 0.0474 - accuracy: 0.9843 - 1s/epoch - 964us/step
Fnoch 276/600
1268/1268 - 1s - loss: 0.0473 - accuracy: 0.9842 - 1s/epoch - 972us/step
Epoch 277/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9842 - 1s/epoch - 990us/step
Epoch 278/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9848 - 1s/epoch - 985us/step
Epoch 279/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9844 - 1s/epoch - 972us/step
Epoch 280/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9843 - 1s/epoch - 991us/step
Epoch 281/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9845 - 1s/epoch - 969us/step
Epoch 282/600
1268/1268 - 1s - loss: 0.0474 - accuracy: 0.9839 - 1s/epoch - 982us/step
Epoch 283/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9847 - 1s/epoch - 964us/step
Epoch 284/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9844 - 1s/epoch - 987us/step
Epoch 285/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9846 - 1s/epoch - 973us/step
Epoch 286/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9843 - 1s/epoch - 987us/step
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Epoch 287/600
1268/1268 - 1s - loss: 0.0468 - accuracy: 0.9845 - 1s/epoch - 966us/step
Epoch 288/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9851 - 1s/epoch - 982us/step
Epoch 289/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9846 - 1s/epoch - 967us/step
Epoch 290/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9846 - 1s/epoch - 992us/step
Epoch 291/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9844 - 1s/epoch - 971us/step
Epoch 292/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9849 - 1s/epoch - 989us/step
Epoch 293/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9845 - 1s/epoch - 967us/step
Epoch 294/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9846 - 1s/epoch - 976us/step
Epoch 295/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9845 - 1s/epoch - 960us/step
Epoch 296/600
1268/1268 - 1s - loss: 0.0462 - accuracy: 0.9849 - 1s/epoch - 981us/step
Epoch 297/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9845 - 1s/epoch - 966us/step
Epoch 298/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9846 - 1s/epoch - 986us/step
Epoch 299/600
1268/1268 - 1s - loss: 0.0460 - accuracy: 0.9852 - 1s/epoch - 967us/step
Epoch 300/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9846 - 1s/epoch - 990us/step
Epoch 301/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9846 - 1s/epoch - 967us/step
Epoch 302/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9845 - 1s/epoch - 988us/step
Epoch 303/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9845 - 1s/epoch - 963us/step
Epoch 304/600
1268/1268 - 1s - loss: 0.0462 - accuracy: 0.9847 - 1s/epoch - 983us/step
Epoch 305/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9847 - 1s/epoch - 965us/step
Epoch 306/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9850 - 1s/epoch - 989us/step
Epoch 307/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9848 - 1s/epoch - 969us/step
Epoch 308/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9847 - 1s/epoch - 986us/step
Epoch 309/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9847 - 1s/epoch - 965us/step
Epoch 310/600
1268/1268 - 1s - loss: 0.0460 - accuracy: 0.9850 - 1s/epoch - 978us/step
Epoch 311/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9848 - 1s/epoch - 963us/step
Epoch 312/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9851 - 1s/epoch - 989us/step
Epoch 313/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9850 - 1s/epoch - 964us/step
Epoch 314/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9848 - 1s/epoch - 988us/step
Epoch 315/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9847 - 1s/epoch - 962us/step
Epoch 316/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9850 - 1s/epoch - 983us/step
Epoch 317/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9852 - 1s/epoch - 976us/step
Epoch 318/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9848 - 1s/epoch - 981us/step
Epoch 319/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9849 - 1s/epoch - 963us/step
Epoch 320/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9849 - 1s/epoch - 987us/step
Epoch 321/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9849 - 1s/epoch - 965us/step
Epoch 322/600
1268/1268 - 1s - loss: 0.0456 - accuracy: 0.9849 - 1s/epoch - 979us/step
Epoch 323/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9849 - 1s/epoch - 962us/step
Epoch 324/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9846 - 1s/epoch - 982us/step
Epoch 325/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9853 - 1s/epoch - 967us/step
Epoch 326/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9849 - 1s/epoch - 989us/step
Epoch 327/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9848 - 1s/epoch - 959us/step
Epoch 328/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9853 - 1s/epoch - 981us/step
Epoch 329/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9850 - 1s/epoch - 970us/step
Epoch 330/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9851 - 1s/epoch - 990us/step
Epoch 331/600
```

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1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9850 - 1s/epoch - 964us/step
Epoch 332/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9858 - 1s/epoch - 986us/step
Epoch 333/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9848 - 1s/epoch - 974us/step
Epoch 334/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9853 - 1s/epoch - 987us/step
Epoch 335/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9855 - 1s/epoch - 963us/step
Epoch 336/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9853 - 1s/epoch - 980us/step
Epoch 337/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9852 - 1s/epoch - 962us/step
Epoch 338/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9850 - 1s/epoch - 995us/step
Epoch 339/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9849 - 1s/epoch - 969us/step
Epoch 340/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9851 - 1s/epoch - 980us/step
Epoch 341/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9851 - 1s/epoch - 966us/step
Epoch 342/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9856 - 1s/epoch - 971us/step
Epoch 343/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9852 - 1s/epoch - 983us/step
Epoch 344/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9855 - 1s/epoch - 964us/step
Epoch 345/600
1268/1268 - 1s - loss: 0.0448 - accuracy: 0.9852 - 1s/epoch - 987us/step
Epoch 346/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9858 - 1s/epoch - 974us/step
Epoch 347/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9852 - 1s/epoch - 977us/step
Epoch 348/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9861 - 1s/epoch - 962us/step
Epoch 349/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9853 - 1s/epoch - 967us/step
Epoch 350/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9851 - 1s/epoch - 986us/step
Epoch 351/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9852 - 1s/epoch - 985us/step
Epoch 352/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9854 - 1s/epoch - 961us/step
Epoch 353/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9852 - 1s/epoch - 987us/step
Epoch 354/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9855 - 1s/epoch - 972us/step
Epoch 355/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9854 - 1s/epoch - 989us/step
Epoch 356/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9851 - 1s/epoch - 967us/step
Epoch 357/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9859 - 1s/epoch - 991us/step
Epoch 358/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9853 - 1s/epoch - 971us/step
Epoch 359/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9856 - 1s/epoch - 982us/step
Epoch 360/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9854 - 1s/epoch - 971us/step
Epoch 361/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9855 - 1s/epoch - 985us/step
Epoch 362/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 363/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9854 - 1s/epoch - 980us/step
Epoch 364/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9857 - 1s/epoch - 987us/step
Epoch 365/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 366/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9853 - 1s/epoch - 975us/step
Epoch 367/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9856 - 1s/epoch - 987us/step
Epoch 368/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9856 - 1s/epoch - 967us/step
Epoch 369/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9858 - 1s/epoch - 983us/step
Epoch 370/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9859 - 1s/epoch - 967us/step
Epoch 371/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9855 - 1s/epoch - 981us/step
Epoch 372/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9852 - 1s/epoch - 967us/step
Epoch 373/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9856 - 1s/epoch - 982us/step
Epoch 374/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9858 - 1s/epoch - 963us/step
Epoch 375/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9856 - 1s/epoch - 986us/step
```

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Epoch 376/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9857 - 1s/epoch - 965us/step
Epoch 377/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9857 - 1s/epoch - 983us/step
Epoch 378/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9855 - 1s/epoch - 968us/step
Epoch 379/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9856 - 1s/epoch - 987us/step
Epoch 380/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9858 - 1s/epoch - 966us/step
Epoch 381/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9857 - 1s/epoch - 986us/step
Epoch 382/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9857 - 1s/epoch - 965us/step
Epoch 383/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9856 - 1s/epoch - 986us/step
Epoch 384/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9859 - 1s/epoch - 961us/step
Epoch 385/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9856 - 1s/epoch - 991us/step
Epoch 386/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9852 - 1s/epoch - 968us/step
Epoch 387/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9857 - 1s/epoch - 984us/step
Epoch 388/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9860 - 1s/epoch - 962us/step
Epoch 389/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9856 - 1s/epoch - 998us/step
Epoch 390/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9861 - 1s/epoch - 979us/step
Epoch 391/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9861 - 1s/epoch - 972us/step
Epoch 392/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9856 - 1s/epoch - 986us/step
Epoch 393/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9855 - 1s/epoch - 993us/step
Epoch 394/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9860 - 1s/epoch - 981us/step
Epoch 395/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9858 - 1s/epoch - 992us/step
Epoch 396/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9855 - 1s/epoch - 967us/step
Epoch 397/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9854 - 1s/epoch - 997us/step
Epoch 398/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9859 - 1s/epoch - 967us/step
Epoch 399/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9860 - 1s/epoch - 974us/step
Epoch 400/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9857 - 1s/epoch - 989us/step
Epoch 401/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9861 - 1s/epoch - 976us/step
Epoch 402/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9859 - 1s/epoch - 963us/step
Epoch 403/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9863 - 1s/epoch - 981us/step
Epoch 404/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9860 - 1s/epoch - 962us/step
Epoch 405/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9858 - 1s/epoch - 985us/step
Epoch 406/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9859 - 1s/epoch - 967us/step
Epoch 407/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9862 - 1s/epoch - 989us/step
Epoch 408/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9861 - 1s/epoch - 970us/step
Epoch 409/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 410/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9864 - 1s/epoch - 976us/step
Epoch 411/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9860 - 1s/epoch - 990us/step
Epoch 412/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9859 - 1s/epoch - 967us/step
Epoch 413/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9859 - 1s/epoch - 986us/step
Epoch 414/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9862 - 1s/epoch - 993us/step
Epoch 415/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9860 - 1s/epoch - 999us/step
Epoch 416/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9862 - 1s/epoch - 969us/step
Epoch 417/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9860 - 1s/epoch - 969us/step
Epoch 418/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9863 - 1s/epoch - 989us/step
Epoch 419/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9857 - 1s/epoch - 990us/step
Epoch 420/600
```

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1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9860 - 1s/epoch - 972us/step
Epoch 421/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9861 - 1s/epoch - 989us/step
Epoch 422/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9858 - 1s/epoch - 967us/step
Epoch 423/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9860 - 1s/epoch - 988us/step
Epoch 424/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9865 - 1s/epoch - 974us/step
Epoch 425/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9861 - 1s/epoch - 984us/step
Epoch 426/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9859 - 1s/epoch - 966us/step
Epoch 427/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9863 - 1s/epoch - 983us/step
Epoch 428/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9859 - 1s/epoch - 967us/step
Epoch 429/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9858 - 1s/epoch - 976us/step
Epoch 430/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9863 - 1s/epoch - 965us/step
Epoch 431/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9862 - 1s/epoch - 981us/step
Epoch 432/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9860 - 1s/epoch - 967us/step
Epoch 433/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9859 - 1s/epoch - 987us/step
Epoch 434/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9861 - 1s/epoch - 969us/step
Epoch 435/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9859 - 1s/epoch - 988us/step
Epoch 436/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9862 - 1s/epoch - 965us/step
Epoch 437/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9862 - 1s/epoch - 990us/step
Epoch 438/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9863 - 1s/epoch - 968us/step
Epoch 439/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 440/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9857 - 1s/epoch - 984us/step
Epoch 441/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9863 - 1s/epoch - 998us/step
Epoch 442/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9862 - 1s/epoch - 974us/step
Epoch 443/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9862 - 1s/epoch - 991us/step
Epoch 444/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9864 - 1s/epoch - 964us/step
Epoch 445/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9863 - 1s/epoch - 993us/step
Epoch 446/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9857 - 1s/epoch - 981us/step
Epoch 447/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 448/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9865 - 1s/epoch - 976us/step
Epoch 449/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9860 - 1s/epoch - 983us/step
Epoch 450/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9863 - 1s/epoch - 972us/step
Epoch 451/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9861 - 1s/epoch - 999us/step
Epoch 452/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9862 - 1s/epoch - 968us/step
Epoch 453/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9864 - 1s/epoch - 989us/step
Fnoch 454/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9863 - 1s/epoch - 968us/step
Epoch 455/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9863 - 1s/epoch - 984us/step
Epoch 456/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9864 - 1s/epoch - 980us/step
Epoch 457/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9864 - 1s/epoch - 978us/step
Epoch 458/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9865 - 1s/epoch - 972us/step
Epoch 459/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9862 - 1s/epoch - 981us/step
Epoch 460/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9864 - 1s/epoch - 970us/step
Epoch 461/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9863 - 1s/epoch - 985us/step
Epoch 462/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9865 - 1s/epoch - 980us/step
Epoch 463/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9865 - 1s/epoch - 988us/step
Epoch 464/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9861 - 1s/epoch - 963us/step
```

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Epoch 465/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9866 - 1s/epoch - 990us/step
Epoch 466/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9867 - 1s/epoch - 995us/step
Epoch 467/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 970us/step
Epoch 468/600
. 1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9862 - 1s/epoch - 994us/step
Epoch 469/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9865 - 1s/epoch - 984us/step
Epoch 470/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9868 - 1s/epoch - 964us/step
Epoch 471/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9860 - 1s/epoch - 986us/step
Epoch 472/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9868 - 1s/epoch - 963us/step
Epoch 473/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9861 - 1s/epoch - 974us/step
Epoch 474/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9867 - 1s/epoch - 965us/step
Epoch 475/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9864 - 1s/epoch - 986us/step
Epoch 476/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9863 - 1s/epoch - 962us/step
Epoch 477/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9867 - 1s/epoch - 961us/step
Epoch 478/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9866 - 1s/epoch - 984us/step
Epoch 479/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9867 - 1s/epoch - 982us/step
Epoch 480/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9867 - 1s/epoch - 964us/step
Epoch 481/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9868 - 1s/epoch - 977us/step
Epoch 482/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9866 - 1s/epoch - 967us/step
Epoch 483/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9865 - 1s/epoch - 983us/step
Epoch 484/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9868 - 1s/epoch - 962us/step
Epoch 485/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9861 - 1s/epoch - 976us/step
Epoch 486/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9867 - 1s/epoch - 962us/step
Epoch 487/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9866 - 1s/epoch - 985us/step
Epoch 488/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9864 - 1s/epoch - 969us/step
Epoch 489/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9867 - 1s/epoch - 984us/step
Epoch 490/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9867 - 1s/epoch - 965us/step
Epoch 491/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9864 - 1s/epoch - 984us/step
Epoch 492/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9868 - 1s/epoch - 969us/step
Epoch 493/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9863 - 1s/epoch - 980us/step
Epoch 494/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9866 - 1s/epoch - 966us/step
Epoch 495/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9869 - 1s/epoch - 986us/step
Epoch 496/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9867 - 1s/epoch - 970us/step
Epoch 497/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9865 - 1s/epoch - 988us/step
Epoch 498/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9868 - 1s/epoch - 967us/step
Epoch 499/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9865 - 1s/epoch - 989us/step
Epoch 500/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9873 - 1s/epoch - 966us/step
Epoch 501/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9864 - 1s/epoch - 980us/step
Epoch 502/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9869 - 1s/epoch - 962us/step
Epoch 503/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9864 - 1s/epoch - 980us/step
Epoch 504/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9865 - 1s/epoch - 958us/step
Epoch 505/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9867 - 1s/epoch - 988us/step
Epoch 506/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9866 - 1s/epoch - 961us/step
Epoch 507/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9868 - 1s/epoch - 984us/step
Epoch 508/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9871 - 1s/epoch - 967us/step
Epoch 509/600
```

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1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9866 - 1s/epoch - 986us/step
Epoch 510/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9868 - 1s/epoch - 966us/step
Epoch 511/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9864 - 1s/epoch - 995us/step
Epoch 512/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9869 - 1s/epoch - 966us/step
Epoch 513/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9870 - 1s/epoch - 966us/step
Epoch 514/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9862 - 1s/epoch - 986us/step
Epoch 515/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9869 - 1s/epoch - 983us/step
Epoch 516/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9870 - 1s/epoch - 964us/step
Epoch 517/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9865 - 1s/epoch - 976us/step
Epoch 518/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9867 - 1s/epoch - 971us/step
Epoch 519/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9869 - 1s/epoch - 988us/step
Epoch 520/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9870 - 1s/epoch - 966us/step
Epoch 521/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9869 - 1s/epoch - 982us/step
Epoch 522/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9867 - 1s/epoch - 967us/step
Epoch 523/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9870 - 1s/epoch - 980us/step
Epoch 524/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9868 - 1s/epoch - 967us/step
Epoch 525/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9866 - 1s/epoch - 978us/step
Epoch 526/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9868 - 1s/epoch - 965us/step
Epoch 527/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9867 - 1s/epoch - 986us/step
Epoch 528/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9865 - 1s/epoch - 971us/step
Epoch 529/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9869 - 1s/epoch - 988us/step
Epoch 530/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9870 - 1s/epoch - 963us/step
Epoch 531/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9866 - 1s/epoch - 983us/step
Epoch 532/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9866 - 1s/epoch - 961us/step
Epoch 533/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9871 - 1s/epoch - 988us/step
Epoch 534/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9872 - 1s/epoch - 973us/step
Epoch 535/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9870 - 1s/epoch - 979us/step
Epoch 536/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9871 - 1s/epoch - 968us/step
Epoch 537/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9870 - 1s/epoch - 990us/step
Epoch 538/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9868 - 1s/epoch - 965us/step
Epoch 539/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9867 - 1s/epoch - 986us/step
Epoch 540/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9871 - 1s/epoch - 966us/step
Epoch 541/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9869 - 1s/epoch - 987us/step
Epoch 542/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9869 - 1s/epoch - 965us/step
Fnoch 543/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9865 - 1s/epoch - 986us/step
Epoch 544/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 545/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 546/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9871 - 1s/epoch - 989us/step
Epoch 547/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9869 - 1s/epoch - 998us/step
Epoch 548/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9872 - 1s/epoch - 983us/step
Epoch 549/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9869 - 1s/epoch - 991us/step
Epoch 550/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9873 - 1s/epoch - 978us/step
Epoch 551/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9868 - 1s/epoch - 991us/step
Epoch 552/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9868 - 1s/epoch - 968us/step
Epoch 553/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9874 - 1s/epoch - 982us/step
```

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Epoch 554/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9871 - 1s/epoch - 970us/step
Epoch 555/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9871 - 1s/epoch - 980us/step
Epoch 556/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9867 - 1s/epoch - 968us/step
Epoch 557/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9872 - 1s/epoch - 986us/step
Epoch 558/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9868 - 1s/epoch - 968us/step
Epoch 559/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 988us/step
Epoch 560/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9869 - 1s/epoch - 964us/step
Epoch 561/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9872 - 1s/epoch - 994us/step
Epoch 562/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9871 - 1s/epoch - 973us/step
Epoch 563/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9867 - 1s/epoch - 989us/step
Epoch 564/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9868 - 1s/epoch - 968us/step
Epoch 565/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9871 - 1s/epoch - 982us/step
Epoch 566/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9868 - 1s/epoch - 968us/step
Epoch 567/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9873 - 1s/epoch - 985us/step
Epoch 568/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9869 - 1s/epoch - 970us/step
Epoch 569/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9871 - 1s/epoch - 987us/step
Epoch 570/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9871 - 1s/epoch - 972us/step
Epoch 571/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9872 - 1s/epoch - 988us/step
Epoch 572/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9873 - 1s/epoch - 970us/step
Epoch 573/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 975us/step
Epoch 574/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9867 - 1s/epoch - 963us/step
Epoch 575/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9874 - 1s/epoch - 990us/step
Epoch 576/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9871 - 1s/epoch - 966us/step
Epoch 577/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9869 - 1s/epoch - 985us/step
Epoch 578/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9874 - 1s/epoch - 974us/step
Epoch 579/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9874 - 1s/epoch - 969us/step
Epoch 580/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9873 - 1s/epoch - 988us/step
Epoch 581/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9869 - 1s/epoch - 984us/step
Epoch 582/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9871 - 1s/epoch - 974us/step
Epoch 583/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9869 - 1s/epoch - 989us/step
Epoch 584/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9870 - 1s/epoch - 967us/step
Epoch 585/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9871 - 1s/epoch - 982us/step
Epoch 586/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9872 - 1s/epoch - 969us/step
Epoch 587/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9866 - 1s/epoch - 983us/step
Epoch 588/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9876 - 1s/epoch - 975us/step
Epoch 589/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9866 - 1s/epoch - 995us/step
Epoch 590/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9873 - 1s/epoch - 969us/step
Epoch 591/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9873 - 1s/epoch - 988us/step
Epoch 592/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9869 - 1s/epoch - 972us/step
Epoch 593/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9874 - 1s/epoch - 984us/step
Epoch 594/600
Epoch 595/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9866 - 1s/epoch - 989us/step
Epoch 596/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9872 - 1s/epoch - 967us/step
Epoch 597/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9868 - 1s/epoch - 995us/step
Epoch 598/600
```

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1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9873 - 1s/epoch - 971us/step
Epoch 599/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9871 - 1s/epoch - 989us/step
Epoch 600/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9876 - 1s/epoch - 967us/step
990/990 [=======] - 1s 691us/step
Epoch 1/600
1268/1268 - 2s - loss: 0.3606 - accuracy: 0.8360 - 2s/epoch - 1ms/step
Epoch 2/600
1268/1268 - 1s - loss: 0.2239 - accuracy: 0.9110 - 1s/epoch - 965us/step
Epoch 3/600
1268/1268 - 1s - loss: 0.1838 - accuracy: 0.9302 - 1s/epoch - 989us/step
Epoch 4/600
1268/1268 - 1s - loss: 0.1639 - accuracy: 0.9392 - 1s/epoch - 964us/step
Epoch 5/600
1268/1268 - 1s - loss: 0.1525 - accuracy: 0.9444 - 1s/epoch - 985us/step
Epoch 6/600
1268/1268 - 1s - loss: 0.1432 - accuracy: 0.9484 - 1s/epoch - 967us/step
Epoch 7/600
1268/1268 - 1s - loss: 0.1357 - accuracy: 0.9515 - 1s/epoch - 995us/step
Epoch 8/600
1268/1268 - 1s - loss: 0.1298 - accuracy: 0.9543 - 1s/epoch - 961us/step
Fnoch 9/600
1268/1268 - 1s - loss: 0.1254 - accuracy: 0.9562 - 1s/epoch - 985us/step
Epoch 10/600
1268/1268 - 1s - loss: 0.1211 - accuracy: 0.9578 - 1s/epoch - 961us/step
Epoch 11/600
1268/1268 - 1s - loss: 0.1177 - accuracy: 0.9594 - 1s/epoch - 978us/step
Epoch 12/600
1268/1268 - 1s - loss: 0.1143 - accuracy: 0.9615 - 1s/epoch - 956us/step
Epoch 13/600
1268/1268 - 1s - loss: 0.1109 - accuracy: 0.9622 - 1s/epoch - 981us/step
Epoch 14/600
1268/1268 - 1s - loss: 0.1092 - accuracy: 0.9634 - 1s/epoch - 959us/step
Epoch 15/600
1268/1268 - 1s - loss: 0.1066 - accuracy: 0.9639 - 1s/epoch - 980us/step
Epoch 16/600
1268/1268 - 1s - loss: 0.1043 - accuracy: 0.9650 - 1s/epoch - 960us/step
Epoch 17/600
1268/1268 - 1s - loss: 0.1023 - accuracy: 0.9655 - 1s/epoch - 988us/step
Epoch 18/600
1268/1268 - 1s - loss: 0.1010 - accuracy: 0.9663 - 1s/epoch - 959us/step
Epoch 19/600
1268/1268 - 1s - loss: 0.0990 - accuracy: 0.9666 - 1s/epoch - 982us/step
Epoch 20/600
1268/1268 - 1s - loss: 0.0979 - accuracy: 0.9677 - 1s/epoch - 962us/step
Epoch 21/600
1268/1268 - 1s - loss: 0.0958 - accuracy: 0.9682 - 1s/epoch - 986us/step
Epoch 22/600
1268/1268 - 1s - loss: 0.0946 - accuracy: 0.9686 - 1s/epoch - 958us/step
Epoch 23/600
1268/1268 - 1s - loss: 0.0935 - accuracy: 0.9695 - 1s/epoch - 955us/step
Epoch 24/600
1268/1268 - 1s - loss: 0.0929 - accuracy: 0.9692 - 1s/epoch - 978us/step
Epoch 25/600
1268/1268 - 1s - loss: 0.0920 - accuracy: 0.9698 - 1s/epoch - 982us/step
Epoch 26/600
1268/1268 - 1s - loss: 0.0906 - accuracy: 0.9703 - 1s/epoch - 961us/step
Epoch 27/600
1268/1268 - 1s - loss: 0.0903 - accuracy: 0.9705 - 1s/epoch - 981us/step
Epoch 28/600
1268/1268 - 1s - loss: 0.0891 - accuracy: 0.9713 - 1s/epoch - 960us/step
Epoch 29/600
1268/1268 - 1s - loss: 0.0878 - accuracy: 0.9717 - 1s/epoch - 984us/step
Epoch 30/600
1268/1268 - 1s - loss: 0.0872 - accuracy: 0.9715 - 1s/epoch - 958us/step
Epoch 31/600
1268/1268 - 1s - loss: 0.0862 - accuracy: 0.9724 - 1s/epoch - 980us/step
Epoch 32/600
1268/1268 - 1s - loss: 0.0863 - accuracy: 0.9718 - 1s/epoch - 966us/step
Epoch 33/600
1268/1268 - 1s - loss: 0.0856 - accuracy: 0.9718 - 1s/epoch - 985us/step
Epoch 34/600
1268/1268 - 1s - loss: 0.0846 - accuracy: 0.9726 - 1s/epoch - 961us/step
Epoch 35/600
1268/1268 - 1s - loss: 0.0836 - accuracy: 0.9727 - 1s/epoch - 977us/step
Epoch 36/600
1268/1268 - 1s - loss: 0.0833 - accuracy: 0.9732 - 1s/epoch - 965us/step
Epoch 37/600
1268/1268 - 1s - loss: 0.0822 - accuracy: 0.9733 - 1s/epoch - 983us/step
Epoch 38/600
1268/1268 - 1s - loss: 0.0819 - accuracy: 0.9738 - 1s/epoch - 962us/step
Epoch 39/600
1268/1268 - 1s - loss: 0.0805 - accuracy: 0.9741 - 1s/epoch - 980us/step
Epoch 40/600
1268/1268 - 1s - loss: 0.0808 - accuracy: 0.9744 - 1s/epoch - 963us/step
Epoch 41/600
1268/1268 - 1s - loss: 0.0797 - accuracy: 0.9743 - 1s/epoch - 982us/step
Epoch 42/600
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1268/1268 - 1s - loss: 0.0797 - accuracy: 0.9743 - 1s/epoch - 964us/step
Epoch 43/600
1268/1268 - 1s - loss: 0.0787 - accuracy: 0.9747 - 1s/epoch - 990us/step
Epoch 44/600
1268/1268 - 1s - loss: 0.0783 - accuracy: 0.9749 - 1s/epoch - 962us/step
Epoch 45/600
1268/1268 - 1s - loss: 0.0777 - accuracy: 0.9754 - 1s/epoch - 980us/step
Epoch 46/600
1268/1268 - 1s - loss: 0.0774 - accuracy: 0.9754 - 1s/epoch - 960us/step
Epoch 47/600
1268/1268 - 1s - loss: 0.0772 - accuracy: 0.9752 - 1s/epoch - 984us/step
Epoch 48/600
1268/1268 - 1s - loss: 0.0765 - accuracy: 0.9755 - 1s/epoch - 959us/step
Epoch 49/600
1268/1268 - 1s - loss: 0.0761 - accuracy: 0.9760 - 1s/epoch - 982us/step
Epoch 50/600
1268/1268 - 1s - loss: 0.0758 - accuracy: 0.9759 - 1s/epoch - 959us/step
Epoch 51/600
1268/1268 - 1s - loss: 0.0755 - accuracy: 0.9762 - 1s/epoch - 982us/step
Epoch 52/600
1268/1268 - 1s - loss: 0.0753 - accuracy: 0.9760 - 1s/epoch - 963us/step
Epoch 53/600
1268/1268 - 1s - loss: 0.0740 - accuracy: 0.9763 - 1s/epoch - 981us/step
Epoch 54/600
1268/1268 - 1s - loss: 0.0746 - accuracy: 0.9763 - 1s/epoch - 965us/step
Epoch 55/600
1268/1268 - 1s - loss: 0.0737 - accuracy: 0.9762 - 1s/epoch - 984us/step
Epoch 56/600
1268/1268 - 1s - loss: 0.0732 - accuracy: 0.9772 - 1s/epoch - 964us/step
Epoch 57/600
1268/1268 - 1s - loss: 0.0734 - accuracy: 0.9765 - 1s/epoch - 981us/step
Epoch 58/600
1268/1268 - 1s - loss: 0.0725 - accuracy: 0.9767 - 1s/epoch - 959us/step
Epoch 59/600
1268/1268 - 1s - loss: 0.0723 - accuracy: 0.9769 - 1s/epoch - 984us/step
Epoch 60/600
1268/1268 - 1s - loss: 0.0717 - accuracy: 0.9775 - 1s/epoch - 965us/step
Epoch 61/600
1268/1268 - 1s - loss: 0.0725 - accuracy: 0.9768 - 1s/epoch - 982us/step
Epoch 62/600
1268/1268 - 1s - loss: 0.0716 - accuracy: 0.9773 - 1s/epoch - 960us/step
Epoch 63/600
1268/1268 - 1s - loss: 0.0708 - accuracy: 0.9776 - 1s/epoch - 982us/step
Epoch 64/600
1268/1268 - 1s - loss: 0.0707 - accuracy: 0.9775 - 1s/epoch - 962us/step
Epoch 65/600
1268/1268 - 1s - loss: 0.0703 - accuracy: 0.9779 - 1s/epoch - 982us/step
Epoch 66/600
1268/1268 - 1s - loss: 0.0703 - accuracy: 0.9776 - 1s/epoch - 962us/step
Epoch 67/600
1268/1268 - 1s - loss: 0.0696 - accuracy: 0.9783 - 1s/epoch - 987us/step
Epoch 68/600
1268/1268 - 1s - loss: 0.0698 - accuracy: 0.9778 - 1s/epoch - 967us/step
Epoch 69/600
1268/1268 - 1s - loss: 0.0693 - accuracy: 0.9778 - 1s/epoch - 984us/step
Epoch 70/600
1268/1268 - 1s - loss: 0.0690 - accuracy: 0.9783 - 1s/epoch - 959us/step
Epoch 71/600
1268/1268 - 1s - loss: 0.0693 - accuracy: 0.9783 - 1s/epoch - 981us/step
Epoch 72/600
1268/1268 - 1s - loss: 0.0686 - accuracy: 0.9785 - 1s/epoch - 962us/step
Epoch 73/600
1268/1268 - 1s - loss: 0.0685 - accuracy: 0.9783 - 1s/epoch - 975us/step
Epoch 74/600
1268/1268 - 1s - loss: 0.0685 - accuracy: 0.9781 - 1s/epoch - 963us/step
Epoch 75/600
1268/1268 - 1s - loss: 0.0678 - accuracy: 0.9783 - 1s/epoch - 975us/step
Fnoch 76/600
1268/1268 - 1s - loss: 0.0676 - accuracy: 0.9786 - 1s/epoch - 970us/step
Epoch 77/600
1268/1268 - 1s - loss: 0.0673 - accuracy: 0.9787 - 1s/epoch - 984us/step
Epoch 78/600
1268/1268 - 1s - loss: 0.0674 - accuracy: 0.9788 - 1s/epoch - 992us/step
Epoch 79/600
1268/1268 - 1s - loss: 0.0673 - accuracy: 0.9786 - 1s/epoch - 991us/step
Epoch 80/600
1268/1268 - 1s - loss: 0.0664 - accuracy: 0.9789 - 1s/epoch - 961us/step
Epoch 81/600
1268/1268 - 1s - loss: 0.0661 - accuracy: 0.9790 - 1s/epoch - 973us/step
Epoch 82/600
1268/1268 - 1s - loss: 0.0661 - accuracy: 0.9790 - 1s/epoch - 962us/step
Epoch 83/600
1268/1268 - 1s - loss: 0.0660 - accuracy: 0.9789 - 1s/epoch - 974us/step
Epoch 84/600
1268/1268 - 1s - loss: 0.0656 - accuracy: 0.9791 - 1s/epoch - 961us/step
Epoch 85/600
1268/1268 - 1s - loss: 0.0658 - accuracy: 0.9792 - 1s/epoch - 976us/step
Epoch 86/600
1268/1268 - 1s - loss: 0.0653 - accuracy: 0.9793 - 1s/epoch - 959us/step
```

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Epoch 87/600
1268/1268 - 1s - loss: 0.0650 - accuracy: 0.9794 - 1s/epoch - 969us/step
Epoch 88/600
1268/1268 - 1s - loss: 0.0648 - accuracy: 0.9795 - 1s/epoch - 961us/step
Epoch 89/600
1268/1268 - 1s - loss: 0.0642 - accuracy: 0.9797 - 1s/epoch - 976us/step
Epoch 90/600
. 1268/1268 - 1s - loss: 0.0651 - accuracy: 0.9792 - 1s/epoch - 956us/step
Epoch 91/600
1268/1268 - 1s - loss: 0.0639 - accuracy: 0.9800 - 1s/epoch - 964us/step
Epoch 92/600
1268/1268 - 1s - loss: 0.0639 - accuracy: 0.9796 - 1s/epoch - 988us/step
Epoch 93/600
1268/1268 - 1s - loss: 0.0639 - accuracy: 0.9800 - 1s/epoch - 984us/step
Epoch 94/600
1268/1268 - 1s - loss: 0.0640 - accuracy: 0.9794 - 1s/epoch - 963us/step
Epoch 95/600
1268/1268 - 1s - loss: 0.0636 - accuracy: 0.9799 - 1s/epoch - 971us/step
Epoch 96/600
1268/1268 - 1s - loss: 0.0633 - accuracy: 0.9802 - 1s/epoch - 964us/step
Epoch 97/600
1268/1268 - 1s - loss: 0.0626 - accuracy: 0.9802 - 1s/epoch - 984us/step
Epoch 98/600
1268/1268 - 1s - loss: 0.0625 - accuracy: 0.9803 - 1s/epoch - 963us/step
Epoch 99/600
1268/1268 - 1s - loss: 0.0627 - accuracy: 0.9804 - 1s/epoch - 974us/step
Epoch 100/600
1268/1268 - 1s - loss: 0.0623 - accuracy: 0.9804 - 1s/epoch - 962us/step
Epoch 101/600
1268/1268 - 1s - loss: 0.0624 - accuracy: 0.9801 - 1s/epoch - 982us/step
Epoch 102/600
1268/1268 - 1s - loss: 0.0614 - accuracy: 0.9807 - 1s/epoch - 954us/step
Epoch 103/600
1268/1268 - 1s - loss: 0.0616 - accuracy: 0.9802 - 1s/epoch - 980us/step
Epoch 104/600
1268/1268 - 1s - loss: 0.0617 - accuracy: 0.9807 - 1s/epoch - 971us/step
Epoch 105/600
1268/1268 - 1s - loss: 0.0612 - accuracy: 0.9802 - 1s/epoch - 988us/step
Epoch 106/600
1268/1268 - 1s - loss: 0.0610 - accuracy: 0.9805 - 1s/epoch - 967us/step
Epoch 107/600
1268/1268 - 1s - loss: 0.0613 - accuracy: 0.9803 - 1s/epoch - 983us/step
Epoch 108/600
1268/1268 - 1s - loss: 0.0608 - accuracy: 0.9804 - 1s/epoch - 963us/step
Epoch 109/600
1268/1268 - 1s - loss: 0.0610 - accuracy: 0.9806 - 1s/epoch - 1000us/step
Epoch 110/600
1268/1268 - 1s - loss: 0.0610 - accuracy: 0.9806 - 1s/epoch - 962us/step
Epoch 111/600
1268/1268 - 1s - loss: 0.0604 - accuracy: 0.9806 - 1s/epoch - 977us/step
Epoch 112/600
1268/1268 - 1s - loss: 0.0601 - accuracy: 0.9810 - 1s/epoch - 958us/step
Epoch 113/600
1268/1268 - 1s - loss: 0.0599 - accuracy: 0.9809 - 1s/epoch - 979us/step
Epoch 114/600
1268/1268 - 1s - loss: 0.0596 - accuracy: 0.9811 - 1s/epoch - 958us/step
Epoch 115/600
1268/1268 - 1s - loss: 0.0594 - accuracy: 0.9812 - 1s/epoch - 993us/step
Epoch 116/600
1268/1268 - 1s - loss: 0.0598 - accuracy: 0.9811 - 1s/epoch - 965us/step
Epoch 117/600
1268/1268 - 1s - loss: 0.0598 - accuracy: 0.9805 - 1s/epoch - 982us/step
Epoch 118/600
1268/1268 - 1s - loss: 0.0594 - accuracy: 0.9810 - 1s/epoch - 961us/step
Epoch 119/600
1268/1268 - 1s - loss: 0.0589 - accuracy: 0.9812 - 1s/epoch - 976us/step
Epoch 120/600
1268/1268 - 1s - loss: 0.0592 - accuracy: 0.9809 - 1s/epoch - 965us/step
Epoch 121/600
1268/1268 - 1s - loss: 0.0584 - accuracy: 0.9817 - 1s/epoch - 980us/step
Epoch 122/600
1268/1268 - 1s - loss: 0.0588 - accuracy: 0.9810 - 1s/epoch - 956us/step
Epoch 123/600
1268/1268 - 1s - loss: 0.0588 - accuracy: 0.9811 - 1s/epoch - 984us/step
Epoch 124/600
1268/1268 - 1s - loss: 0.0589 - accuracy: 0.9810 - 1s/epoch - 960us/step
Epoch 125/600
1268/1268 - 1s - loss: 0.0582 - accuracy: 0.9817 - 1s/epoch - 984us/step
Epoch 126/600
1268/1268 - 1s - loss: 0.0581 - accuracy: 0.9814 - 1s/epoch - 963us/step
Epoch 127/600
1268/1268 - 1s - loss: 0.0579 - accuracy: 0.9813 - 1s/epoch - 987us/step
Epoch 128/600
1268/1268 - 1s - loss: 0.0576 - accuracy: 0.9815 - 1s/epoch - 974us/step
Epoch 129/600
1268/1268 - 1s - loss: 0.0578 - accuracy: 0.9813 - 1s/epoch - 985us/step
Epoch 130/600
1268/1268 - 1s - loss: 0.0583 - accuracy: 0.9816 - 1s/epoch - 965us/step
Epoch 131/600
```

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1268/1268 - 1s - loss: 0.0575 - accuracy: 0.9817 - 1s/epoch - 984us/step
Epoch 132/600
1268/1268 - 1s - loss: 0.0576 - accuracy: 0.9812 - 1s/epoch - 965us/step
Epoch 133/600
1268/1268 - 1s - loss: 0.0570 - accuracy: 0.9819 - 1s/epoch - 983us/step
Epoch 134/600
1268/1268 - 1s - loss: 0.0574 - accuracy: 0.9813 - 1s/epoch - 961us/step
Epoch 135/600
1268/1268 - 1s - loss: 0.0571 - accuracy: 0.9818 - 1s/epoch - 979us/step
Epoch 136/600
1268/1268 - 1s - loss: 0.0576 - accuracy: 0.9812 - 1s/epoch - 1ms/step
Epoch 137/600
1268/1268 - 1s - loss: 0.0560 - accuracy: 0.9820 - 1s/epoch - 988us/step
Epoch 138/600
1268/1268 - 1s - loss: 0.0568 - accuracy: 0.9816 - 1s/epoch - 995us/step
Epoch 139/600
1268/1268 - 1s - loss: 0.0567 - accuracy: 0.9816 - 1s/epoch - 968us/step
Epoch 140/600
1268/1268 - 1s - loss: 0.0568 - accuracy: 0.9819 - 1s/epoch - 987us/step
Epoch 141/600
1268/1268 - 1s - loss: 0.0558 - accuracy: 0.9818 - 1s/epoch - 971us/step
Epoch 142/600
1268/1268 - 1s - loss: 0.0565 - accuracy: 0.9818 - 1s/epoch - 985us/step
Epoch 143/600
1268/1268 - 1s - loss: 0.0560 - accuracy: 0.9818 - 1s/epoch - 964us/step
Epoch 144/600
1268/1268 - 1s - loss: 0.0558 - accuracy: 0.9822 - 1s/epoch - 982us/step
Epoch 145/600
1268/1268 - 1s - loss: 0.0563 - accuracy: 0.9819 - 1s/epoch - 967us/step
Epoch 146/600
1268/1268 - 1s - loss: 0.0557 - accuracy: 0.9825 - 1s/epoch - 984us/step
Epoch 147/600
1268/1268 - 1s - loss: 0.0561 - accuracy: 0.9820 - 1s/epoch - 966us/step
Epoch 148/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9823 - 1s/epoch - 974us/step
Epoch 149/600
1268/1268 - 1s - loss: 0.0559 - accuracy: 0.9821 - 1s/epoch - 956us/step
Epoch 150/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9819 - 1s/epoch - 955us/step
Epoch 151/600
1268/1268 - 1s - loss: 0.0549 - accuracy: 0.9823 - 1s/epoch - 978us/step
Epoch 152/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9819 - 1s/epoch - 971us/step
Epoch 153/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9821 - 1s/epoch - 977us/step
Epoch 154/600
1268/1268 - 1s - loss: 0.0553 - accuracy: 0.9825 - 1s/epoch - 980us/step
Epoch 155/600
1268/1268 - 1s - loss: 0.0552 - accuracy: 0.9824 - 1s/epoch - 965us/step
Epoch 156/600
1268/1268 - 1s - loss: 0.0552 - accuracy: 0.9819 - 1s/epoch - 983us/step
Epoch 157/600
1268/1268 - 1s - loss: 0.0550 - accuracy: 0.9823 - 1s/epoch - 971us/step
Epoch 158/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9826 - 1s/epoch - 984us/step
Epoch 159/600
1268/1268 - 1s - loss: 0.0549 - accuracy: 0.9823 - 1s/epoch - 969us/step
Epoch 160/600
1268/1268 - 1s - loss: 0.0545 - accuracy: 0.9827 - 1s/epoch - 981us/step
Epoch 161/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9823 - 1s/epoch - 963us/step
Epoch 162/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9823 - 1s/epoch - 988us/step
Epoch 163/600
1268/1268 - 1s - loss: 0.0538 - accuracy: 0.9825 - 1s/epoch - 972us/step
Epoch 164/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9823 - 1s/epoch - 990us/step
Fnoch 165/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9824 - 1s/epoch - 968us/step
Epoch 166/600
1268/1268 - 1s - loss: 0.0534 - accuracy: 0.9828 - 1s/epoch - 980us/step
Epoch 167/600
1268/1268 - 1s - loss: 0.0538 - accuracy: 0.9821 - 1s/epoch - 972us/step
Epoch 168/600
1268/1268 - 1s - loss: 0.0538 - accuracy: 0.9825 - 1s/epoch - 984us/step
Epoch 169/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9823 - 1s/epoch - 968us/step
Epoch 170/600
1268/1268 - 1s - loss: 0.0535 - accuracy: 0.9823 - 1s/epoch - 981us/step
Epoch 171/600
1268/1268 - 1s - loss: 0.0531 - accuracy: 0.9831 - 1s/epoch - 961us/step
Epoch 172/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9830 - 1s/epoch - 987us/step
Epoch 173/600
1268/1268 - 1s - loss: 0.0531 - accuracy: 0.9828 - 1s/epoch - 962us/step
Epoch 174/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9829 - 1s/epoch - 982us/step
Epoch 175/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9827 - 1s/epoch - 971us/step
```

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Epoch 176/600
1268/1268 - 1s - loss: 0.0526 - accuracy: 0.9831 - 1s/epoch - 974us/step
Epoch 177/600
1268/1268 - 1s - loss: 0.0534 - accuracy: 0.9823 - 1s/epoch - 966us/step
Epoch 178/600
1268/1268 - 1s - loss: 0.0525 - accuracy: 0.9831 - 1s/epoch - 959us/step
Epoch 179/600
1268/1268 - 1s - loss: 0.0531 - accuracy: 0.9827 - 1s/epoch - 984us/step
Epoch 180/600
1268/1268 - 1s - loss: 0.0528 - accuracy: 0.9827 - 1s/epoch - 966us/step
Epoch 181/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9832 - 1s/epoch - 985us/step
Epoch 182/600
1268/1268 - 1s - loss: 0.0526 - accuracy: 0.9829 - 1s/epoch - 965us/step
Epoch 183/600
1268/1268 - 1s - loss: 0.0523 - accuracy: 0.9831 - 1s/epoch - 976us/step
Epoch 184/600
1268/1268 - 1s - loss: 0.0522 - accuracy: 0.9830 - 1s/epoch - 962us/step
Epoch 185/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9831 - 1s/epoch - 982us/step
Epoch 186/600
.
1268/1268 - 1s - loss: 0.0518 - accuracy: 0.9828 - 1s/epoch - 982us/step
Epoch 187/600
1268/1268 - 1s - loss: 0.0523 - accuracy: 0.9833 - 1s/epoch - 961us/step
Epoch 188/600
1268/1268 - 1s - loss: 0.0518 - accuracy: 0.9833 - 1s/epoch - 965us/step
Epoch 189/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9832 - 1s/epoch - 985us/step
Epoch 190/600
1268/1268 - 1s - loss: 0.0513 - accuracy: 0.9834 - 1s/epoch - 969us/step
Epoch 191/600
1268/1268 - 1s - loss: 0.0517 - accuracy: 0.9835 - 1s/epoch - 982us/step
Epoch 192/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9831 - 1s/epoch - 984us/step
Epoch 193/600
1268/1268 - 1s - loss: 0.0518 - accuracy: 0.9831 - 1s/epoch - 969us/step
Epoch 194/600
1268/1268 - 1s - loss: 0.0510 - accuracy: 0.9834 - 1s/epoch - 986us/step
Epoch 195/600
1268/1268 - 1s - loss: 0.0507 - accuracy: 0.9832 - 1s/epoch - 962us/step
Epoch 196/600
1268/1268 - 1s - loss: 0.0512 - accuracy: 0.9832 - 1s/epoch - 985us/step
Epoch 197/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9836 - 1s/epoch - 967us/step
Epoch 198/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9834 - 1s/epoch - 989us/step
Epoch 199/600
1268/1268 - 1s - loss: 0.0512 - accuracy: 0.9835 - 1s/epoch - 965us/step
Epoch 200/600
1268/1268 - 1s - loss: 0.0507 - accuracy: 0.9835 - 1s/epoch - 968us/step
Epoch 201/600
1268/1268 - 1s - loss: 0.0506 - accuracy: 0.9832 - 1s/epoch - 986us/step
Epoch 202/600
1268/1268 - 1s - loss: 0.0509 - accuracy: 0.9832 - 1s/epoch - 976us/step
Epoch 203/600
1268/1268 - 1s - loss: 0.0504 - accuracy: 0.9838 - 1s/epoch - 987us/step
Epoch 204/600
1268/1268 - 1s - loss: 0.0502 - accuracy: 0.9838 - 1s/epoch - 965us/step
Epoch 205/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9840 - 1s/epoch - 981us/step
Epoch 206/600
1268/1268 - 1s - loss: 0.0507 - accuracy: 0.9835 - 1s/epoch - 984us/step
Epoch 207/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9836 - 1s/epoch - 965us/step
Epoch 208/600
1268/1268 - 1s - loss: 0.0503 - accuracy: 0.9836 - 1s/epoch - 985us/step
Epoch 209/600
1268/1268 - 1s - loss: 0.0504 - accuracy: 0.9832 - 1s/epoch - 970us/step
Epoch 210/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9836 - 1s/epoch - 990us/step
Epoch 211/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9836 - 1s/epoch - 964us/step
Epoch 212/600
1268/1268 - 1s - loss: 0.0503 - accuracy: 0.9836 - 1s/epoch - 995us/step
Epoch 213/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9838 - 1s/epoch - 978us/step
Epoch 214/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9835 - 1s/epoch - 963us/step
Epoch 215/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9836 - 1s/epoch - 986us/step
Epoch 216/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9839 - 1s/epoch - 965us/step
Epoch 217/600
1268/1268 - 1s - loss: 0.0494 - accuracy: 0.9839 - 1s/epoch - 991us/step
Epoch 218/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9838 - 1s/epoch - 973us/step
Epoch 219/600
1268/1268 - 1s - loss: 0.0496 - accuracy: 0.9836 - 1s/epoch - 985us/step
Epoch 220/600
```

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1268/1268 - 1s - loss: 0.0499 - accuracy: 0.9838 - 1s/epoch - 969us/step
Epoch 221/600
1268/1268 - 1s - loss: 0.0496 - accuracy: 0.9836 - 1s/epoch - 987us/step
Epoch 222/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9838 - 1s/epoch - 961us/step
Epoch 223/600
1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9838 - 1s/epoch - 980us/step
Epoch 224/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9836 - 1s/epoch - 965us/step
Epoch 225/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9840 - 1s/epoch - 994us/step
Epoch 226/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9840 - 1s/epoch - 968us/step
Epoch 227/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9842 - 1s/epoch - 975us/step
Epoch 228/600
1268/1268 - 1s - loss: 0.0491 - accuracy: 0.9841 - 1s/epoch - 969us/step
Epoch 229/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9841 - 1s/epoch - 985us/step
Epoch 230/600
1268/1268 - 1s - loss: 0.0491 - accuracy: 0.9837 - 1s/epoch - 967us/step
Epoch 231/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9842 - 1s/epoch - 983us/step
Epoch 232/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9839 - 1s/epoch - 962us/step
Epoch 233/600
1268/1268 - 1s - loss: 0.0490 - accuracy: 0.9841 - 1s/epoch - 983us/step
Epoch 234/600
1268/1268 - 1s - loss: 0.0484 - accuracy: 0.9844 - 1s/epoch - 969us/step
Epoch 235/600
1268/1268 - 1s - loss: 0.0485 - accuracy: 0.9842 - 1s/epoch - 984us/step
Epoch 236/600
1268/1268 - 1s - loss: 0.0488 - accuracy: 0.9842 - 1s/epoch - 967us/step
Epoch 237/600
1268/1268 - 1s - loss: 0.0483 - accuracy: 0.9844 - 1s/epoch - 983us/step
Epoch 238/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9845 - 1s/epoch - 968us/step
Epoch 239/600
1268/1268 - 1s - loss: 0.0483 - accuracy: 0.9844 - 1s/epoch - 975us/step
Epoch 240/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9844 - 1s/epoch - 970us/step
Epoch 241/600
1268/1268 - 1s - loss: 0.0477 - accuracy: 0.9845 - 1s/epoch - 991us/step
Epoch 242/600
1268/1268 - 1s - loss: 0.0483 - accuracy: 0.9841 - 1s/epoch - 967us/step
Epoch 243/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9844 - 1s/epoch - 986us/step
Epoch 244/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9843 - 1s/epoch - 966us/step
Epoch 245/600
1268/1268 - 1s - loss: 0.0479 - accuracy: 0.9847 - 1s/epoch - 985us/step
Epoch 246/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9840 - 1s/epoch - 965us/step
Epoch 247/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9844 - 1s/epoch - 988us/step
Epoch 248/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9848 - 1s/epoch - 966us/step
Epoch 249/600
1268/1268 - 1s - loss: 0.0479 - accuracy: 0.9840 - 1s/epoch - 984us/step
Epoch 250/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9843 - 1s/epoch - 968us/step
Epoch 251/600
1268/1268 - 1s - loss: 0.0473 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 252/600
1268/1268 - 1s - loss: 0.0473 - accuracy: 0.9846 - 1s/epoch - 961us/step
Epoch 253/600
1268/1268 - 1s - loss: 0.0476 - accuracy: 0.9843 - 1s/epoch - 981us/step
Epoch 254/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9848 - 1s/epoch - 963us/step
Epoch 255/600
1268/1268 - 1s - loss: 0.0475 - accuracy: 0.9845 - 1s/epoch - 979us/step
Epoch 256/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9847 - 1s/epoch - 958us/step
Epoch 257/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9844 - 1s/epoch - 978us/step
Epoch 258/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9842 - 1s/epoch - 966us/step
Epoch 259/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9848 - 1s/epoch - 983us/step
Epoch 260/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9843 - 1s/epoch - 964us/step
Epoch 261/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9845 - 1s/epoch - 965us/step
Epoch 262/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9844 - 1s/epoch - 985us/step
Epoch 263/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9847 - 1s/epoch - 986us/step
Epoch 264/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9846 - 1s/epoch - 965us/step
```

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Epoch 265/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9845 - 1s/epoch - 992us/step
Epoch 266/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9843 - 1s/epoch - 966us/step
Epoch 267/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9846 - 1s/epoch - 983us/step
Epoch 268/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9846 - 1s/epoch - 960us/step
Epoch 269/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9845 - 1s/epoch - 985us/step
Epoch 270/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9847 - 1s/epoch - 967us/step
Epoch 271/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9844 - 1s/epoch - 978us/step
Epoch 272/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9847 - 1s/epoch - 972us/step
Epoch 273/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9848 - 1s/epoch - 988us/step
Epoch 274/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9850 - 1s/epoch - 966us/step
Epoch 275/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9845 - 1s/epoch - 996us/step
Epoch 276/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9843 - 1s/epoch - 964us/step
Epoch 277/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9847 - 1s/epoch - 986us/step
Epoch 278/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9849 - 1s/epoch - 969us/step
Epoch 279/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9847 - 1s/epoch - 968us/step
Epoch 280/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9849 - 1s/epoch - 986us/step
Epoch 281/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9845 - 1s/epoch - 974us/step
Epoch 282/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9848 - 1s/epoch - 971us/step
Epoch 283/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9848 - 1s/epoch - 983us/step
Epoch 284/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9850 - 1s/epoch - 963us/step
Epoch 285/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9849 - 1s/epoch - 967us/step
Epoch 286/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9849 - 1s/epoch - 980us/step
Epoch 287/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9849 - 1s/epoch - 991us/step
Epoch 288/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9846 - 1s/epoch - 964us/step
Epoch 289/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9851 - 1s/epoch - 985us/step
Epoch 290/600
1268/1268 - 1s - loss: 0.0449 - accuracy: 0.9855 - 1s/epoch - 969us/step
Epoch 291/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9849 - 1s/epoch - 968us/step
Epoch 292/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9846 - 1s/epoch - 978us/step
Epoch 293/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9850 - 1s/epoch - 982us/step
Epoch 294/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9851 - 1s/epoch - 964us/step
Epoch 295/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9850 - 1s/epoch - 987us/step
Epoch 296/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9853 - 1s/epoch - 970us/step
Epoch 297/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9851 - 1s/epoch - 987us/step
Epoch 298/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9852 - 1s/epoch - 963us/step
Epoch 299/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9851 - 1s/epoch - 978us/step
Epoch 300/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9845 - 1s/epoch - 982us/step
Epoch 301/600
1268/1268 - 1s - loss: 0.0447 - accuracy: 0.9851 - 1s/epoch - 986us/step
Epoch 302/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9848 - 1s/epoch - 969us/step
Epoch 303/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9850 - 1s/epoch - 991us/step
Epoch 304/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9854 - 1s/epoch - 986us/step
Epoch 305/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9848 - 1s/epoch - 964us/step
Epoch 306/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9853 - 1s/epoch - 963us/step
Epoch 307/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9847 - 1s/epoch - 984us/step
Epoch 308/600
1268/1268 - 1s - loss: 0.0448 - accuracy: 0.9851 - 1s/epoch - 984us/step
Epoch 309/600
```

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1268/1268 - 1s - loss: 0.0448 - accuracy: 0.9852 - 1s/epoch - 968us/step
Epoch 310/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9853 - 1s/epoch - 961us/step
Epoch 311/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9853 - 1s/epoch - 986us/step
Epoch 312/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9853 - 1s/epoch - 971us/step
Epoch 313/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9851 - 1s/epoch - 961us/step
Epoch 314/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9854 - 1s/epoch - 982us/step
Epoch 315/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9851 - 1s/epoch - 961us/step
Epoch 316/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9852 - 1s/epoch - 969us/step
Epoch 317/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9856 - 1s/epoch - 965us/step
Epoch 318/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9853 - 1s/epoch - 991us/step
Epoch 319/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9855 - 1s/epoch - 968us/step
Epoch 320/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9855 - 1s/epoch - 985us/step
Epoch 321/600
1268/1268 - 1s - loss: 0.0444 - accuracy: 0.9853 - 1s/epoch - 966us/step
Epoch 322/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9852 - 1s/epoch - 986us/step
Epoch 323/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9856 - 1s/epoch - 965us/step
Epoch 324/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9851 - 1s/epoch - 986us/step
Epoch 325/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9850 - 1s/epoch - 961us/step
Epoch 326/600
1268/1268 - 1s - loss: 0.0443 - accuracy: 0.9852 - 1s/epoch - 964us/step
Epoch 327/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9854 - 1s/epoch - 985us/step
Epoch 328/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9853 - 1s/epoch - 976us/step
Epoch 329/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9852 - 1s/epoch - 963us/step
Epoch 330/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9857 - 1s/epoch - 963us/step
Epoch 331/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9856 - 1s/epoch - 985us/step
Epoch 332/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9858 - 1s/epoch - 982us/step
Epoch 333/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9855 - 1s/epoch - 967us/step
Epoch 334/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9855 - 1s/epoch - 987us/step
Epoch 335/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9856 - 1s/epoch - 961us/step
Epoch 336/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9852 - 1s/epoch - 989us/step
Epoch 337/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9856 - 1s/epoch - 964us/step
Epoch 338/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9855 - 1s/epoch - 988us/step
Epoch 339/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9854 - 1s/epoch - 966us/step
Epoch 340/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9857 - 1s/epoch - 983us/step
Epoch 341/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9856 - 1s/epoch - 965us/step
Epoch 342/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9856 - 1s/epoch - 978us/step
Fnoch 343/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9858 - 1s/epoch - 965us/step
Epoch 344/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9857 - 1s/epoch - 984us/step
Epoch 345/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9855 - 1s/epoch - 972us/step
Epoch 346/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9856 - 1s/epoch - 987us/step
Epoch 347/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9855 - 1s/epoch - 965us/step
Epoch 348/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9857 - 1s/epoch - 990us/step
Epoch 349/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9859 - 1s/epoch - 965us/step
Epoch 350/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9859 - 1s/epoch - 982us/step
Epoch 351/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9854 - 1s/epoch - 960us/step
Epoch 352/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9854 - 1s/epoch - 996us/step
Epoch 353/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9858 - 1s/epoch - 967us/step
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Epoch 354/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9860 - 1s/epoch - 983us/step
Epoch 355/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9852 - 1s/epoch - 972us/step
Epoch 356/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9859 - 1s/epoch - 988us/step
Epoch 357/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9862 - 1s/epoch - 965us/step
Epoch 358/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9857 - 1s/epoch - 967us/step
Epoch 359/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9861 - 1s/epoch - 982us/step
Epoch 360/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9860 - 1s/epoch - 990us/step
Epoch 361/600
1268/1268 - 1s - loss: 0.0433 - accuracy: 0.9855 - 1s/epoch - 961us/step
Epoch 362/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9856 - 1s/epoch - 964us/step
Epoch 363/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9854 - 1s/epoch - 983us/step
Epoch 364/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9860 - 1s/epoch - 972us/step
Epoch 365/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9855 - 1s/epoch - 965us/step
Epoch 366/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9860 - 1s/epoch - 954us/step
Epoch 367/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9862 - 1s/epoch - 973us/step
Epoch 368/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9858 - 1s/epoch - 980us/step
Epoch 369/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9858 - 1s/epoch - 968us/step
Epoch 370/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9858 - 1s/epoch - 983us/step
Epoch 371/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9861 - 1s/epoch - 966us/step
Epoch 372/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9861 - 1s/epoch - 957us/step
Epoch 373/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9860 - 1s/epoch - 978us/step
Epoch 374/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9862 - 1s/epoch - 969us/step
Epoch 375/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9862 - 1s/epoch - 960us/step
Epoch 376/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9861 - 1s/epoch - 985us/step
Epoch 377/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9857 - 1s/epoch - 959us/step
Epoch 378/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9860 - 1s/epoch - 975us/step
Epoch 379/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9862 - 1s/epoch - 956us/step
Epoch 380/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9860 - 1s/epoch - 989us/step
Epoch 381/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9861 - 1s/epoch - 963us/step
Epoch 382/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9856 - 1s/epoch - 988us/step
Epoch 383/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9862 - 1s/epoch - 961us/step
Epoch 384/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9862 - 1s/epoch - 988us/step
Epoch 385/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9861 - 1s/epoch - 971us/step
Epoch 386/600
1268/1268 - 1s - loss: 0.0417 - accuracy: 0.9858 - 1s/epoch - 970us/step
Epoch 387/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9861 - 1s/epoch - 965us/step
Epoch 388/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9860 - 1s/epoch - 980us/step
Epoch 389/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9864 - 1s/epoch - 957us/step
Epoch 390/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9865 - 1s/epoch - 977us/step
Epoch 391/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9862 - 1s/epoch - 959us/step
Epoch 392/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9860 - 1s/epoch - 978us/step
Epoch 393/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9865 - 1s/epoch - 959us/step
Epoch 394/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9861 - 1s/epoch - 977us/step
Epoch 395/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9861 - 1s/epoch - 962us/step
Epoch 396/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9865 - 1s/epoch - 970us/step
Epoch 397/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9859 - 1s/epoch - 965us/step
Epoch 398/600
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1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9863 - 1s/epoch - 980us/step
Epoch 399/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9863 - 1s/epoch - 962us/step
Epoch 400/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9863 - 1s/epoch - 982us/step
Epoch 401/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9861 - 1s/epoch - 970us/step
Epoch 402/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9863 - 1s/epoch - 983us/step
Epoch 403/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9861 - 1s/epoch - 969us/step
Epoch 404/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9862 - 1s/epoch - 984us/step
Epoch 405/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9863 - 1s/epoch - 973us/step
Epoch 406/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9862 - 1s/epoch - 970us/step
Epoch 407/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9863 - 1s/epoch - 971us/step
Epoch 408/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9863 - 1s/epoch - 982us/step
Epoch 409/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9859 - 1s/epoch - 967us/step
Epoch 410/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9866 - 1s/epoch - 983us/step
Epoch 411/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9863 - 1s/epoch - 961us/step
Epoch 412/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9865 - 1s/epoch - 986us/step
Epoch 413/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9867 - 1s/epoch - 964us/step
Epoch 414/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9863 - 1s/epoch - 989us/step
Epoch 415/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9863 - 1s/epoch - 966us/step
Epoch 416/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9864 - 1s/epoch - 972us/step
Epoch 417/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9863 - 1s/epoch - 966us/step
Epoch 418/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9867 - 1s/epoch - 978us/step
Epoch 419/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9864 - 1s/epoch - 991us/step
Epoch 420/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9861 - 1s/epoch - 965us/step
Epoch 421/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9867 - 1s/epoch - 982us/step
Epoch 422/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9867 - 1s/epoch - 963us/step
Epoch 423/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9868 - 1s/epoch - 984us/step
Epoch 424/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9866 - 1s/epoch - 969us/step
Epoch 425/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9864 - 1s/epoch - 988us/step
Epoch 426/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9865 - 1s/epoch - 955us/step
Epoch 427/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 428/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9863 - 1s/epoch - 969us/step
Epoch 429/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9863 - 1s/epoch - 996us/step
Epoch 430/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9865 - 1s/epoch - 965us/step
Epoch 431/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9867 - 1s/epoch - 991us/step
Fnoch 432/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9863 - 1s/epoch - 963us/step
Epoch 433/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9865 - 1s/epoch - 982us/step
Epoch 434/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9866 - 1s/epoch - 959us/step
Epoch 435/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9866 - 1s/epoch - 974us/step
Epoch 436/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9866 - 1s/epoch - 959us/step
Epoch 437/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9866 - 1s/epoch - 992us/step
Epoch 438/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9866 - 1s/epoch - 964us/step
Epoch 439/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9865 - 1s/epoch - 961us/step
Epoch 440/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9866 - 1s/epoch - 980us/step
Epoch 441/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9868 - 1s/epoch - 986us/step
Epoch 442/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9867 - 1s/epoch - 961us/step
```

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Epoch 443/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9864 - 1s/epoch - 984us/step
Epoch 444/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9867 - 1s/epoch - 987us/step
Epoch 445/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9864 - 1s/epoch - 961us/step
Epoch 446/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9869 - 1s/epoch - 989us/step
Epoch 447/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9867 - 1s/epoch - 984us/step
Epoch 448/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9868 - 1s/epoch - 961us/step
Epoch 449/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9864 - 1s/epoch - 968us/step
Epoch 450/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9867 - 1s/epoch - 988us/step
Epoch 451/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9868 - 1s/epoch - 984us/step
Epoch 452/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 963us/step
Epoch 453/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9868 - 1s/epoch - 978us/step
Fnoch 454/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9867 - 1s/epoch - 963us/step
Epoch 455/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9868 - 1s/epoch - 971us/step
Epoch 456/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9866 - 1s/epoch - 970us/step
Epoch 457/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 986us/step
Epoch 458/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9869 - 1s/epoch - 965us/step
Epoch 459/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9869 - 1s/epoch - 965us/step
Epoch 460/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9866 - 1s/epoch - 990us/step
Epoch 461/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9869 - 1s/epoch - 984us/step
Epoch 462/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9865 - 1s/epoch - 971us/step
Epoch 463/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9868 - 1s/epoch - 984us/step
Epoch 464/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9867 - 1s/epoch - 965us/step
Epoch 465/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9871 - 1s/epoch - 972us/step
Epoch 466/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9868 - 1s/epoch - 973us/step
Epoch 467/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9866 - 1s/epoch - 957us/step
Epoch 468/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9873 - 1s/epoch - 975us/step
Epoch 469/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9866 - 1s/epoch - 958us/step
Epoch 470/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9869 - 1s/epoch - 965us/step
Epoch 471/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9866 - 1s/epoch - 979us/step
Epoch 472/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9867 - 1s/epoch - 959us/step
Epoch 473/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9867 - 1s/epoch - 975us/step
Epoch 474/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9871 - 1s/epoch - 967us/step
Epoch 475/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9866 - 1s/epoch - 977us/step
Epoch 476/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9870 - 1s/epoch - 957us/step
Epoch 477/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9867 - 1s/epoch - 975us/step
Epoch 478/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9869 - 1s/epoch - 958us/step
Epoch 479/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9868 - 1s/epoch - 979us/step
Epoch 480/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9872 - 1s/epoch - 956us/step
Epoch 481/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9872 - 1s/epoch - 977us/step
Epoch 482/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9869 - 1s/epoch - 965us/step
Epoch 483/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9869 - 1s/epoch - 964us/step
Epoch 484/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9868 - 1s/epoch - 974us/step
Epoch 485/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9871 - 1s/epoch - 967us/step
Epoch 486/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 984us/step
Epoch 487/600
```

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1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9867 - 1s/epoch - 979us/step
Epoch 488/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9870 - 1s/epoch - 964us/step
Epoch 489/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9871 - 1s/epoch - 974us/step
Epoch 490/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9870 - 1s/epoch - 966us/step
Epoch 491/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 979us/step
Epoch 492/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9873 - 1s/epoch - 966us/step
Epoch 493/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9868 - 1s/epoch - 987us/step
Epoch 494/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9871 - 1s/epoch - 965us/step
Epoch 495/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9870 - 1s/epoch - 992us/step
Epoch 496/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9872 - 1s/epoch - 962us/step
Epoch 497/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9869 - 1s/epoch - 977us/step
Epoch 498/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9871 - 1s/epoch - 963us/step
Epoch 499/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9870 - 1s/epoch - 976us/step
Epoch 500/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9876 - 1s/epoch - 956us/step
Epoch 501/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9870 - 1s/epoch - 978us/step
Epoch 502/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9871 - 1s/epoch - 961us/step
Epoch 503/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9872 - 1s/epoch - 983us/step
Epoch 504/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9872 - 1s/epoch - 960us/step
Epoch 505/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 983us/step
Epoch 506/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9875 - 1s/epoch - 967us/step
Epoch 507/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9871 - 1s/epoch - 986us/step
Epoch 508/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9870 - 1s/epoch - 968us/step
Epoch 509/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9874 - 1s/epoch - 982us/step
Epoch 510/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9867 - 1s/epoch - 968us/step
Epoch 511/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9875 - 1s/epoch - 980us/step
Epoch 512/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9872 - 1s/epoch - 966us/step
Epoch 513/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9868 - 1s/epoch - 959us/step
Epoch 514/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9879 - 1s/epoch - 983us/step
Epoch 515/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9876 - 1s/epoch - 982us/step
Epoch 516/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9872 - 1s/epoch - 963us/step
Epoch 517/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9874 - 1s/epoch - 984us/step
Epoch 518/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9877 - 1s/epoch - 982us/step
Epoch 519/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9874 - 1s/epoch - 986us/step
Epoch 520/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9870 - 1s/epoch - 970us/step
Fnoch 521/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 986us/step
Epoch 522/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9872 - 1s/epoch - 961us/step
Epoch 523/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9876 - 1s/epoch - 985us/step
Epoch 524/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9873 - 1s/epoch - 992us/step
Epoch 525/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9868 - 1s/epoch - 965us/step
Epoch 526/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9880 - 1s/epoch - 982us/step
Epoch 527/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9876 - 1s/epoch - 964us/step
Epoch 528/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9872 - 1s/epoch - 982us/step
Epoch 529/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9871 - 1s/epoch - 963us/step
Epoch 530/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9871 - 1s/epoch - 986us/step
Epoch 531/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9870 - 1s/epoch - 995us/step
```

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Epoch 532/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9874 - 1s/epoch - 970us/step
Epoch 533/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9876 - 1s/epoch - 985us/step
Epoch 534/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9871 - 1s/epoch - 968us/step
Epoch 535/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9878 - 1s/epoch - 985us/step
Epoch 536/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9871 - 1s/epoch - 981us/step
Epoch 537/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9872 - 1s/epoch - 966us/step
Epoch 538/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9873 - 1s/epoch - 986us/step
Epoch 539/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9871 - 1s/epoch - 971us/step
Epoch 540/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9873 - 1s/epoch - 984us/step
Epoch 541/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9873 - 1s/epoch - 966us/step
Epoch 542/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9872 - 1s/epoch - 991us/step
Epoch 543/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9872 - 1s/epoch - 998us/step
Epoch 544/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9875 - 1s/epoch - 973us/step
Epoch 545/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9874 - 1s/epoch - 986us/step
Epoch 546/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9874 - 1s/epoch - 964us/step
Epoch 547/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9871 - 1s/epoch - 983us/step
Epoch 548/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9876 - 1s/epoch - 962us/step
Epoch 549/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9871 - 1s/epoch - 971us/step
Epoch 550/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9874 - 1s/epoch - 958us/step
Epoch 551/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9878 - 1s/epoch - 960us/step
Epoch 552/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9872 - 1s/epoch - 984us/step
Epoch 553/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9876 - 1s/epoch - 976us/step
Epoch 554/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9874 - 1s/epoch - 961us/step
Epoch 555/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9874 - 1s/epoch - 992us/step
Epoch 556/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9873 - 1s/epoch - 969us/step
Epoch 557/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9876 - 1s/epoch - 967us/step
Epoch 558/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9873 - 1s/epoch - 984us/step
Epoch 559/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9870 - 1s/epoch - 986us/step
Epoch 560/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9876 - 1s/epoch - 975us/step
Epoch 561/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9877 - 1s/epoch - 990us/step
Epoch 562/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9875 - 1s/epoch - 963us/step
Epoch 563/600
1268/1268 - 1s - loss: 0.0376 - accuracy: 0.9870 - 1s/epoch - 988us/step
Epoch 564/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9875 - 1s/epoch - 989us/step
Epoch 565/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9876 - 1s/epoch - 961us/step
Epoch 566/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9873 - 1s/epoch - 984us/step
Epoch 567/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9876 - 1s/epoch - 970us/step
Epoch 568/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 569/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9875 - 1s/epoch - 985us/step
Epoch 570/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9876 - 1s/epoch - 967us/step
Epoch 571/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9874 - 1s/epoch - 989us/step
Epoch 572/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9873 - 1s/epoch - 968us/step
Epoch 573/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9875 - 1s/epoch - 981us/step
Epoch 574/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9878 - 1s/epoch - 956us/step
Epoch 575/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9876 - 1s/epoch - 973us/step
Epoch 576/600
```

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1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9876 - 1s/epoch - 982us/step
Epoch 577/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9875 - 1s/epoch - 966us/step
Epoch 578/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9871 - 1s/epoch - 973us/step
Epoch 579/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9872 - 1s/epoch - 992us/step
Epoch 580/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9875 - 1s/epoch - 964us/step
Epoch 581/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9875 - 1s/epoch - 984us/step
Epoch 582/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9876 - 1s/epoch - 966us/step
Epoch 583/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9875 - 1s/epoch - 980us/step
Epoch 584/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9882 - 1s/epoch - 990us/step
Epoch 585/600
1268/1268 - 1s - loss: 0.0369 - accuracy: 0.9875 - 1s/epoch - 963us/step
Epoch 586/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9878 - 1s/epoch - 982us/step
Epoch 587/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9875 - 1s/epoch - 987us/step
Epoch 588/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9871 - 1s/epoch - 966us/step
Epoch 589/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9877 - 1s/epoch - 998us/step
Epoch 590/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9878 - 1s/epoch - 983us/step
Epoch 591/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9877 - 1s/epoch - 991us/step
Epoch 592/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9876 - 1s/epoch - 992us/step
Epoch 593/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9877 - 1s/epoch - 990us/step
Epoch 594/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9878 - 1s/epoch - 967us/step
Epoch 595/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 596/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9878 - 1s/epoch - 988us/step
Epoch 597/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9879 - 1s/epoch - 965us/step
Epoch 598/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9876 - 1s/epoch - 984us/step
Epoch 599/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9876 - 1s/epoch - 986us/step
Epoch 600/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9877 - 1s/epoch - 967us/step
990/990 [====
                                  =====] - 1s 722us/step
Epoch 1/600
1268/1268 - 2s - loss: 0.3681 - accuracy: 0.8322 - 2s/epoch - 1ms/step
Epoch 2/600
1268/1268 - 1s - loss: 0.2339 - accuracy: 0.9059 - 1s/epoch - 1ms/step
Epoch 3/600
1268/1268 - 1s - loss: 0.1881 - accuracy: 0.9273 - 1s/epoch - 1ms/step
Epoch 4/600
1268/1268 - 1s - loss: 0.1633 - accuracy: 0.9389 - 1s/epoch - 1ms/step
Epoch 5/600
1268/1268 - 1s - loss: 0.1481 - accuracy: 0.9463 - 1s/epoch - 1ms/step
Fnoch 6/600
1268/1268 - 1s - loss: 0.1379 - accuracy: 0.9506 - 1s/epoch - 1ms/step
Epoch 7/600
1268/1268 - 1s - loss: 0.1298 - accuracy: 0.9544 - 1s/epoch - 1ms/step
Epoch 8/600
1268/1268 - 1s - loss: 0.1249 - accuracy: 0.9566 - 1s/epoch - 1ms/step
Epoch 9/600
1268/1268 - 1s - loss: 0.1200 - accuracy: 0.9583 - 1s/epoch - 1ms/step
Epoch 10/600
1268/1268 - 1s - loss: 0.1159 - accuracy: 0.9608 - 1s/epoch - 1ms/step
Epoch 11/600
1268/1268 - 1s - loss: 0.1125 - accuracy: 0.9614 - 1s/epoch - 1ms/step
Epoch 12/600
1268/1268 - 1s - loss: 0.1090 - accuracy: 0.9639 - 1s/epoch - 1ms/step
Epoch 13/600
1268/1268 - 1s - loss: 0.1063 - accuracy: 0.9644 - 1s/epoch - 1ms/step
Epoch 14/600
1268/1268 - 1s - loss: 0.1039 - accuracy: 0.9658 - 1s/epoch - 1ms/step
Epoch 15/600
1268/1268 - 1s - loss: 0.1025 - accuracy: 0.9662 - 1s/epoch - 1ms/step
Epoch 16/600
1268/1268 - 1s - loss: 0.0998 - accuracy: 0.9670 - 1s/epoch - 1ms/step
Epoch 17/600
1268/1268 - 1s - loss: 0.0979 - accuracy: 0.9682 - 1s/epoch - 1ms/step
Epoch 18/600
1268/1268 - 1s - loss: 0.0968 - accuracy: 0.9683 - 1s/epoch - 1ms/step
Epoch 19/600
1268/1268 - 1s - loss: 0.0951 - accuracy: 0.9689 - 1s/epoch - 1ms/step
Epoch 20/600
```

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1268/1268 - 1s - loss: 0.0934 - accuracy: 0.9693 - 1s/epoch - 1ms/step
Epoch 21/600
1268/1268 - 1s - loss: 0.0920 - accuracy: 0.9699 - 1s/epoch - 1ms/step
Epoch 22/600
1268/1268 - 1s - loss: 0.0908 - accuracy: 0.9704 - 1s/epoch - 1ms/step
Epoch 23/600
1268/1268 - 1s - loss: 0.0902 - accuracy: 0.9707 - 1s/epoch - 1ms/step
Epoch 24/600
1268/1268 - 1s - loss: 0.0893 - accuracy: 0.9715 - 1s/epoch - 1ms/step
Epoch 25/600
1268/1268 - 1s - loss: 0.0878 - accuracy: 0.9720 - 1s/epoch - 1ms/step
Epoch 26/600
1268/1268 - 1s - loss: 0.0866 - accuracy: 0.9719 - 1s/epoch - 1ms/step
Epoch 27/600
1268/1268 - 1s - loss: 0.0859 - accuracy: 0.9728 - 1s/epoch - 1ms/step
Epoch 28/600
1268/1268 - 1s - loss: 0.0850 - accuracy: 0.9729 - 1s/epoch - 1ms/step
Epoch 29/600
1268/1268 - 1s - loss: 0.0839 - accuracy: 0.9731 - 1s/epoch - 1ms/step
Epoch 30/600
1268/1268 - 1s - loss: 0.0837 - accuracy: 0.9734 - 1s/epoch - 1ms/step
Epoch 31/600
1268/1268 - 1s - loss: 0.0826 - accuracy: 0.9738 - 1s/epoch - 1ms/step
Epoch 32/600
1268/1268 - 1s - loss: 0.0820 - accuracy: 0.9738 - 1s/epoch - 1ms/step
Epoch 33/600
1268/1268 - 1s - loss: 0.0807 - accuracy: 0.9746 - 1s/epoch - 1ms/step
Epoch 34/600
1268/1268 - 1s - loss: 0.0805 - accuracy: 0.9742 - 1s/epoch - 1ms/step
Epoch 35/600
1268/1268 - 1s - loss: 0.0795 - accuracy: 0.9751 - 1s/epoch - 1ms/step
Epoch 36/600
1268/1268 - 1s - loss: 0.0792 - accuracy: 0.9748 - 1s/epoch - 1ms/step
Epoch 37/600
1268/1268 - 1s - loss: 0.0791 - accuracy: 0.9752 - 1s/epoch - 1ms/step
Epoch 38/600
1268/1268 - 1s - loss: 0.0788 - accuracy: 0.9750 - 1s/epoch - 1ms/step
Epoch 39/600
1268/1268 - 1s - loss: 0.0771 - accuracy: 0.9759 - 1s/epoch - 1ms/step
Epoch 40/600
1268/1268 - 1s - loss: 0.0774 - accuracy: 0.9754 - 1s/epoch - 1ms/step
Epoch 41/600
1268/1268 - 1s - loss: 0.0768 - accuracy: 0.9757 - 1s/epoch - 1ms/step
Epoch 42/600
1268/1268 - 1s - loss: 0.0761 - accuracy: 0.9759 - 1s/epoch - 999us/step
Epoch 43/600
1268/1268 - 1s - loss: 0.0754 - accuracy: 0.9762 - 1s/epoch - 1ms/step
Epoch 44/600
1268/1268 - 1s - loss: 0.0749 - accuracy: 0.9764 - 1s/epoch - 1ms/step
Epoch 45/600
1268/1268 - 1s - loss: 0.0753 - accuracy: 0.9760 - 1s/epoch - 1ms/step
Epoch 46/600
1268/1268 - 1s - loss: 0.0740 - accuracy: 0.9765 - 1s/epoch - 1ms/step
Epoch 47/600
1268/1268 - 1s - loss: 0.0734 - accuracy: 0.9767 - 1s/epoch - 1ms/step
Epoch 48/600
1268/1268 - 1s - loss: 0.0734 - accuracy: 0.9767 - 1s/epoch - 1ms/step
Epoch 49/600
1268/1268 - 1s - loss: 0.0729 - accuracy: 0.9769 - 1s/epoch - 1ms/step
Epoch 50/600
1268/1268 - 1s - loss: 0.0728 - accuracy: 0.9771 - 1s/epoch - 1ms/step
Epoch 51/600
1268/1268 - 1s - loss: 0.0720 - accuracy: 0.9773 - 1s/epoch - 1ms/step
Epoch 52/600
1268/1268 - 1s - loss: 0.0722 - accuracy: 0.9770 - 1s/epoch - 1ms/step
Epoch 53/600
1268/1268 - 1s - loss: 0.0712 - accuracy: 0.9779 - 1s/epoch - 1ms/step
Fnoch 54/600
1268/1268 - 1s - loss: 0.0713 - accuracy: 0.9775 - 1s/epoch - 1ms/step
Epoch 55/600
1268/1268 - 1s - loss: 0.0707 - accuracy: 0.9774 - 1s/epoch - 1ms/step
Epoch 56/600
1268/1268 - 1s - loss: 0.0702 - accuracy: 0.9777 - 1s/epoch - 1ms/step
Epoch 57/600
1268/1268 - 1s - loss: 0.0701 - accuracy: 0.9777 - 1s/epoch - 1ms/step
Epoch 58/600
1268/1268 - 1s - loss: 0.0697 - accuracy: 0.9778 - 1s/epoch - 1ms/step
Epoch 59/600
1268/1268 - 1s - loss: 0.0691 - accuracy: 0.9779 - 1s/epoch - 1ms/step
Epoch 60/600
1268/1268 - 1s - loss: 0.0690 - accuracy: 0.9780 - 1s/epoch - 1ms/step
Epoch 61/600
1268/1268 - 1s - loss: 0.0691 - accuracy: 0.9779 - 1s/epoch - 1ms/step
Epoch 62/600
1268/1268 - 1s - loss: 0.0684 - accuracy: 0.9786 - 1s/epoch - 1ms/step
Epoch 63/600
1268/1268 - 1s - loss: 0.0688 - accuracy: 0.9781 - 1s/epoch - 1ms/step
Epoch 64/600
1268/1268 - 1s - loss: 0.0681 - accuracy: 0.9784 - 1s/epoch - 1ms/step
```

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Epoch 65/600
1268/1268 - 1s - loss: 0.0680 - accuracy: 0.9781 - 1s/epoch - 1ms/step
Epoch 66/600
1268/1268 - 1s - loss: 0.0675 - accuracy: 0.9789 - 1s/epoch - 1ms/step
Epoch 67/600
1268/1268 - 1s - loss: 0.0677 - accuracy: 0.9783 - 1s/epoch - 1ms/step
Epoch 68/600
1268/1268 - 1s - loss: 0.0666 - accuracy: 0.9786 - 1s/epoch - 999us/step
Epoch 69/600
1268/1268 - 1s - loss: 0.0669 - accuracy: 0.9787 - 1s/epoch - 1ms/step
Epoch 70/600
1268/1268 - 1s - loss: 0.0661 - accuracy: 0.9788 - 1s/epoch - 1ms/step
Epoch 71/600
1268/1268 - 1s - loss: 0.0662 - accuracy: 0.9789 - 1s/epoch - 1ms/step
Epoch 72/600
1268/1268 - 1s - loss: 0.0663 - accuracy: 0.9789 - 1s/epoch - 1ms/step
Epoch 73/600
1268/1268 - 1s - loss: 0.0658 - accuracy: 0.9790 - 1s/epoch - 1ms/step
Epoch 74/600
1268/1268 - 1s - loss: 0.0657 - accuracy: 0.9794 - 1s/epoch - 1ms/step
Epoch 75/600
1268/1268 - 1s - loss: 0.0652 - accuracy: 0.9793 - 1s/epoch - 1ms/step
Epoch 76/600
1268/1268 - 1s - loss: 0.0654 - accuracy: 0.9789 - 1s/epoch - 1ms/step
Epoch 77/600
1268/1268 - 1s - loss: 0.0648 - accuracy: 0.9793 - 1s/epoch - 1000us/step
Epoch 78/600
1268/1268 - 1s - loss: 0.0644 - accuracy: 0.9795 - 1s/epoch - 1ms/step
Epoch 79/600
1268/1268 - 1s - loss: 0.0644 - accuracy: 0.9798 - 1s/epoch - 1ms/step
Epoch 80/600
1268/1268 - 1s - loss: 0.0640 - accuracy: 0.9797 - 1s/epoch - 1000us/step
Epoch 81/600
1268/1268 - 1s - loss: 0.0638 - accuracy: 0.9798 - 1s/epoch - 1ms/step
Epoch 82/600
1268/1268 - 1s - loss: 0.0635 - accuracy: 0.9800 - 1s/epoch - 1ms/step
Epoch 83/600
1268/1268 - 1s - loss: 0.0637 - accuracy: 0.9799 - 1s/epoch - 1ms/step
Epoch 84/600
1268/1268 - 1s - loss: 0.0634 - accuracy: 0.9797 - 1s/epoch - 1ms/step
Epoch 85/600
1268/1268 - 1s - loss: 0.0628 - accuracy: 0.9801 - 1s/epoch - 1ms/step
Epoch 86/600
1268/1268 - 1s - loss: 0.0628 - accuracy: 0.9801 - 1s/epoch - 1ms/step
Epoch 87/600
1268/1268 - 1s - loss: 0.0627 - accuracy: 0.9802 - 1s/epoch - 1ms/step
Epoch 88/600
1268/1268 - 1s - loss: 0.0625 - accuracy: 0.9801 - 1s/epoch - 1ms/step
Epoch 89/600
1268/1268 - 1s - loss: 0.0618 - accuracy: 0.9802 - 1s/epoch - 999us/step
Epoch 90/600
1268/1268 - 1s - loss: 0.0621 - accuracy: 0.9805 - 1s/epoch - 1ms/step
Epoch 91/600
1268/1268 - 1s - loss: 0.0618 - accuracy: 0.9805 - 1s/epoch - 1ms/step
Epoch 92/600
1268/1268 - 1s - loss: 0.0614 - accuracy: 0.9803 - 1s/epoch - 1ms/step
Epoch 93/600
1268/1268 - 1s - loss: 0.0613 - accuracy: 0.9806 - 1s/epoch - 1ms/step
Epoch 94/600
1268/1268 - 1s - loss: 0.0617 - accuracy: 0.9804 - 1s/epoch - 1ms/step
Epoch 95/600
1268/1268 - 1s - loss: 0.0610 - accuracy: 0.9805 - 1s/epoch - 1ms/step
Epoch 96/600
1268/1268 - 1s - loss: 0.0609 - accuracy: 0.9803 - 1s/epoch - 1ms/step
Epoch 97/600
1268/1268 - 1s - loss: 0.0606 - accuracy: 0.9807 - 1s/epoch - 1ms/step
Epoch 98/600
1268/1268 - 1s - loss: 0.0605 - accuracy: 0.9805 - 1s/epoch - 1ms/step
Epoch 99/600
1268/1268 - 1s - loss: 0.0601 - accuracy: 0.9810 - 1s/epoch - 1ms/step
Epoch 100/600
1268/1268 - 1s - loss: 0.0604 - accuracy: 0.9810 - 1s/epoch - 1ms/step
Epoch 101/600
1268/1268 - 1s - loss: 0.0604 - accuracy: 0.9808 - 1s/epoch - 1ms/step
Epoch 102/600
1268/1268 - 1s - loss: 0.0600 - accuracy: 0.9811 - 1s/epoch - 1ms/step
Epoch 103/600
1268/1268 - 1s - loss: 0.0600 - accuracy: 0.9808 - 1s/epoch - 1ms/step
Epoch 104/600
1268/1268 - 1s - loss: 0.0592 - accuracy: 0.9815 - 1s/epoch - 1ms/step
Epoch 105/600
1268/1268 - 1s - loss: 0.0594 - accuracy: 0.9811 - 1s/epoch - 999us/step
Epoch 106/600
1268/1268 - 1s - loss: 0.0590 - accuracy: 0.9808 - 1s/epoch - 1ms/step
Epoch 107/600
1268/1268 - 1s - loss: 0.0587 - accuracy: 0.9813 - 1s/epoch - 1ms/step
Epoch 108/600
1268/1268 - 1s - loss: 0.0590 - accuracy: 0.9809 - 1s/epoch - 999us/step
Epoch 109/600
```

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1268/1268 - 1s - loss: 0.0589 - accuracy: 0.9808 - 1s/epoch - 1ms/step
Epoch 110/600
1268/1268 - 1s - loss: 0.0584 - accuracy: 0.9814 - 1s/epoch - 1ms/step
Epoch 111/600
1268/1268 - 1s - loss: 0.0586 - accuracy: 0.9814 - 1s/epoch - 1ms/step
Epoch 112/600
1268/1268 - 1s - loss: 0.0587 - accuracy: 0.9813 - 1s/epoch - 1ms/step
Epoch 113/600
1268/1268 - 1s - loss: 0.0581 - accuracy: 0.9810 - 1s/epoch - 1ms/step
Epoch 114/600
1268/1268 - 1s - loss: 0.0584 - accuracy: 0.9811 - 1s/epoch - 999us/step
Epoch 115/600
1268/1268 - 1s - loss: 0.0579 - accuracy: 0.9816 - 1s/epoch - 1ms/step
Epoch 116/600
1268/1268 - 1s - loss: 0.0580 - accuracy: 0.9814 - 1s/epoch - 1ms/step
Epoch 117/600
1268/1268 - 1s - loss: 0.0574 - accuracy: 0.9817 - 1s/epoch - 997us/step
Epoch 118/600
1268/1268 - 1s - loss: 0.0574 - accuracy: 0.9819 - 1s/epoch - 1ms/step
Epoch 119/600
1268/1268 - 1s - loss: 0.0571 - accuracy: 0.9818 - 1s/epoch - 1ms/step
Epoch 120/600
1268/1268 - 1s - loss: 0.0575 - accuracy: 0.9816 - 1s/epoch - 1ms/step
Epoch 121/600
1268/1268 - 1s - loss: 0.0576 - accuracy: 0.9815 - 1s/epoch - 1ms/step
Epoch 122/600
1268/1268 - 1s - loss: 0.0564 - accuracy: 0.9821 - 1s/epoch - 1ms/step
Epoch 123/600
1268/1268 - 1s - loss: 0.0566 - accuracy: 0.9821 - 1s/epoch - 998us/step
Epoch 124/600
1268/1268 - 1s - loss: 0.0570 - accuracy: 0.9819 - 1s/epoch - 1ms/step
Epoch 125/600
1268/1268 - 1s - loss: 0.0565 - accuracy: 0.9820 - 1s/epoch - 1ms/step
Epoch 126/600
1268/1268 - 1s - loss: 0.0566 - accuracy: 0.9819 - 1s/epoch - 1ms/step
Epoch 127/600
1268/1268 - 1s - loss: 0.0565 - accuracy: 0.9818 - 1s/epoch - 1ms/step
Epoch 128/600
1268/1268 - 1s - loss: 0.0564 - accuracy: 0.9820 - 1s/epoch - 1ms/step
Epoch 129/600
1268/1268 - 1s - loss: 0.0562 - accuracy: 0.9818 - 1s/epoch - 1000us/step
Epoch 130/600
1268/1268 - 1s - loss: 0.0556 - accuracy: 0.9821 - 1s/epoch - 1ms/step
Epoch 131/600
1268/1268 - 1s - loss: 0.0556 - accuracy: 0.9823 - 1s/epoch - 1ms/step
Epoch 132/600
1268/1268 - 1s - loss: 0.0555 - accuracy: 0.9821 - 1s/epoch - 1ms/step
Epoch 133/600
1268/1268 - 1s - loss: 0.0556 - accuracy: 0.9821 - 1s/epoch - 1ms/step
Epoch 134/600
1268/1268 - 1s - loss: 0.0557 - accuracy: 0.9819 - 1s/epoch - 994us/step
Epoch 135/600
1268/1268 - 1s - loss: 0.0550 - accuracy: 0.9826 - 1s/epoch - 1ms/step
Epoch 136/600
1268/1268 - 1s - loss: 0.0555 - accuracy: 0.9822 - 1s/epoch - 1ms/step
Epoch 137/600
1268/1268 - 1s - loss: 0.0554 - accuracy: 0.9822 - 1s/epoch - 1ms/step
Epoch 138/600
1268/1268 - 1s - loss: 0.0548 - accuracy: 0.9818 - 1s/epoch - 1ms/step
Epoch 139/600
1268/1268 - 1s - loss: 0.0551 - accuracy: 0.9821 - 1s/epoch - 1ms/step
Epoch 140/600
1268/1268 - 1s - loss: 0.0550 - accuracy: 0.9826 - 1s/epoch - 1ms/step
Epoch 141/600
1268/1268 - 1s - loss: 0.0548 - accuracy: 0.9824 - 1s/epoch - 1ms/step
Epoch 142/600
1268/1268 - 1s - loss: 0.0544 - accuracy: 0.9829 - 1s/epoch - 1ms/step
Epoch 143/600
1268/1268 - 1s - loss: 0.0546 - accuracy: 0.9824 - 1s/epoch - 998us/step
Epoch 144/600
1268/1268 - 1s - loss: 0.0547 - accuracy: 0.9824 - 1s/epoch - 1ms/step
Epoch 145/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9824 - 1s/epoch - 1ms/step
Epoch 146/600
1268/1268 - 1s - loss: 0.0545 - accuracy: 0.9823 - 1s/epoch - 1ms/step
Epoch 147/600
1268/1268 - 1s - loss: 0.0539 - accuracy: 0.9828 - 1s/epoch - 1ms/step
Epoch 148/600
1268/1268 - 1s - loss: 0.0542 - accuracy: 0.9825 - 1s/epoch - 1ms/step
Epoch 149/600
1268/1268 - 1s - loss: 0.0536 - accuracy: 0.9829 - 1s/epoch - 1ms/step
Epoch 150/600
1268/1268 - 1s - loss: 0.0541 - accuracy: 0.9824 - 1s/epoch - 1ms/step
Epoch 151/600
1268/1268 - 1s - loss: 0.0536 - accuracy: 0.9829 - 1s/epoch - 1ms/step
Epoch 152/600
1268/1268 - 1s - loss: 0.0532 - accuracy: 0.9828 - 1s/epoch - 1ms/step
Epoch 153/600
1268/1268 - 1s - loss: 0.0534 - accuracy: 0.9829 - 1s/epoch - 997us/step
```

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Epoch 154/600
1268/1268 - 1s - loss: 0.0529 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 155/600
1268/1268 - 1s - loss: 0.0533 - accuracy: 0.9827 - 1s/epoch - 1ms/step
Epoch 156/600
1268/1268 - 1s - loss: 0.0534 - accuracy: 0.9832 - 1s/epoch - 995us/step
Epoch 157/600
1268/1268 - 1s - loss: 0.0526 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 158/600
1268/1268 - 1s - loss: 0.0529 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 159/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9830 - 1s/epoch - 1ms/step
Epoch 160/600
1268/1268 - 1s - loss: 0.0528 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 161/600
1268/1268 - 1s - loss: 0.0530 - accuracy: 0.9828 - 1s/epoch - 1ms/step
Epoch 162/600
1268/1268 - 1s - loss: 0.0525 - accuracy: 0.9830 - 1s/epoch - 999us/step
Epoch 163/600
1268/1268 - 1s - loss: 0.0524 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 164/600
1268/1268 - 1s - loss: 0.0526 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 165/600
1268/1268 - 1s - loss: 0.0528 - accuracy: 0.9830 - 1s/epoch - 1ms/step
Epoch 166/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9835 - 1s/epoch - 1ms/step
Epoch 167/600
1268/1268 - 1s - loss: 0.0522 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 168/600
1268/1268 - 1s - loss: 0.0526 - accuracy: 0.9830 - 1s/epoch - 1ms/step
Epoch 169/600
1268/1268 - 1s - loss: 0.0518 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 170/600
1268/1268 - 1s - loss: 0.0518 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 171/600
1268/1268 - 1s - loss: 0.0520 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 172/600
1268/1268 - 1s - loss: 0.0518 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 173/600
1268/1268 - 1s - loss: 0.0519 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 174/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9834 - 1s/epoch - 1ms/step
Epoch 175/600
1268/1268 - 1s - loss: 0.0517 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 176/600
1268/1268 - 1s - loss: 0.0514 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 177/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9837 - 1s/epoch - 1000us/step
Epoch 178/600
1268/1268 - 1s - loss: 0.0515 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 179/600
1268/1268 - 1s - loss: 0.0516 - accuracy: 0.9831 - 1s/epoch - 1ms/step
Epoch 180/600
1268/1268 - 1s - loss: 0.0509 - accuracy: 0.9838 - 1s/epoch - 1ms/step
Epoch 181/600
1268/1268 - 1s - loss: 0.0511 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 182/600
1268/1268 - 1s - loss: 0.0506 - accuracy: 0.9837 - 1s/epoch - 1ms/step
Epoch 183/600
1268/1268 - 1s - loss: 0.0510 - accuracy: 0.9834 - 1s/epoch - 1ms/step
Epoch 184/600
1268/1268 - 1s - loss: 0.0507 - accuracy: 0.9838 - 1s/epoch - 998us/step
Epoch 185/600
1268/1268 - 1s - loss: 0.0510 - accuracy: 0.9832 - 1s/epoch - 1ms/step
Epoch 186/600
1268/1268 - 1s - loss: 0.0502 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 187/600
1268/1268 - 1s - loss: 0.0505 - accuracy: 0.9835 - 1s/epoch - 1ms/step
Epoch 188/600
1268/1268 - 1s - loss: 0.0506 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 189/600
1268/1268 - 1s - loss: 0.0508 - accuracy: 0.9835 - 1s/epoch - 1ms/step
Epoch 190/600
1268/1268 - 1s - loss: 0.0502 - accuracy: 0.9837 - 1s/epoch - 1ms/step
Epoch 191/600
1268/1268 - 1s - loss: 0.0502 - accuracy: 0.9838 - 1s/epoch - 1ms/step
Epoch 192/600
1268/1268 - 1s - loss: 0.0504 - accuracy: 0.9837 - 1s/epoch - 1ms/step
Epoch 193/600
1268/1268 - 1s - loss: 0.0503 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 194/600
1268/1268 - 1s - loss: 0.0501 - accuracy: 0.9838 - 1s/epoch - 1ms/step
Epoch 195/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9835 - 1s/epoch - 1ms/step
Epoch 196/600
1268/1268 - 1s - loss: 0.0500 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 197/600
1268/1268 - 1s - loss: 0.0498 - accuracy: 0.9839 - 1s/epoch - 1ms/step
Epoch 198/600
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1268/1268 - 1s - loss: 0.0495 - accuracy: 0.9840 - 1s/epoch - 1ms/step
Epoch 199/600
1268/1268 - 1s - loss: 0.0503 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 200/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 201/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9840 - 1s/epoch - 1ms/step
Epoch 202/600
1268/1268 - 1s - loss: 0.0499 - accuracy: 0.9838 - 1s/epoch - 1ms/step
Epoch 203/600
1268/1268 - 1s - loss: 0.0494 - accuracy: 0.9840 - 1s/epoch - 1ms/step
Epoch 204/600
1268/1268 - 1s - loss: 0.0497 - accuracy: 0.9837 - 1s/epoch - 1ms/step
Epoch 205/600
1268/1268 - 1s - loss: 0.0497 - accuracy: 0.9837 - 1s/epoch - 1ms/step
Epoch 206/600
1268/1268 - 1s - loss: 0.0490 - accuracy: 0.9840 - 1s/epoch - 1ms/step
Epoch 207/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 208/600
1268/1268 - 1s - loss: 0.0491 - accuracy: 0.9836 - 1s/epoch - 1ms/step
Epoch 209/600
1268/1268 - 1s - loss: 0.0493 - accuracy: 0.9843 - 1s/epoch - 997us/step
Epoch 210/600
1268/1268 - 1s - loss: 0.0491 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 211/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9838 - 1s/epoch - 1ms/step
Epoch 212/600
1268/1268 - 1s - loss: 0.0489 - accuracy: 0.9841 - 1s/epoch - 1ms/step
Epoch 213/600
1268/1268 - 1s - loss: 0.0492 - accuracy: 0.9840 - 1s/epoch - 1ms/step
Epoch 214/600
1268/1268 - 1s - loss: 0.0488 - accuracy: 0.9839 - 1s/epoch - 1ms/step
Epoch 215/600
1268/1268 - 1s - loss: 0.0486 - accuracy: 0.9841 - 1s/epoch - 1ms/step
Epoch 216/600
1268/1268 - 1s - loss: 0.0490 - accuracy: 0.9834 - 1s/epoch - 1ms/step
Epoch 217/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9845 - 1s/epoch - 1ms/step
Epoch 218/600
1268/1268 - 1s - loss: 0.0484 - accuracy: 0.9844 - 1s/epoch - 998us/step
Epoch 219/600
1268/1268 - 1s - loss: 0.0479 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 220/600
1268/1268 - 1s - loss: 0.0490 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 221/600
1268/1268 - 1s - loss: 0.0482 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 222/600
1268/1268 - 1s - loss: 0.0483 - accuracy: 0.9838 - 1s/epoch - 1ms/step
Epoch 223/600
1268/1268 - 1s - loss: 0.0481 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 224/600
1268/1268 - 1s - loss: 0.0483 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 225/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9845 - 1s/epoch - 1ms/step
Epoch 226/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9846 - 1s/epoch - 1ms/step
Epoch 227/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 228/600
1268/1268 - 1s - loss: 0.0479 - accuracy: 0.9840 - 1s/epoch - 1ms/step
Epoch 229/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9843 - 1s/epoch - 1ms/step
Epoch 230/600
1268/1268 - 1s - loss: 0.0478 - accuracy: 0.9843 - 1s/epoch - 1ms/step
Epoch 231/600
1268/1268 - 1s - loss: 0.0480 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Fnoch 232/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9845 - 1s/epoch - 1ms/step
Epoch 233/600
1268/1268 - 1s - loss: 0.0476 - accuracy: 0.9838 - 1s/epoch - 1ms/step
Epoch 234/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 235/600
1268/1268 - 1s - loss: 0.0473 - accuracy: 0.9847 - 1s/epoch - 1ms/step
Epoch 236/600
1268/1268 - 1s - loss: 0.0474 - accuracy: 0.9843 - 1s/epoch - 1ms/step
Epoch 237/600
1268/1268 - 1s - loss: 0.0470 - accuracy: 0.9845 - 1s/epoch - 1ms/step
Epoch 238/600
1268/1268 - 1s - loss: 0.0473 - accuracy: 0.9845 - 1s/epoch - 1ms/step
Epoch 239/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 240/600
1268/1268 - 1s - loss: 0.0474 - accuracy: 0.9843 - 1s/epoch - 1ms/step
Epoch 241/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9842 - 1s/epoch - 1ms/step
Epoch 242/600
1268/1268 - 1s - loss: 0.0471 - accuracy: 0.9845 - 1s/epoch - 1ms/step
```

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Epoch 243/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9847 - 1s/epoch - 1ms/step
Epoch 244/600
1268/1268 - 1s - loss: 0.0472 - accuracy: 0.9846 - 1s/epoch - 1ms/step
Epoch 245/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9845 - 1s/epoch - 1ms/step
Epoch 246/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9847 - 1s/epoch - 1ms/step
Epoch 247/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9847 - 1s/epoch - 1ms/step
Epoch 248/600
1268/1268 - 1s - loss: 0.0465 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 249/600
1268/1268 - 1s - loss: 0.0469 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 250/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 251/600
1268/1268 - 1s - loss: 0.0463 - accuracy: 0.9846 - 1s/epoch - 1ms/step
Epoch 252/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9848 - 1s/epoch - 1ms/step
Epoch 253/600
1268/1268 - 1s - loss: 0.0464 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 254/600
1268/1268 - 1s - loss: 0.0467 - accuracy: 0.9843 - 1s/epoch - 1ms/step
Epoch 255/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9846 - 1s/epoch - 1ms/step
Epoch 256/600
1268/1268 - 1s - loss: 0.0458 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 257/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9847 - 1s/epoch - 1ms/step
Epoch 258/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9850 - 1s/epoch - 1ms/step
Epoch 259/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 260/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9850 - 1s/epoch - 1ms/step
Epoch 261/600
1268/1268 - 1s - loss: 0.0466 - accuracy: 0.9846 - 1s/epoch - 1ms/step
Epoch 262/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9851 - 1s/epoch - 1ms/step
Epoch 263/600
1268/1268 - 1s - loss: 0.0461 - accuracy: 0.9844 - 1s/epoch - 1ms/step
Epoch 264/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 265/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 266/600
1268/1268 - 1s - loss: 0.0457 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 267/600
1268/1268 - 1s - loss: 0.0459 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 268/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 269/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 270/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9845 - 1s/epoch - 1ms/step
Epoch 271/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9850 - 1s/epoch - 1ms/step
Epoch 272/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9848 - 1s/epoch - 1ms/step
Epoch 273/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 274/600
1268/1268 - 1s - loss: 0.0454 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 275/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9850 - 1s/epoch - 1ms/step
Epoch 276/600
1268/1268 - 1s - loss: 0.0450 - accuracy: 0.9851 - 1s/epoch - 1ms/step
Epoch 277/600
1268/1268 - 1s - loss: 0.0453 - accuracy: 0.9848 - 1s/epoch - 1ms/step
Epoch 278/600
1268/1268 - 1s - loss: 0.0452 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 279/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 280/600
1268/1268 - 1s - loss: 0.0455 - accuracy: 0.9848 - 1s/epoch - 997us/step
Epoch 281/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9851 - 1s/epoch - 1ms/step
Epoch 282/600
1268/1268 - 1s - loss: 0.0449 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 283/600
1268/1268 - 1s - loss: 0.0446 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 284/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9849 - 1s/epoch - 1ms/step
Epoch 285/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 286/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9848 - 1s/epoch - 1ms/step
Epoch 287/600
```

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1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 288/600
1268/1268 - 1s - loss: 0.0451 - accuracy: 0.9850 - 1s/epoch - 1ms/step
Epoch 289/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9855 - 1s/epoch - 1ms/step
Epoch 290/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 291/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 292/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 293/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 294/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 295/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 296/600
1268/1268 - 1s - loss: 0.0445 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 297/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 298/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9852 - 1s/epoch - 1ms/step
Epoch 299/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 300/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 301/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 302/600
1268/1268 - 1s - loss: 0.0442 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 303/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 304/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 305/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 306/600
1268/1268 - 1s - loss: 0.0440 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 307/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 308/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 309/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 310/600
1268/1268 - 1s - loss: 0.0435 - accuracy: 0.9855 - 1s/epoch - 1ms/step
Epoch 311/600
1268/1268 - 1s - loss: 0.0438 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 312/600
1268/1268 - 1s - loss: 0.0437 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 313/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9855 - 1s/epoch - 1ms/step
Epoch 314/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 315/600
1268/1268 - 1s - loss: 0.0439 - accuracy: 0.9851 - 1s/epoch - 1ms/step
Epoch 316/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 317/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9858 - 1s/epoch - 1ms/step
Epoch 318/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 319/600
1268/1268 - 1s - loss: 0.0441 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 320/600
1268/1268 - 1s - loss: 0.0436 - accuracy: 0.9855 - 1s/epoch - 1ms/step
Fnoch 321/600
1268/1268 - 1s - loss: 0.0429 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 322/600
1268/1268 - 1s - loss: 0.0434 - accuracy: 0.9854 - 1s/epoch - 1ms/step
Epoch 323/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 324/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 325/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9858 - 1s/epoch - 1ms/step
Epoch 326/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 327/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 328/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 329/600
1268/1268 - 1s - loss: 0.0427 - accuracy: 0.9855 - 1s/epoch - 1ms/step
Epoch 330/600
1268/1268 - 1s - loss: 0.0430 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 331/600
1268/1268 - 1s - loss: 0.0431 - accuracy: 0.9856 - 1s/epoch - 1ms/step
```

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Epoch 332/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9858 - 1s/epoch - 1ms/step
Epoch 333/600
1268/1268 - 1s - loss: 0.0432 - accuracy: 0.9853 - 1s/epoch - 1ms/step
Epoch 334/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 335/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 336/600
1268/1268 - 1s - loss: 0.0428 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 337/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 338/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 339/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Epoch 340/600
1268/1268 - 1s - loss: 0.0426 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 341/600
1268/1268 - 1s - loss: 0.0424 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Epoch 342/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Fnoch 343/600
1268/1268 - 1s - loss: 0.0423 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 344/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 345/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 346/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 347/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 348/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 349/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 350/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Epoch 351/600
1268/1268 - 1s - loss: 0.0422 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 352/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 353/600
1268/1268 - 1s - loss: 0.0419 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 354/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 355/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 356/600
1268/1268 - 1s - loss: 0.0425 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 357/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 358/600
1268/1268 - 1s - loss: 0.0420 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 359/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 360/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 361/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 362/600
1268/1268 - 1s - loss: 0.0421 - accuracy: 0.9856 - 1s/epoch - 1ms/step
Epoch 363/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 364/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 365/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9857 - 1s/epoch - 1ms/step
Epoch 366/600
1268/1268 - 1s - loss: 0.0418 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Epoch 367/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 368/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 369/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 370/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 371/600
1268/1268 - 1s - loss: 0.0416 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 372/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Epoch 373/600
1268/1268 - 1s - loss: 0.0413 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 374/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 375/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 376/600
```

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1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 377/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 378/600
1268/1268 - 1s - loss: 0.0410 - accuracy: 0.9860 - 1s/epoch - 996us/step
Epoch 379/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 380/600
1268/1268 - 1s - loss: 0.0415 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 381/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 382/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 383/600
1268/1268 - 1s - loss: 0.0409 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 384/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9863 - 1s/epoch - 999us/step
Epoch 385/600
1268/1268 - 1s - loss: 0.0411 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 386/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9865 - 1s/epoch - 999us/step
Epoch 387/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 388/600
1268/1268 - 1s - loss: 0.0414 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 389/600
1268/1268 - 1s - loss: 0.0400 - accuracy: 0.9866 - 1s/epoch - 997us/step
Epoch 390/600
1268/1268 - 1s - loss: 0.0412 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 391/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 392/600
1268/1268 - 1s - loss: 0.0406 - accuracy: 0.9863 - 1s/epoch - 994us/step
Epoch 393/600
1268/1268 - 1s - loss: 0.0408 - accuracy: 0.9859 - 1s/epoch - 1ms/step
Epoch 394/600
1268/1268 - 1s - loss: 0.0405 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 395/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9866 - 1s/epoch - 996us/step
Epoch 396/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9861 - 1s/epoch - 1ms/step
Epoch 397/600
1268/1268 - 1s - loss: 0.0407 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 398/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 399/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 400/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 401/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9866 - 1s/epoch - 998us/step
Epoch 402/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 403/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 404/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 405/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 406/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 407/600
1268/1268 - 1s - loss: 0.0404 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 408/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9866 - 1s/epoch - 1ms/step
Epoch 409/600
1268/1268 - 1s - loss: 0.0403 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Fnoch 410/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 411/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 412/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 413/600
1268/1268 - 1s - loss: 0.0399 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 414/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9862 - 1s/epoch - 1ms/step
Epoch 415/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 416/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 417/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9866 - 1s/epoch - 1ms/step
Epoch 418/600
1268/1268 - 1s - loss: 0.0401 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 419/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 420/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9866 - 1s/epoch - 1ms/step
```

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Epoch 421/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9860 - 1s/epoch - 1ms/step
Epoch 422/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 423/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 424/600
1268/1268 - 1s - loss: 0.0397 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 425/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 426/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 427/600
1268/1268 - 1s - loss: 0.0402 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 428/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 429/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 430/600
1268/1268 - 1s - loss: 0.0393 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 431/600
1268/1268 - 1s - loss: 0.0390 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 432/600
1268/1268 - 1s - loss: 0.0398 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 433/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 434/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 435/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 436/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 437/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 438/600
1268/1268 - 1s - loss: 0.0396 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 439/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 440/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 441/600
1268/1268 - 1s - loss: 0.0394 - accuracy: 0.9865 - 1s/epoch - 1ms/step
Epoch 442/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 443/600
1268/1268 - 1s - loss: 0.0389 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 444/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 445/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9863 - 1s/epoch - 1ms/step
Epoch 446/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 447/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 448/600
1268/1268 - 1s - loss: 0.0391 - accuracy: 0.9866 - 1s/epoch - 1ms/step
Epoch 449/600
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 450/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 451/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 452/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 453/600
1268/1268 - 1s - loss: 0.0395 - accuracy: 0.9864 - 1s/epoch - 1ms/step
Epoch 454/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 455/600
1268/1268 - 1s - loss: 0.0388 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 456/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 457/600
1268/1268 - 1s - loss: 0.0392 - accuracy: 0.9866 - 1s/epoch - 1ms/step
Epoch 458/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 459/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 460/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 461/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 462/600
1268/1268 - 1s - loss: 0.0385 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 463/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 464/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 465/600
```

```
1268/1268 - 1s - loss: 0.0387 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 466/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9866 - 1s/epoch - 1ms/step
Epoch 467/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 468/600
1268/1268 - 1s - loss: 0.0384 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 469/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 470/600
1268/1268 - 1s - loss: 0.0386 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 471/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 472/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 473/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 474/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 475/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 476/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 477/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 478/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9867 - 1s/epoch - 1ms/step
Epoch 479/600
1268/1268 - 1s - loss: 0.0383 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 480/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9868 - 1s/epoch - 1ms/step
Epoch 481/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 482/600
1268/1268 - 1s - loss: 0.0380 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 483/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 484/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 485/600
1268/1268 - 1s - loss: 0.0381 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 486/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 487/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 488/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 489/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 490/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 491/600
1268/1268 - 1s - loss: 0.0379 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 492/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 493/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 494/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 495/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 496/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 497/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 498/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Fnoch 499/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 500/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 501/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 502/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 503/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 504/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 505/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 506/600
1268/1268 - 1s - loss: 0.0374 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 507/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 508/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 509/600
1268/1268 - 1s - loss: 0.0378 - accuracy: 0.9871 - 1s/epoch - 1ms/step
```

```
Epoch 510/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 511/600
1268/1268 - 1s - loss: 0.0375 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 512/600
1268/1268 - 1s - loss: 0.0382 - accuracy: 0.9869 - 1s/epoch - 1ms/step
Epoch 513/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 514/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 515/600
1268/1268 - 1s - loss: 0.0369 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 516/600
1268/1268 - 1s - loss: 0.0369 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 517/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 518/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 519/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 520/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 521/600
1268/1268 - 1s - loss: 0.0369 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 522/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 523/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 524/600
1268/1268 - 1s - loss: 0.0372 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 525/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 526/600
1268/1268 - 1s - loss: 0.0377 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 527/600
1268/1268 - 1s - loss: 0.0365 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 528/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 529/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 530/600
1268/1268 - 1s - loss: 0.0368 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 531/600
1268/1268 - 1s - loss: 0.0367 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 532/600
1268/1268 - 1s - loss: 0.0373 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 533/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 534/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 535/600
1268/1268 - 1s - loss: 0.0371 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 536/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 537/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 538/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 539/600
1268/1268 - 1s - loss: 0.0370 - accuracy: 0.9871 - 1s/epoch - 1ms/step
Epoch 540/600
1268/1268 - 1s - loss: 0.0356 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 541/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 542/600
1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 543/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 544/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 545/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 546/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9881 - 1s/epoch - 1ms/step
Epoch 547/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 548/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 549/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9882 - 1s/epoch - 1ms/step
Epoch 550/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 551/600
1268/1268 - 1s - loss: 0.0362 - accuracy: 0.9874 - 1s/epoch - 1ms/step
Epoch 552/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 553/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 554/600
```

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1268/1268 - 1s - loss: 0.0363 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 555/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 556/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 557/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 558/600
1268/1268 - 1s - loss: 0.0366 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 559/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 560/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 561/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 562/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 563/600
1268/1268 - 1s - loss: 0.0364 - accuracy: 0.9872 - 1s/epoch - 1ms/step
Epoch 564/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 565/600
1268/1268 - 1s - loss: 0.0361 - accuracy: 0.9870 - 1s/epoch - 1ms/step
Epoch 566/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 567/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9875 - 1s/epoch - 1ms/step
Epoch 568/600
1268/1268 - 1s - loss: 0.0355 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 569/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 570/600
1268/1268 - 1s - loss: 0.0360 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 571/600
1268/1268 - 1s - loss: 0.0355 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 572/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9873 - 1s/epoch - 1ms/step
Epoch 573/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 574/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 575/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9882 - 1s/epoch - 1ms/step
Epoch 576/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9876 - 1s/epoch - 1ms/step
Epoch 577/600
1268/1268 - 1s - loss: 0.0348 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 578/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 579/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 580/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9883 - 1s/epoch - 1ms/step
Epoch 581/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 582/600
1268/1268 - 1s - loss: 0.0358 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 583/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 584/600
1268/1268 - 1s - loss: 0.0355 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 585/600
1268/1268 - 1s - loss: 0.0353 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 586/600
1268/1268 - 1s - loss: 0.0357 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 587/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 588/600
1268/1268 - 1s - loss: 0.0350 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 589/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9880 - 1s/epoch - 1ms/step
Epoch 590/600
1268/1268 - 1s - loss: 0.0356 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 591/600
1268/1268 - 1s - loss: 0.0349 - accuracy: 0.9882 - 1s/epoch - 1ms/step
Epoch 592/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 593/600
1268/1268 - 1s - loss: 0.0359 - accuracy: 0.9877 - 1s/epoch - 1ms/step
Epoch 594/600
1268/1268 - 1s - loss: 0.0354 - accuracy: 0.9879 - 1s/epoch - 1ms/step
Epoch 595/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9878 - 1s/epoch - 1ms/step
Epoch 596/600
1268/1268 - 1s - loss: 0.0348 - accuracy: 0.9881 - 1s/epoch - 1ms/step
Epoch 597/600
1268/1268 - 1s - loss: 0.0349 - accuracy: 0.9881 - 1s/epoch - 1ms/step
Epoch 598/600
1268/1268 - 1s - loss: 0.0352 - accuracy: 0.9876 - 1s/epoch - 1ms/step
```

```
Epoch 599/600
1268/1268 - 1s - loss: 0.0345 - accuracy: 0.9883 - 1s/epoch - 1ms/step
Epoch 600/600
1268/1268 - 1s - loss: 0.0351 - accuracy: 0.9880 - 1s/epoch - 1ms/step
990/990 [=======] - 1s 710us/step
Final Best Threshold: 0.888888888888888
[[93040 1806]
[ 5247 58299]]
             precision
                          recall f1-score
                                             support
          0
                  0.95
                            0.98
                                      0.96
                                               94846
                  0.97
                            0.92
                                      0.94
                                              63546
          1
   accuracy
                                      0.96
                                              158392
  macro avg
                  0.96
                            0.95
                                      0.95
                                              158392
                            0.96
                                      0.96
weighted avg
                  0.96
                                              158392
```

```
In []: sns.heatmap(conf_matrix, annot=True, fmt='.0f', cmap = 'mako')
   plt.title('Full Data Prediction Matrix - Deep Neural Network Cost Optimized')
   plt.xticks(ticks = [.5,1.5], labels = ['No','Yes'])
   plt.yticks(ticks = [.5,1.5], labels = ['No','Yes'])
   plt.show()
```

Full Data Prediction Matrix - Deep Neural Network Cost Optimized

