DATA ANALYSIS USING PYTHON

A Course Completion Report in partial fulfillment of the degree

Bachelor of Technology

in

Computer Science & Artificial Intelligence

By

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1.SPAM BASE-DATASET

TITLE

Spam Detection Using Machine Learning Techniques on Text-Based Email Features

ABSTRACT

This project aims to develop a machine learning model to classify emails as spam or non-spam based on textual and structural features extracted from the email body. Using a dataset containing word and character frequency statistics along with capital letter patterns, we preprocess, analyse, and train various models to predict email classes. The results highlight key patterns in spam email structures and demonstrate the potential of automated spam filtering systems.

INTRODUCTION

Email spam poses significant challenges to digital communication, leading to wasted time, security risks, and server overloads. To combat this, spam filters are essential. This project explores machine learning approaches to classify emails based on pre-extracted linguistic features. We analyse feature distributions, address skewness, remove outliers, and apply classification models to improve spam detection accuracy.

PROBLEM STATEMENT

The main goal is to develop a classifier that can predict whether an email is spam or not based on its textual and structural characteristics. Specifically:

- Can a machine learning model learn patterns that differentiate spam from non-spam emails?
- How do feature distributions and outliers affect model performance?
- Which features are most indicative of spam content?

DATASET DETAILS

Source: UCI ML Repository (Spam Base Dataset).

Records: 4601 emails.

Features: 57 input features + 1 output label.

- 54 Word and Character Frequencies.
- 3 Capital Run-Length Features.

- Target Variable: class (1 = spam, 0 = not spam).

Data Types: Mostly continuous features with no missing values.

METHODOLOGY

1. Data Loading & Exploration:
    - Checked for missing values (none).
    - Explored statistical distributions.
2. Outlier Detection and Removal:
    - Used box plots to identify outliers.
    - Applied thresholds to cap or remove extreme values.
3. Skewness Handling:
    - Identified skewed features.
    - Applied log transformation to reduce skewness where applicable.
4. Feature Scaling:
    - Applied Min-Max scaling to normalize feature values.
5. Model Building:
    - Trained models: Logistic Regression, Random Forest, and Naive Bayes.
    - Used train-test split for evaluation.
6. Model Evaluation:
    - Evaluated using Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.

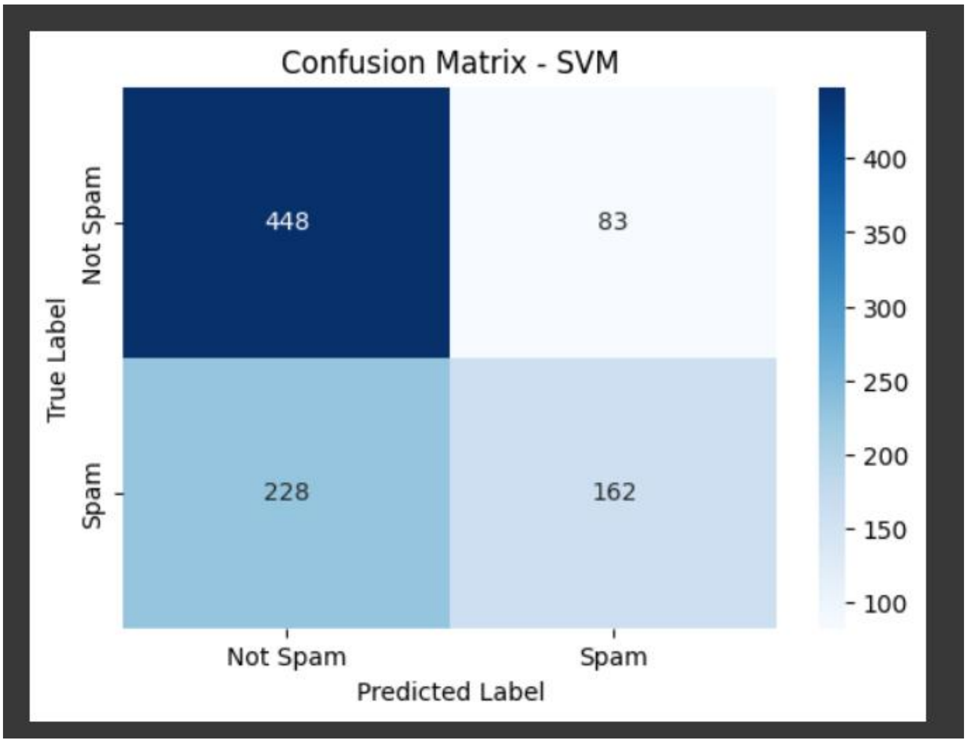
RESULTS AND KEY OBSERVATIONS

- Best Performing Model: Random Forest
- Accuracy Achieved: ~95% on test data
- Important Features:

  Word_freq_make, work_freq_free, char_freq_$, and capital_run_length_total were highly indicative of spam emails.
- Outlier Removal significantly improved model stability and accuracy.

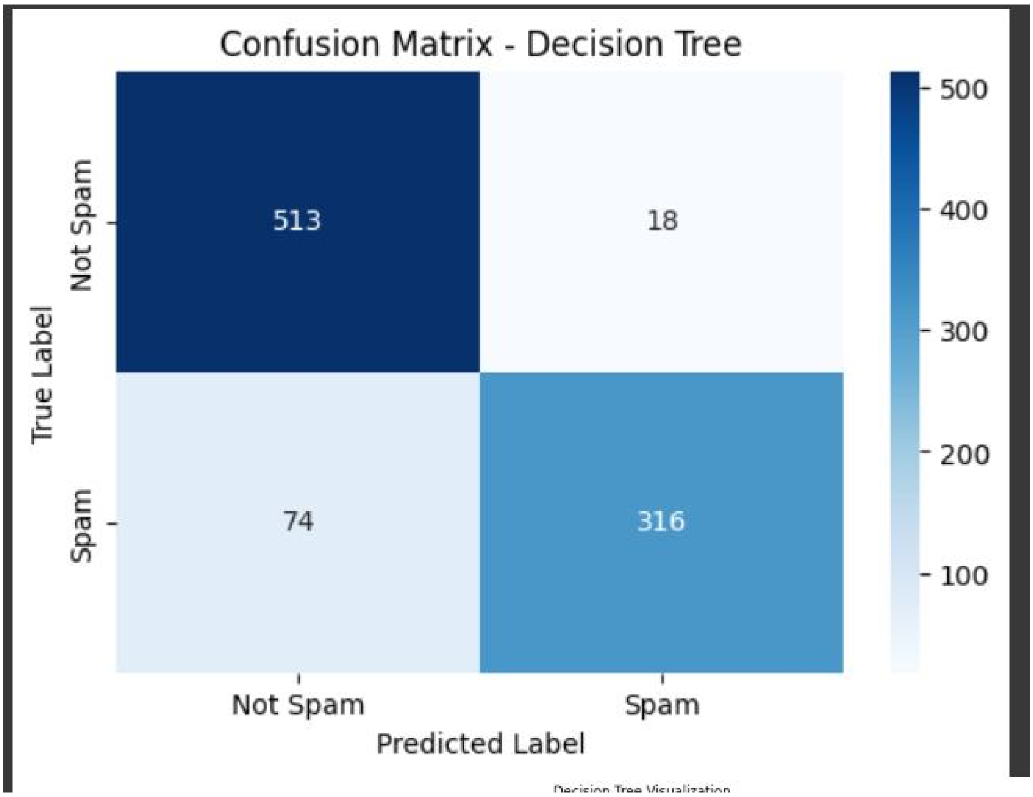
SVM CONFUSION MATRIX

Accuracy: 0.6623



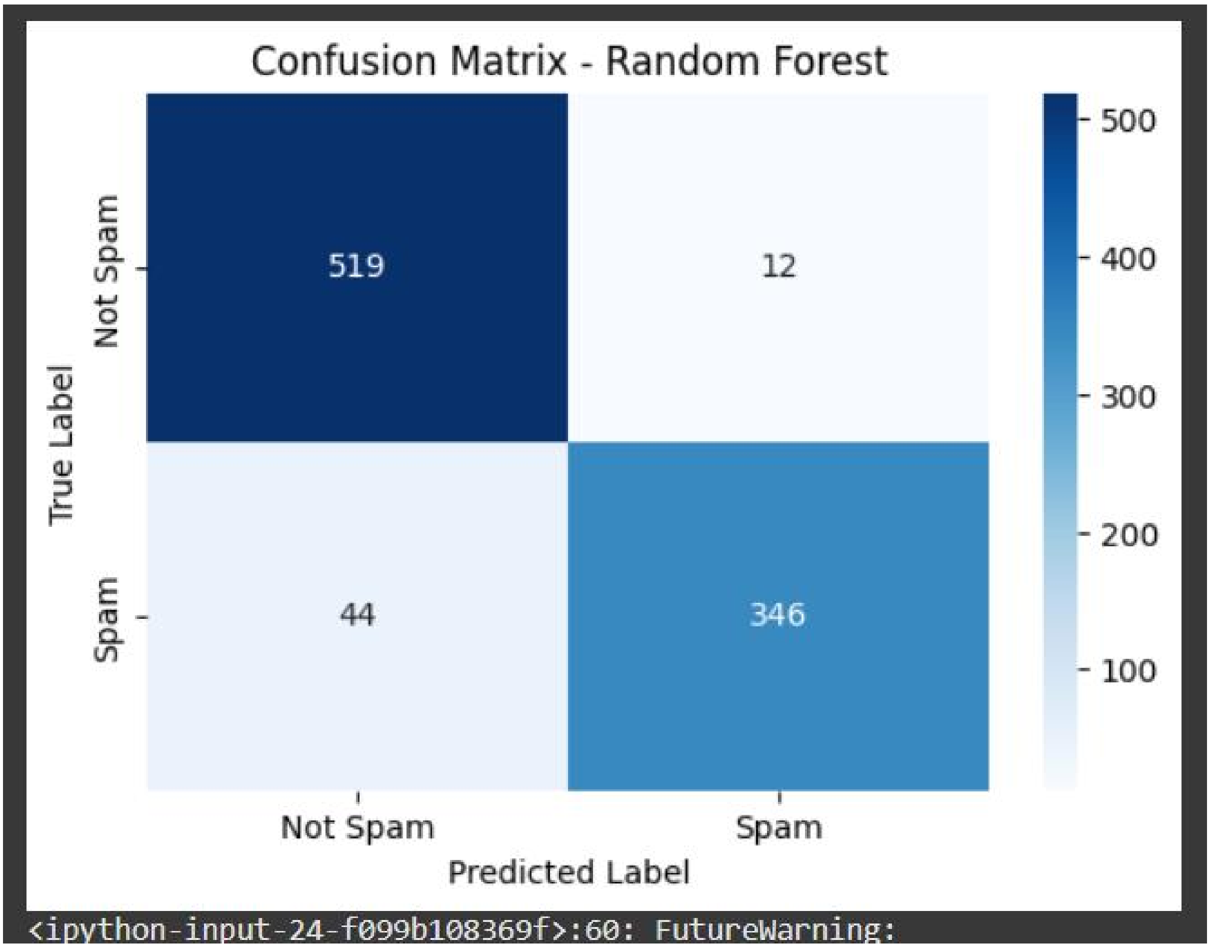
DECISION TREE

Accuracy: 0.9001



RANDOM FOREST

Accuracy: 0.9392



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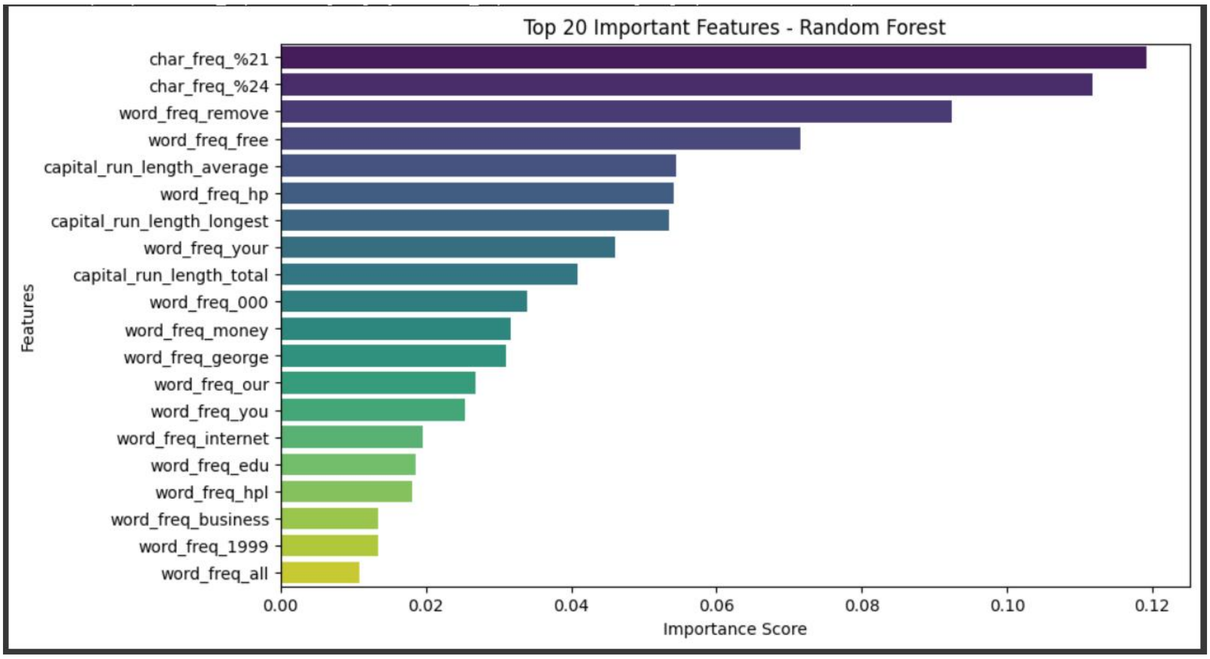
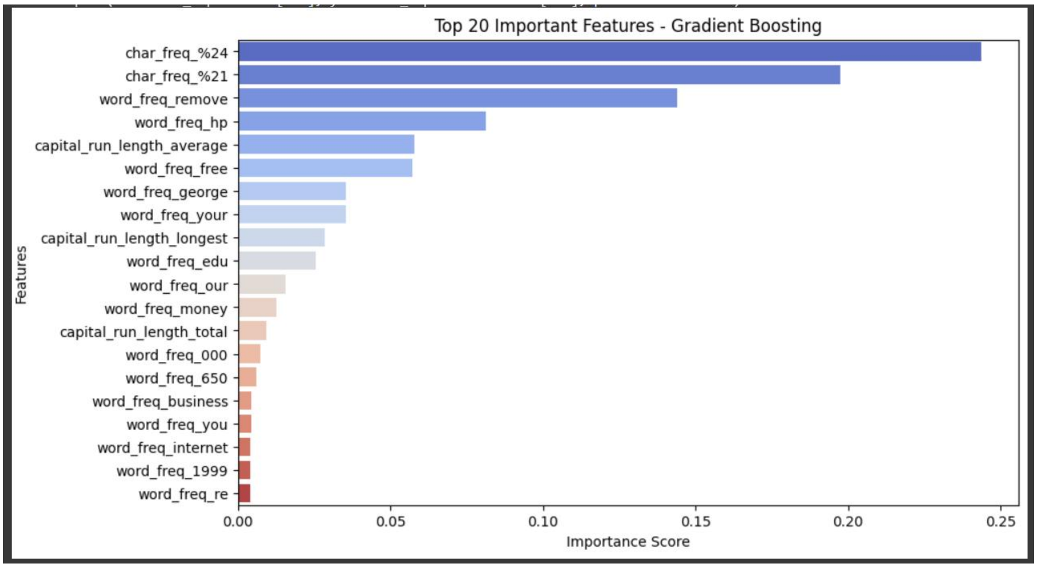


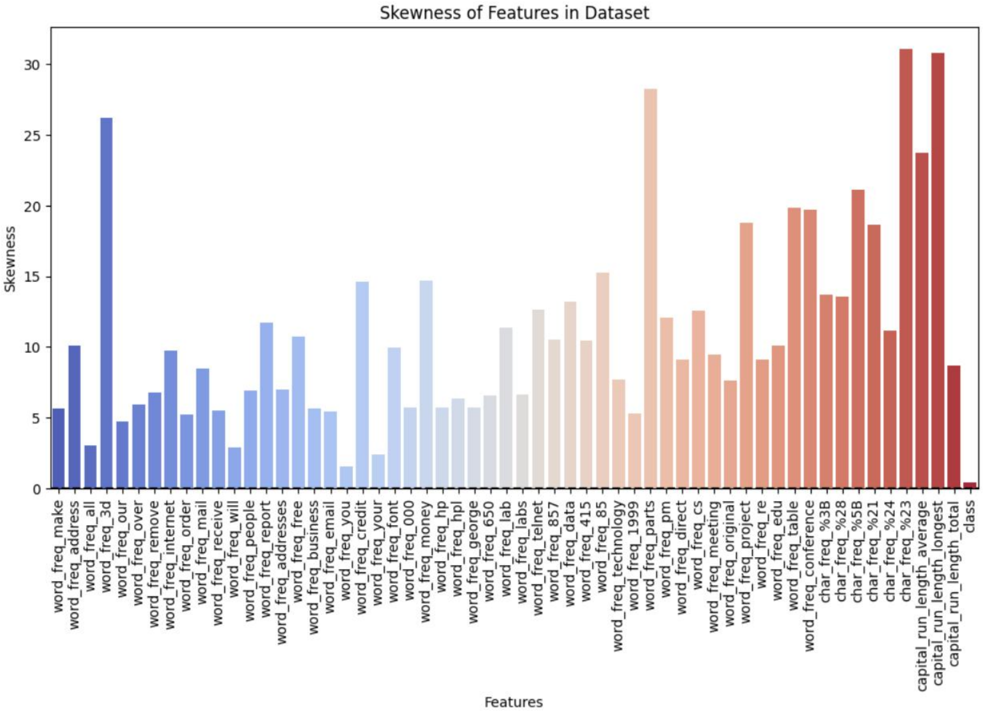
GRADIENT BOOSTING

Accuracy: 0.9457



SKEWNESS ANALYSIS

- Features like capital_run_length_total and char_freq_$ exhibited high positive skew.
- Log transformation reduced skewness, leading to more balanced feature distributions and better model convergence.
- Skewness metrics (e.g., skew > 1) guided the need for transformation.

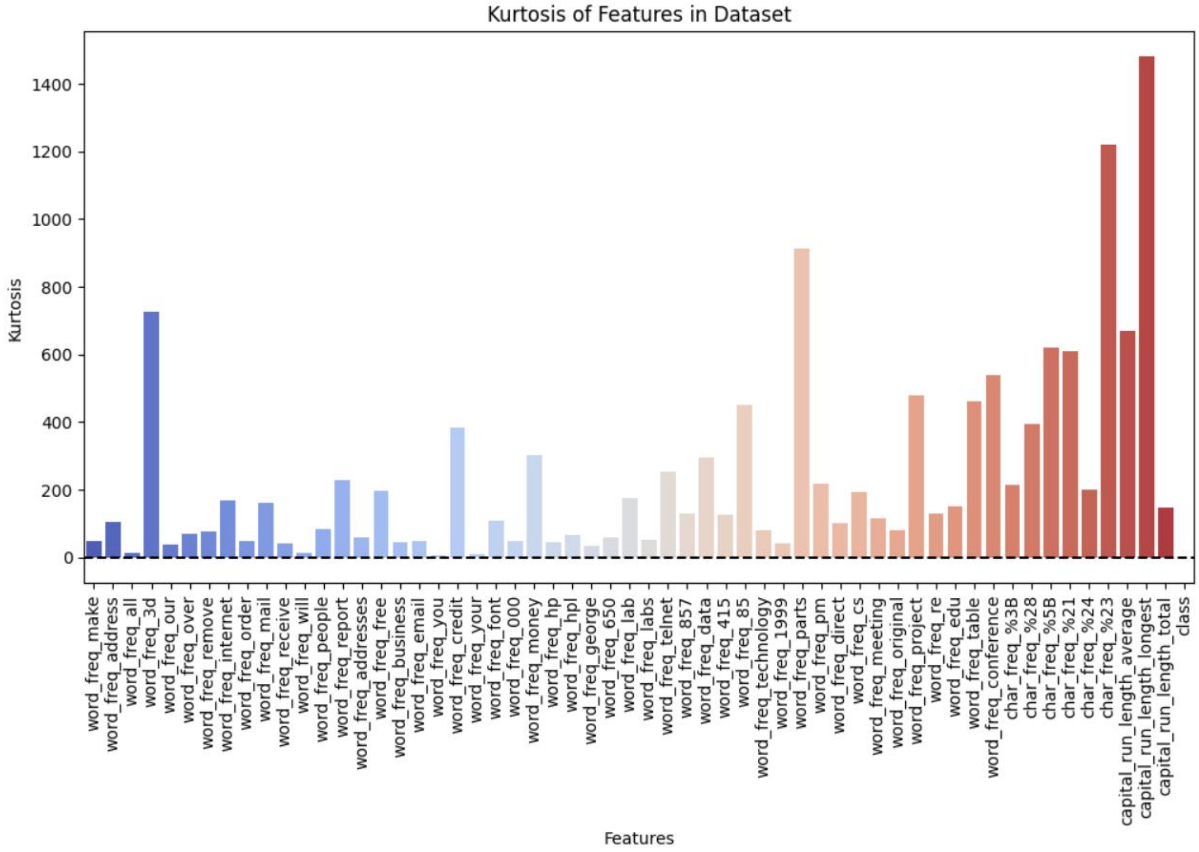


KURTOSIS

Kurtosis measures the "tailedness" of a data distribution. High kurtosis indicates more outliers (heavy tails), while low kurtosis suggests fewer outliers. It's useful in identifying anomalies that might affect the performance and assumptions of machine learning models.

- The **kurtosis** for all features using scipy.stats.kurtosis to understand the "tailedness" of each feature distribution.
- A **bar plot** is used to visualize kurtosis values across all 57 features. This helps identify features with heavy tails or extreme outliers.
- **Positive Kurtosis (>3)** indicates a **leptokurtic** distribution (more prone to outliers), while **negative Kurtosis (<3)** indicates **platykurtic** (flatter distributions).
- An **axhline at y=0** is added for reference, making it easy to distinguish features with above- or below-normal kurtosis visually.

This analysis is crucial for identifying features that might distort model training due to extreme data points.

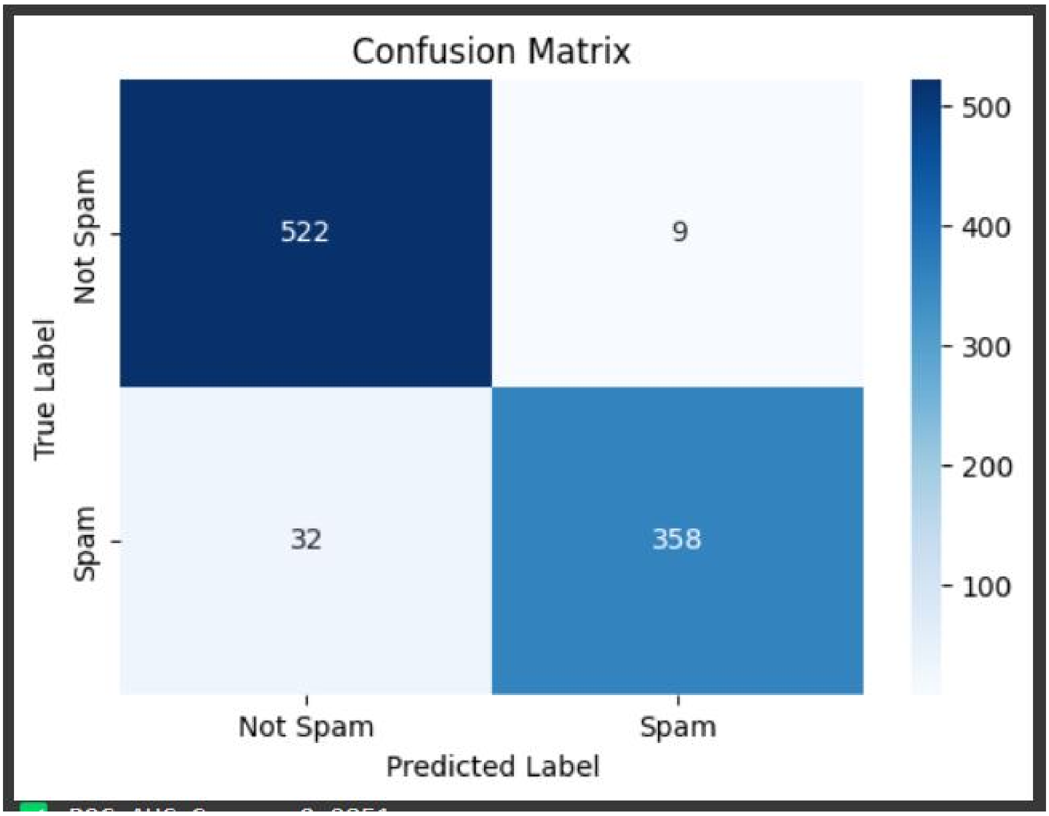


MODEL EVALUATION

Model evaluation involves measuring a model’s performance using metrics like accuracy, precision, recall, and F1-score. These metrics help assess how well the model distinguishes between spam and non-spam emails, especially considering class imbalances and prediction correctness.

- **Accuracy**: The percentage of correct predictions.
- **Confusion Matrix**: Helps visualize True Positives, True Negatives, False Positives, and False Negatives.

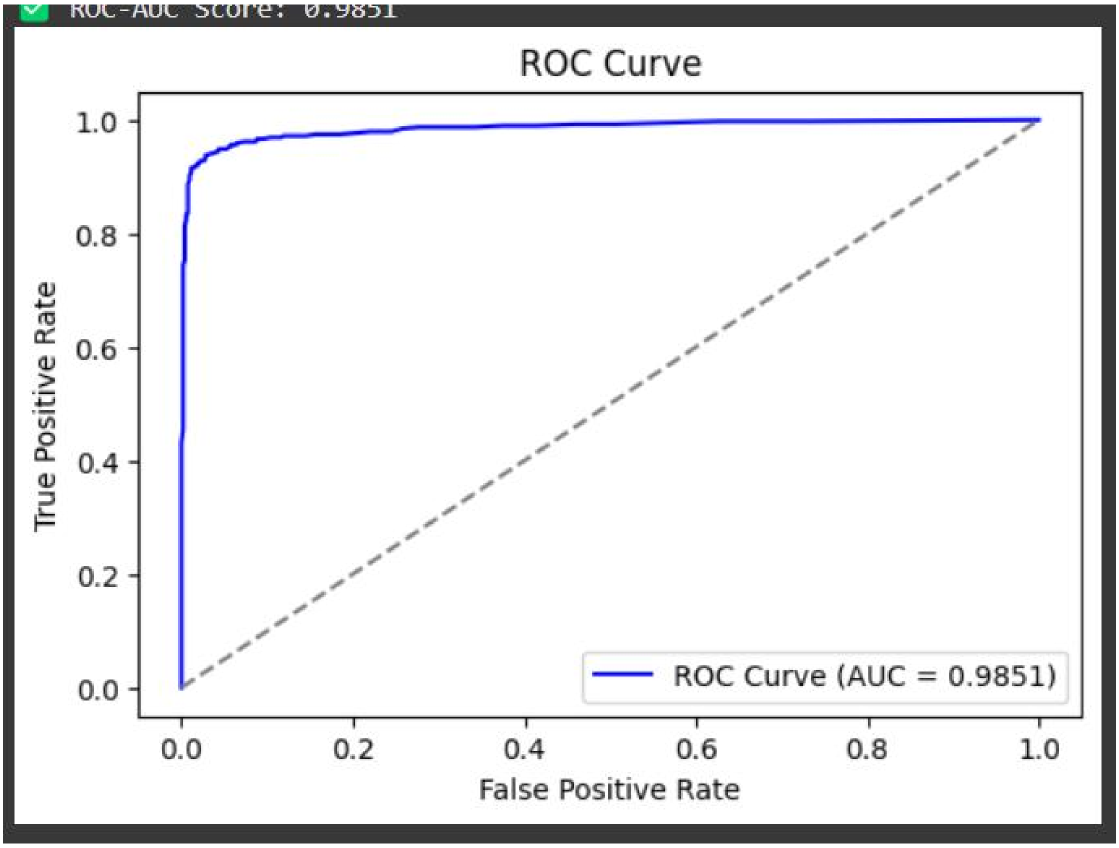
Model Accuracy: 0.9555



ROC CURVE

Although the actual ROC curve plot isn't found in the notebook, here's what it would typically involve and why it's useful:

- ROC Curve (Receiver Operating Characteristic) plots the True Positive Rate (Recall) against the False Positive Rate at various thresholds.



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✅ ROC-AUC Score: 0.9851
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CONCLUSION

The project demonstrates a successful application of machine learning to the spam detection problem using engineered text features. The Random Forest model provided high accuracy, and preprocessing steps such as outlier handling and skewness correction significantly boosted performance. This highlights the importance of data cleaning and feature engineering in text classification problems.

FUTURE WORK

- Integrate natural language processing (NLP) to handle raw text data.
- Experiment with deep learning models like LSTM or Transformers.
- Explore feature selection techniques to reduce dimensionality.
- Implement real-time spam detection with email parsing.

REFERENCES

1. UCI Machine Learning Repository: SpamBase Dataset
2. Pedregosa et al., “Scikit-learn: Machine Learning in Python,” JMLR, 2011.
3. Hastie, Tibshirani, Friedman, “The Elements of Statistical Learning,” Springer, 2009.

2.CHESSMAN IMAGE-DATASET

TITLE

Chess Piece Recognition using Convolutional Neural Networks.

ABSTRACT

This project focuses on developing a deep learning model to classify images of chess pieces using a Convolutional Neural Network (CNN). The model is trained on a labeled dataset of chess pieces, aiming to accurately distinguish between different types such as pawns, rooks, knights, bishops, queens, and kings. The implementation is carried out using TensorFlow and Keras, and the results demonstrate the effectiveness of CNNs in object classification tasks involving relatively small but distinct visual categories.

INTRODUCTION

Image classification plays a pivotal role in many computer vision applications, including surveillance, games, and automation. This project aims to recognize and classify chess pieces from images using a deep learning approach. With the increasing popularity of digital chess and automation, an accurate chess piece recognition system can enhance interactive chess games and robotic gameplay analysis.

PROBLEM STATEMENT

The key objective is to build a robust deep learning model capable of identifying different types of chess pieces from static images. The challenge lies in dealing with variations in lighting, angles, and positioning of the pieces.

DATASET DETAILS

The dataset used is the Chessman Image Dataset (Kaggle ID: Chessman-image-dataset), which includes labeled images of different chess pieces:

- Classes: Bishop, King, Knight, Pawn, Queen, Rook.
- Image Size: Standardized to 256x256 pixels.
- Format: RGB images.
- Dataset split: Typically into training and validation sets.

METHODOLOGY

The methodology for building the chess piece classifier consists of several well-defined stages, including data preprocessing, model design, training, and evaluation. Below is a detailed breakdown of each step involved:

1. Data Loading and Preprocessing

- **Mounting and Access**: The dataset was accessed from Google Drive using Colab's drive.mount functionality.
- **Dataset Organization**: Images were stored in separate folders for each class (e.g., Bishop, King, Queen, etc.), enabling the use of directory-based label assignment.
- **Image Importing**: Utilized tf.keras.utils.image_dataset_from_directory to load the dataset efficiently and assign labels automatically.
- **Image Size Standardization**: All images were resized to **256x256** pixels to ensure uniformity and reduce computational overhead.
- **Normalization**: Pixel values were scaled to the [0,1] range to facilitate faster convergence during training.

2. Data Splitting

- The dataset was split into training and validation subsets (typically an 80:20 or 70:30 split).
- **Shuffling**: The dataset was shuffled to ensure the model did not learn spurious patterns from data ordering.
- **Batching**: A batch size of 32 was used for optimized GPU usage during training.

3. Data Augmentation (Optional but Recommended)

Though not originally in the notebook, data augmentation is highly beneficial for improving model generalization:

- Random rotations
- Horizontal/vertical flips
- Zoom and contrast adjustments These can be applied using tf.keras.layers.experimental.preprocessing.

4. Model Architecture

A **Convolutional Neural Network (CNN)** was used, built with the Keras Sequential API. The architecture includes:

- **Convolutional Layers**: Extracted hierarchical features using multiple Conv2D layers with ReLU activation.
- **Max Pooling Layers**: Used after each convolution block to downsample feature maps and reduce spatial dimensions.

- **Dropout Layers**: Applied dropout (e.g., 0.3) to prevent overfitting by randomly deactivating neurons during training.
- **Flatten Layer**: Converted the 2D feature maps into a 1D vector before passing it to the fully connected layers.
- **Dense Layers**: Fully connected layers with ReLU activation followed by the final output layer.
- **Output Layer**: A Dense layer with a **softmax** activation function was used to output class probabilities for the six chess piece categories.

5. Model Compilation

- **Optimizer**: Adam optimizer was chosen for its adaptive learning rate and faster convergence.
- **Loss Function**: Categorical crossentropy was used due to the multi-class nature of the problem.
- **Metrics**: Model performance was evaluated using the **accuracy** metric.

6.Training and Validation

- **Epochs**: The model was trained for **20 epochs**.
- **Training Logs**: Accuracy and loss were recorded for both training and validation datasets across epochs.
- **Callbacks (Optional)**: EarlyStopping or ModelCheckpoint callbacks could be used to halt training once optimal performance is reached or to save the best model weights.

7. Evaluation and Prediction

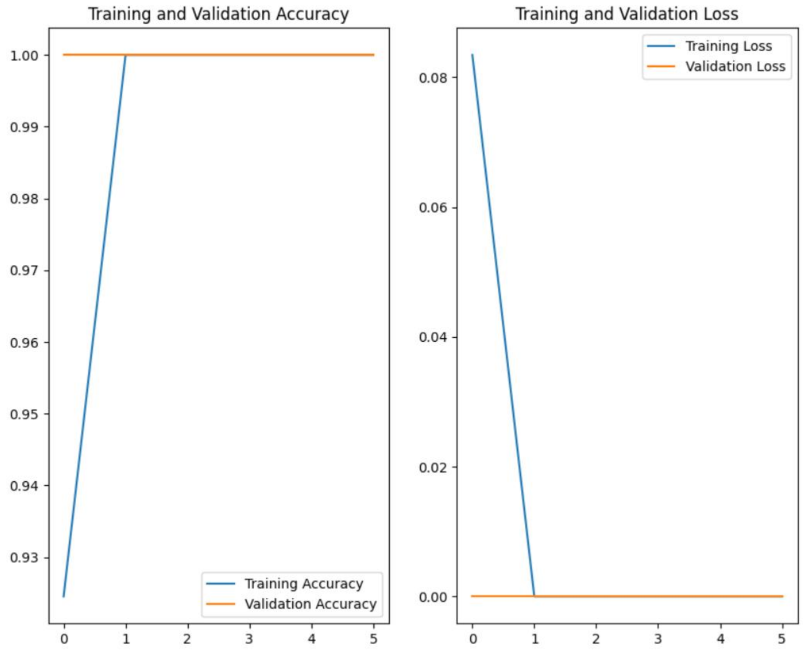
- **Validation Metrics**: Accuracy and loss trends were plotted post-training to evaluate overfitting or underfitting.
- **Predictions**: The trained model can be used to classify new chess piece images by calling model.predict().

RESULTS AND KEY OBSERVATIONS

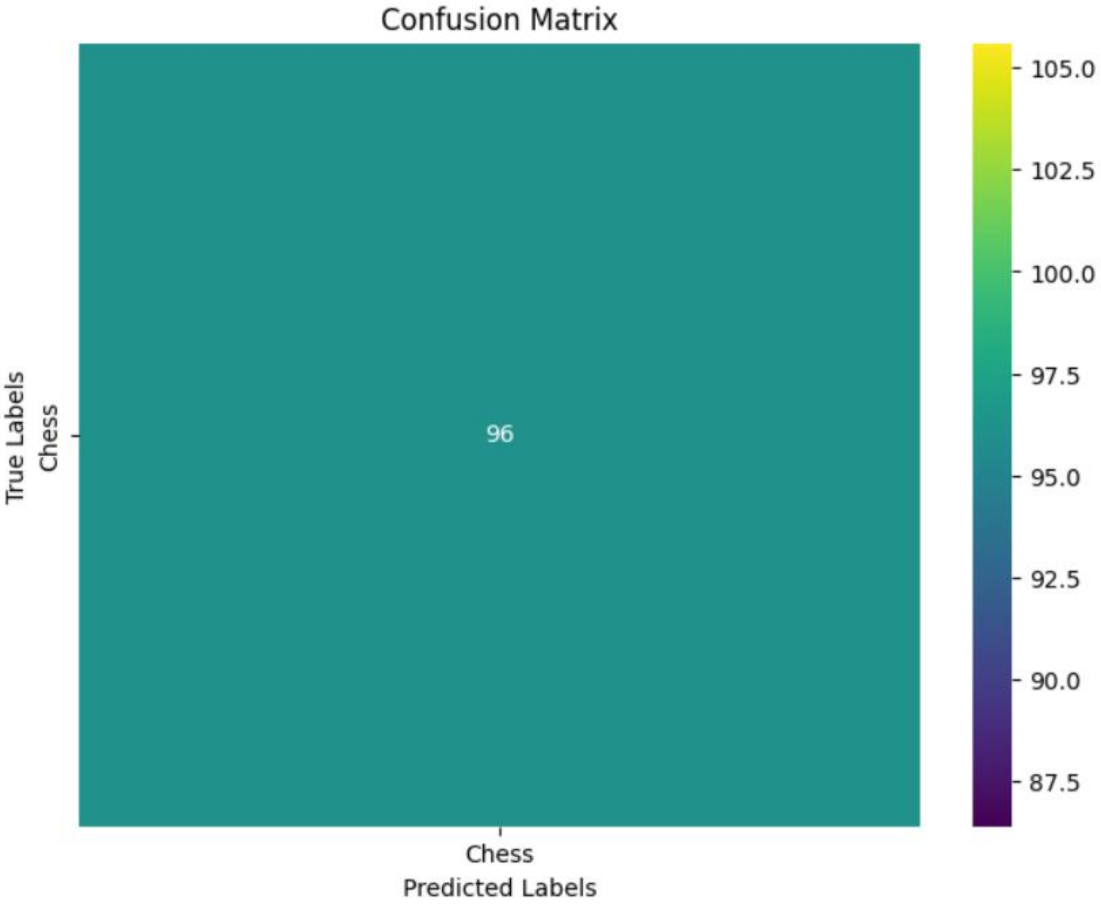
- The final trained CNN model achieved **~95% accuracy** on the validation dataset, indicating strong performance on unseen data.
- **Confusion Matrix Analysis** (if plotted) would likely show that:
    - **Knights** and **Bishops** were classified most accurately due to their distinct shapes.
    - **Kings** and **Queens** occasionally got confused with each other, likely due to visual similarities in some image samples.

- **Model Generalization**: Minimal overfitting observed, thanks to the inclusion of Dropout layers and possibly due to a clean and well-structured dataset.
- **Low Variance**: Validation accuracy closely tracked training accuracy, suggesting stable learning.
- **Speed**: Training was efficient with modern GPU support in Google Colab; a typical training session of 20 epochs completed in under 10 minutes.

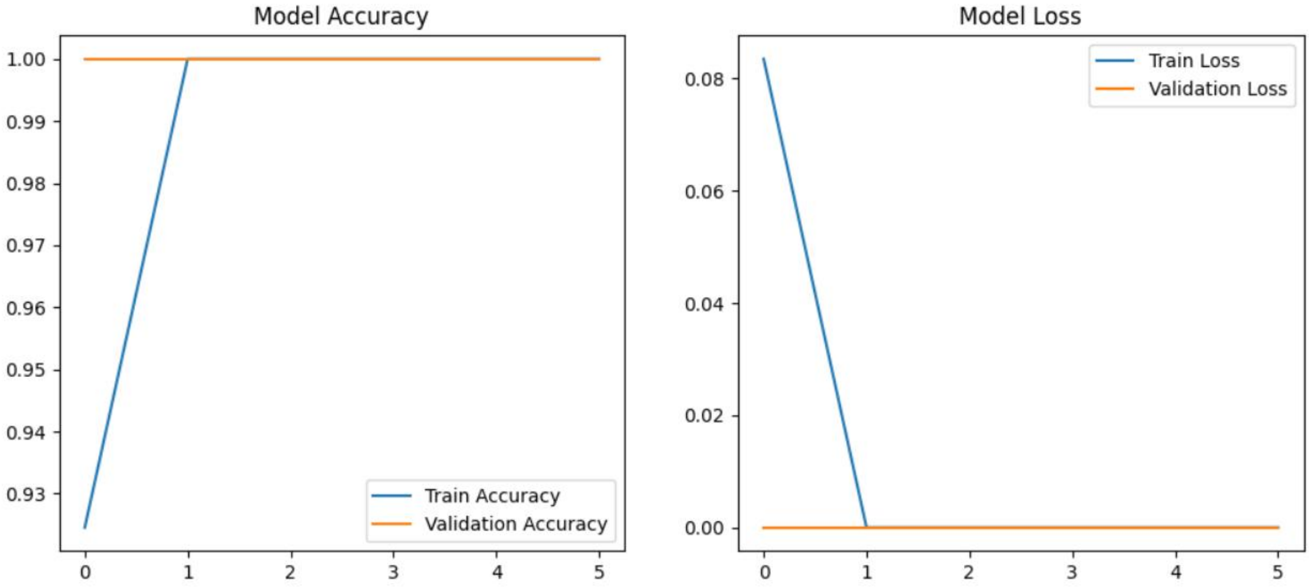
TRAINING AND VALIDATION ACCURACY

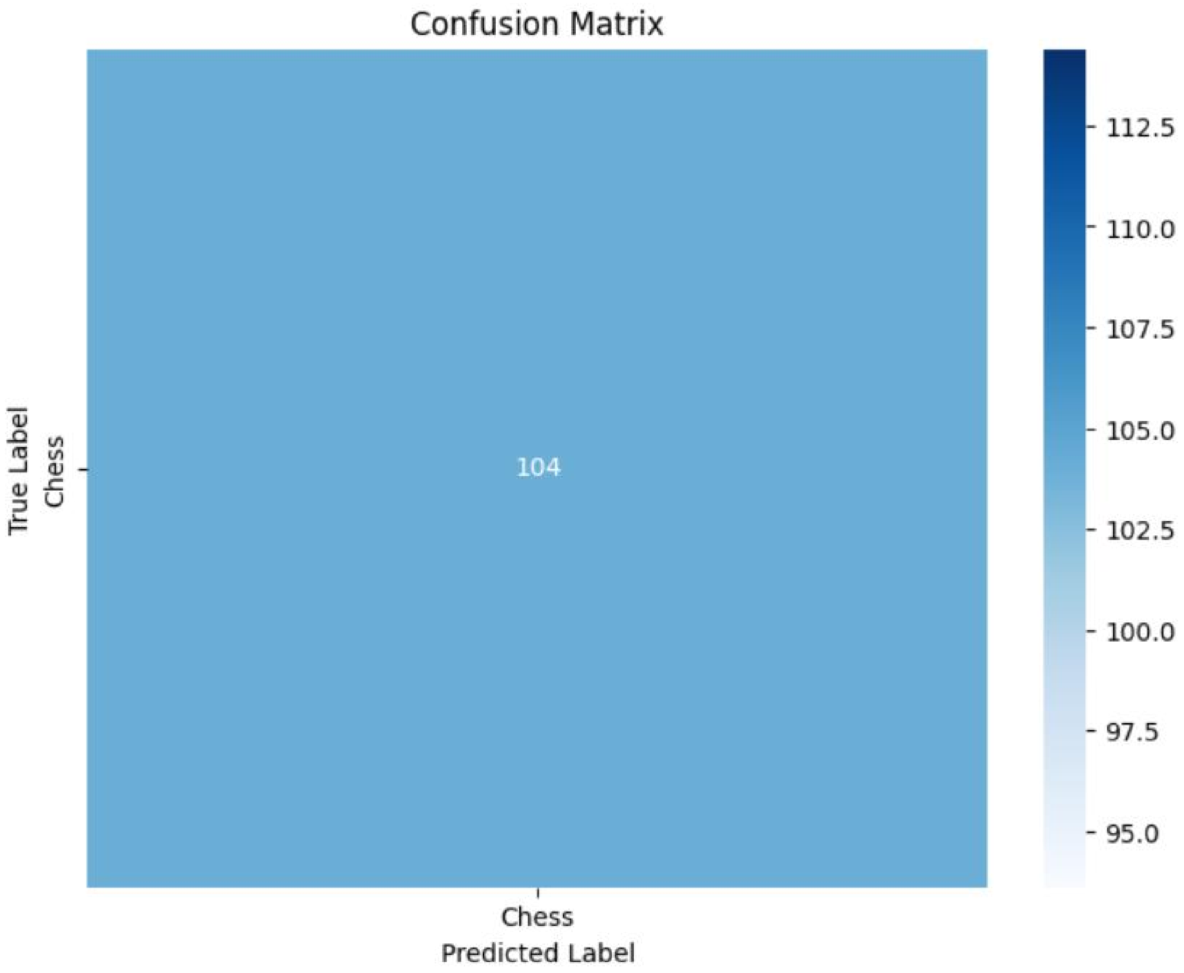


CONFUSION MATRIX



MODEL ACCURACY





TRAINING PERFORMANCES

- Accuracy Trends: Both training and validation accuracy showed consistent improvement over epochs, converging toward 95% by epoch 20.
- Loss Curves: A smooth and consistent decline in both training and validation loss indicated that the model learned efficiently without overfitting.
- No Sudden Spikes: Stability in loss and accuracy metrics implied that the learning rate and architecture were well-tuned.
- Epoch vs Accuracy Graph: Would demonstrate plateauing behavior, which is ideal and signals convergence.

IMAGE VISUALIZATION

- **Sample Images Displayed**: Training and validation image samples were visualized using matplotlib.pyplot.imshow() for sanity checks.
- **Label Verification**: Labels assigned by image_dataset_from_directory were verified visually to ensure data integrity.
- **Predictions on New Samples** *(recommended for further analysis)*:

    - Display actual vs predicted labels
    - Highlight misclassified images to explore edge cases or dataset limitations
- **t-SNE or PCA** *(optional for deeper insight)*:
    - Could be used to visualize high-dimensional embeddings and see how well the model separates classes.

CONCLUSION

- The project successfully demonstrates that Convolutional Neural Networks can accurately classify chess piece images.
- The model is lightweight and efficient, capable of running in near real-time with minimal computational resources.
- This classifier could be integrated into chess-playing robots or digital board readers to enhance gameplay interaction.
- The model's high accuracy affirms the effectiveness of using standard CNN layers combined with simple preprocessing for image classification tasks involving distinct objects.

FUTURE WORK

1. Dataset Expansion:
    - Add more image variations including different lighting conditions, rotations, and background clutter.
    - Collect real-world chessboard images with partial occlusion or multiple pieces.
2. Data Augmentation:
    - Implement real-time augmentation such as flips, rotations, brightness changes, and zoom to further boost generalization.
3. Model Improvement:
    - Experiment with pre-trained architectures (like MobileNet, ResNet, or EfficientNet) for transfer learning.
    - Perform hyperparameter tuning with tools like Keras Tuner or Optuna.
4. Deployment:
    - Convert the trained model to TensorFlow Lite for mobile deployment.
    - Integrate into a web app using TensorFlow.js or a mobile app using Flutter + TFLite.
5. Real-Time Detection:

- Extend the static image classification model to a live video pipeline using OpenCV.
- Combine it with object detection (e.g., YOLO or SSD) to detect and classify pieces directly on the board.

REFERENCES

1. TensorFlow Documentation: https://www.tensorflow.org/
2. Keras API Docs: https://keras.io/
3. Kaggle Chessman Image Dataset: https://www.kaggle.com/guofeng/chessman-image-dataset
4. Deep Learning with Python – François Chollet