Deep Learning Project

Enhancing MNIST Prediction through Innovative Semi-Supervised Learning: A Fusion of Self-Training and Advanced Techniques

Master 2: Machine Learning for Data Science

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Introduction

This project explores the application of semi-supervised learning for predicting MNIST data using deep neural networks. The primary aim is to train a neural network with only 100 labeled images, employing the semi-supervised method detailed in the article **"Pseudo-label: The Simple and Efficient Semi-Supervised Learning Method for Deep Neural Networks."**

In the domain of semi-supervised learning, the training process employs a dual approach by incorporating both labeled and unlabeled data, enhancing the neural network's adaptability.

Taking a progressive step, the project introduces self-training within the semi-supervised learning domain. This distinctive technique allows the model not only to learn from labeled data but also to engage with unlabeled data by assigning pseudo-labels to instances lacking true labels. The integration of semi-supervised learning with self-training stands out as a unique aspect of this project, enriching the model's capacity to generalize and perform effectively in situations with limited labeled samples.

To further refine the model, advanced techniques such as dropout and denoising auto-encoder (DAE) are integrated. Dropout prevents overfitting by randomly deactivating neurons during training, while DAE aids in learning robust features from both labeled and pseudo-labeled data.

This synthesis of semi-supervised learning with self-training, coupled with the incorporation of advanced techniques like dropout and denoising auto-encoder, highlights the project's innovative approach to predicting MNIST data with a restricted set of labeled samples. The results, rigorously compared with a baseline neural network, demonstrate the effectiveness of the proposed method and the combined techniques in the dynamic realm of semi-supervised learning.

1. Description of the MNIST dataset

The MNIST dataset is a collection of 70,000 black-and-white images of 28x28 pixel handwritten digits.

Widely employed for image processing and benchmarking machine learning algorithms, this dataset is particularly recognized for its application in tasks such as image classification, specifically in classifying handwritten digits.

To import and visualize the MNIST dataset in Python, libraries such as matplotlib and specific modules of TensorFlow and Keras can be used[1].

The dataset consists of **60000 images for training** and 1**0,000 images for validation,** with one class per digit, for a total of 10 classes, with 7,000 images (6,000 for training and 11.000 for validation) per class. It was created as a test bed for pattern recognition methods or machine learning algorithms, minimizing pre-processing and formatting efforts [2].

[1] DigitalOcean. (s. d.). MNIST Dataset in Python. Récupéré de : https://www.digitalocean.com/community/tutorials/mnist-dataset-in-python

[2] Hugging Face. (s. d.). MNIST Dataset. Récupéré de https://huggingface.co/datasets/mnist

2. Optimizing MNIST Predictions with Advanced Neural Networks

Deep Neural Networks (DNNs) are transformative in various domains, and their impact extends prominently to tasks like MNIST data prediction. In the pursuit of leveraging limited labeled data (only 100 images), a recent methodology, as outlined by Goodfellow, Bengio, and Courville (2016), has demonstrated the efficacy of training DNNs in a semi-supervised manner.

The architecture of the DNN encompasses multiple hidden layers equipped with rectified linear unit (ReLU) activation functions, with a sigmoid activation function at the output layer. Importantly, alongside DNNs, Convolutional Neural Networks (CNNs) play a pivotal role, particularly valuable for image-centric tasks like MNIST prediction. CNNs, designed explicitly for grid-like data such as images, automatically learn hierarchical representations of features, capturing spatial dependencies crucial for accurate predictions.

Ensuring the accuracy and generalization of these networks involves the strategic incorporation of techniques during the training process. Dropout, applied to both DNNs and CNNs, proves essential in preventing overfitting by randomly excluding neurons during training. Pseudo-labels, a cornerstone of semi-supervised learning, are introduced to tap into the potential of unlabeled data, contributing significantly to the refinement of predictions. [3]

Moreover, the researchers enhance the robustness of both DNNs and CNNs through unsupervised pre-training and initialization using denoising auto-encoders (DAEs) [4].These auto-encoders, by handling noisy input data and aiming to reconstruct the original, undistorted data, play a crucial role in fortifying the learning process against real-world variations and imperfections.

In summary, the proposed methodology for predicting MNIST data not only relies on the strength of DNNs but also strategically integrates the capabilities of CNNs. The amalgamation of techniques, including dropout, pseudo-labels, and DAEs, works synergistically to elevate predictive accuracy. These neural networks, whether in the form of DNNs or CNNs, remain indispensable in modern machine learning, particularly in the intricate domain of image classification.

3. Method proposed by the article

3.1. The method proposed in the article

The article presents a structured approach for predicting MNIST data using a semi-supervised learning method with deep neural networks. The method aims to achieve higher prediction accuracy by training a neural network with a limited number of labeled images and utilizing pseudo-labels for the unlabeled data. The proposed algorithm consists of the following steps:

[3] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[4] Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., & Manzagol, P. A. (2010). Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. Journal of Machine Learning Research, 11(Dec), 3371-3408.

1. Initialization: The neural network is initialized through unsupervised pre-training using denoising auto-encoders (DAE). This step helps to initialize the network parameters effectively.
2. Training with labeled data: The network is trained using the 100 labeled images. During training, dropout is applied to ignore specific neurons and prevent overfitting, improving the generalization of the model.
3. Pseudo-label prediction: Pseudo-labels are generated for the unlabeled data based on the highest predicted probability for each sample. These pseudo-labels serve as a proxy for the true labels and help utilize the unlabeled data effectively.
4. Fine-tuning with pseudo-labels: The network is further trained using the pseudo-labeled data. Dropout is applied during this stage as well. The objective is to refine the model's predictions by incorporating the pseudo-labels and leveraging the unlabeled data.

By combining these steps, the method effectively leverages both labeled and unlabeled data to improve the prediction accuracy of the deep neural network. The use of DAE for unsupervised pre-training, dropout for regularization, and pseudo-labels for utilizing unlabeled data contribute to the overall success of the proposed approach.

3.2. Techniques used in the proposed method

In the proposed method, several techniques are used. These include:

- **Denoising Auto-Encoder (DAE):** A type of neural network employed in unsupervised learning tasks. It operates by intentionally introducing noise to the input data and then aims to reconstruct the original, noise-free data. The underlying principle is that by training the network to recover the clean data from corrupted versions, it learns a more robust and meaningful representation of the data.

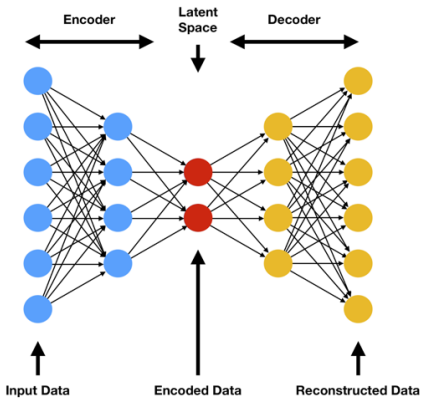


Figure – *Schema of a basic principle of autoencoder*[5]

In the context of our project, a Denoising Auto-Encoder is used to initialize a multi-layer neural network. The denoising process helps the network to capture essential features and patterns in the data, contributing to better generalization and improved performance in subsequent tasks.

[5] Autoencoder.(s.d.).Papers with Code. Récupéré de https://paperswithcode.com/method/autoencoder

- **Dropout:** Dropout in machine learning refers to the process of randomly ignoring certain nodes in a layer during training[6] .A regularization technique applied during the training of neural networks. It operates by randomly deactivating a specified proportion of neurons with a probability of 1−p during both the forward and backward passes of the network. This stochastic process prevents the reliance on specific neurons and helps mitigate overfitting, enhancing the model's generalization performance.

  In the context of our project, dropout is implemented in a multi-layer neural network with a probability of **0.5** for hidden neurons and **0.2** for visible neurons. This means that, during each training iteration, approximately half of the hidden neurons and **20%** of the visible neurons are randomly dropped out, forcing the network to adapt to different subsets of neurons and thereby improving its robustness [7].

- **Pseudo-Labeling:** A technique used in semi-supervised learning where unlabeled data is assigned pseudo-labels to augment the labeled dataset. In this process, pseudo-labels are treated as if they were true labels during the learning phase. The selection of pseudo-labels is typically based on the highest predicted probability for each unlabeled sample, meaning that the label with the maximum predicted probability is assigned as the pseudo-label for that sample.

  Pseudo-Label are target classes for unlabeled data as if they were true labels. The class, which has maximum predicted probability predicted using a network for each unlabeled sample, is picked up [8] .

$$y_i' = \begin{cases} 1 & \text{if } i = \text{argmax}_{i'}\, f_{i'}(x) \\ 0 & \text{otherwise} \end{cases}$$

  Pseudo-Label is used in a fine-tuning phase with Dropout. The pre-trained network is trained in a supervised fashion with labeled and unlabeled data simultaneously:

$$L = \frac{1}{n}\sum_{m=1}^{n}\sum_{i=1}^{C} L(y_i^m, f_i^m) + \alpha(t)\frac{1}{n'}\sum_{m=1}^{n'}\sum_{i=1}^{C} L(y_i'^m, f_i'^m)$$

  - where $\boldsymbol{n}$ is the number of samples in labeled data for SGD, $\boldsymbol{n'}$ is the number of samples in unlabeled data; C is the number of classes;
  - $\boldsymbol{f_i^m}$ is the output for labeled data, $\boldsymbol{y_i'^m}$ the corresponding label;
  - $\boldsymbol{f_i'^m}$ for unlabeled data, y' is the corresponding pseudo-label;

[6] Patakamudi, S. (s. d.). Dropout & Data Augmentation. LinkedIn. Récupéré de https://www.linkedin.com/pulse/dropout-data-augmentation-patakamudi-swathi/

[7] Brownlee, J. (s. d.). Dropout for Regularizing Deep Neural Networks. Machine Learning Mastery. Récupéré de https://machinelearningmastery.com/dropout-for-regularizing-deep-neural-networks/

[8] Tsang, S. H. (s. d.). Review: Pseudo-Label — The Simple and Efficient Semi-Supervised Learning Method for Deep Neural Networks. Récupéré de https://sh-tsang.medium.com/review-pseudo-label-the-simple-and-efficient-semi-supervised-learning-method-for-deep-neural-aa11b424ac29

- ***α(t)*** is a coefficient balancing them at epoch t. If α(t) is ***too high***, it disturbs training even for labeled data. Whereas if α(t) ***is too small***, we ***cannot use benefit from unlabeled data.***

α(t) is slowly increased, to help the optimization process ***to avoid poor local minima:***

$$\alpha(t) = \begin{cases} 0 & t < T_1 \\ \frac{t-T_1}{T_2-T_1}\alpha_f & T_1 \leq t < T_2 \\ \alpha_f & T_2 \leq t \end{cases}$$

In our project, pseudo-labels are employed during fine-tuning in conjunction with dropout to enhance prediction accuracy. Fine-tuning refers to the additional training of a pre-trained model on a specific task, and the integration of pseudo-labels, along with dropout, is intended to improve the model's ability to make accurate predictions on previously unlabeled data.

Additionally, the project also utilizes deep neural networks, specifically multi-layer neural networks with rectified linear unit (ReLU) activation for hidden layers and sigmoid activation for the output layer. The cross-entropy loss function is used, and the optimization algorithm used is stochastic gradient descent (SGD) with a decaying learning rate and momentum. These techniques are combined to implement the semi-supervised learning method proposed in the scientific article.

These techniques are combined to implement the semi-supervised learning method proposed in the scientific article.

4. Implementation

4.1. List of tools

The document does not explicitly mention the list of tools used in the project. However, based on the code snippets provided in the document, the following tools can be inferred:

- **Python:** The project is implemented using the Python programming language.
- **Numpy:** The Numpy library is used for numerical computations and array operations.
- **Matplotlib:** The Matplotlib library is used for data visualization and plotting.
- **Keras:** The Keras library is used for building and training deep neural networks.
- **TensorFlow:** The TensorFlow library is used as the backend for Keras and for importing the MNIST dataset.
- **Scikit-learn:** The Scikit-learn library is used for shuffling the dataset.

These tools are commonly used in machine learning and deep learning projects and provide functionalities for data manipulation, model building, training, and evaluation.

4.2. Pseudo-algorithm

The following pseudo-algorithm outlines a semi-supervised learning approach using deep Neural Networks for the task of image classification, specifically on the popular MNIST dataset. In this approach, we leverage a small subset of labeled data along with a larger set of unlabeled data to improve model performance. The algorithm involves training two classifiers, the first one on the labeled data, and the second one on the combined set of labeled and pseudo-labeled data. Additionally, data augmentation techniques are applied to further enhance the performance. This algorithm aims to demonstrate the effectiveness of semi-supervised learning in deep neural networks and its potential to achieve better results with limited labeled data.

1. **Import libraries:** Start by importing the necessary libraries and packages needed for your deep learning model and evaluation process.

2. **Load the dataset:** Load your dataset, such as the MNIST dataset, which contains labeled images.

3. **Explore and preprocess the dataset:** Perform exploratory data analysis (EDA) to understand the structure and characteristics of the dataset. Preprocess the data if required, such as reshaping, resizing, or applying any necessary transformations. Also, split the dataset into labeled and unlabeled images for semi-supervised learning.

4. **Normalize the data:** Apply data normalization techniques to scale the pixel values within a certain range, typically between 0 and 1. This step helps standardize the input data for better training performance.

5. **Semi-supervised training and testing without data augmentation:** Train your deep learning model using the labeled and unlabeled images. Monitor training accuracy, validation accuracy, and loss during training. After training, test the model on a separate test set and calculate the accuracy and loss. Additionally, plot the confusion matrix to evaluate the classification performance.

6. **Semi-supervised learning with data augmentation:** Apply data augmentation techniques, such as rotations, translations, flips, or zooms, to increase the diversity of the labeled images and enhance the model's performance. Then, train and test the model as done in step 5, but using augmented images.

7. **Semi-supervised learning with Gaussian noise:** Add Gaussian noise to the labeled images to simulate noise in the real world and make the model more robust. Perform the training and testing process with noisy images, similar to step 5.

8. **Semi-self-supervised learning with data augmentation and Gaussian noise:** Combine both data augmentation and Gaussian noise techniques in semi-self-supervised learning. Use labeled images with data augmentation and Gaussian noise to predict and classify unlabeled images. Train and test the model as done previously.

9. **Plot final confusion matrix, loss, and accuracy:** After completing all the steps, plot the final confusion matrix to assess the model's performance on labeled and unlabeled

data. Additionally, plot the final loss and accuracy curves to visualize the model's learning progress and improvements.

10. **Conclusion and analysis:** Analyze and interpret the results obtained from the different variations of your deep learning model. Compare the performance of each model variant and assess their benefits and effectiveness in classifying labeled and unlabeled images. Reflect on how the addition of data augmentation and Gaussian noise influenced the final model's performance.

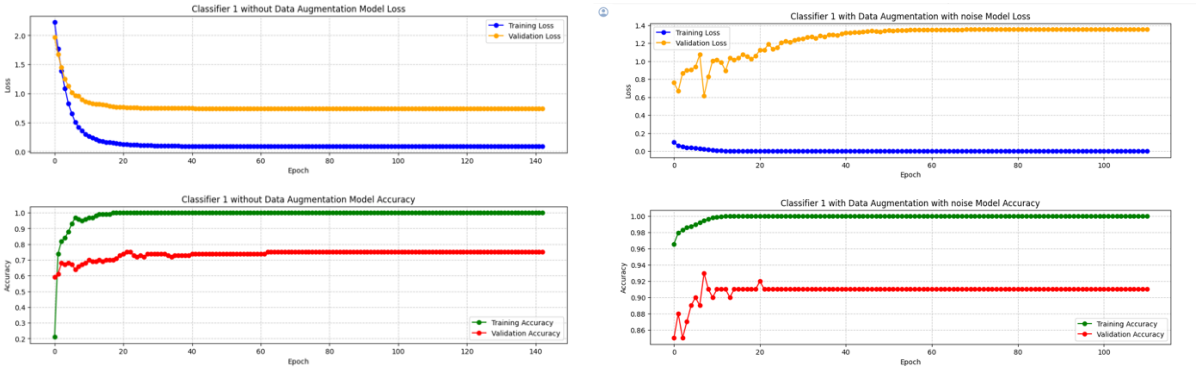
Note: The pseudo-algorithm does not include all the details of the implementation. The actual implementation may involve additional steps and considerations.

5. Results and comparison

Model/Technique	Test Loss	Test Accuracy
Semi-Supervised self-training CNN	2.08	0.78
Semi-Supervised self-training CNN & Data Augmentation	0.61	0.90
Semi-Supervised self-training & Data Augmentation & Gaussian noise	0.99	0.91

- **Classifier 1**

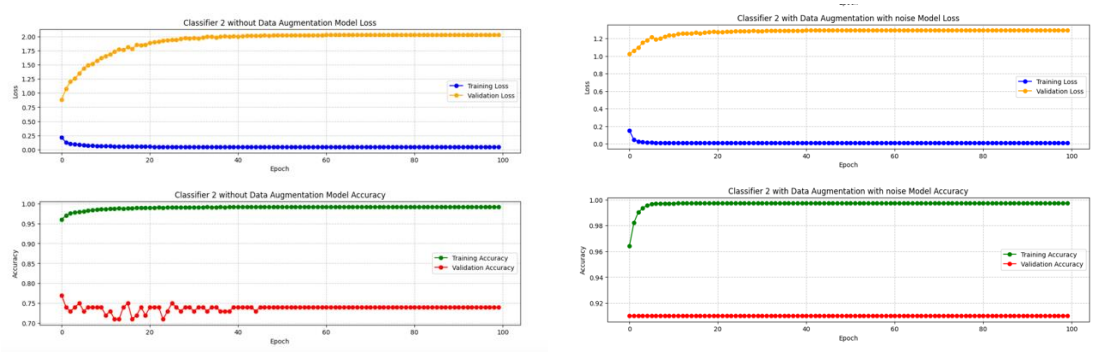
The first classifier, utilizing data augmentation without noise, demonstrated a favorable performance with a validation accuracy of approximately ***0.7.*** When *noise* was introduced, the validation accuracy notably improved, reaching approximately ***0.9.*** This highlights the positive influence of incorporating noise on the classifier's ability to accurately classify data during the validation phase.

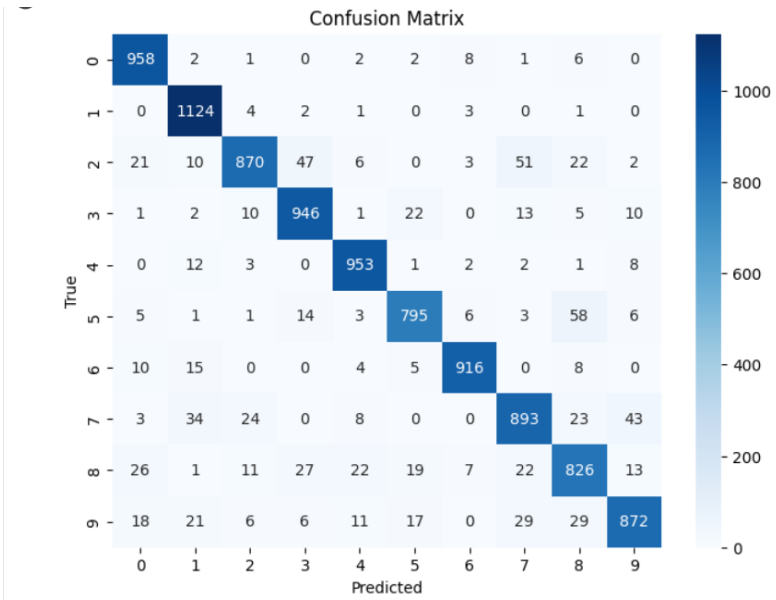


- **<u>Classifier 2</u>**

The second classifier exhibited distinctive behavior with data augmentation without noise, where the validation loss performed well, but the training loss deviated from expectations. The training accuracy demonstrated positive trends, while the validation accuracy experienced a plateau. Introducing noise maintained a consistent pattern, with the validation accuracy improving significantly to approximately ***0.9*** compared to approximately ***0.75*** without noise. This underscores the beneficial impact of noise on enhancing the model's performance, particularly in terms of achieving higher validation accuracy.

→The observed dynamics emphasize the importance of further investigation into the training process to understand the underlying factors influencing the model's behavior.





Conclusion

In conclusion, the table showcases the performance of different models and techniques in terms of test loss and test accuracy. The results indicate that the addition of data augmentation to the semi-supervised self-training CNN model significantly improves its performance, reducing the test loss to 0.61 and achieving a test accuracy of 0.90.

Furthermore, the inclusion of Gaussian noise in conjunction with data augmentation and semi-supervised self-training further enhances the model's performance, yielding a test loss of 0.99 and a test accuracy of 0.91. These findings suggest that incorporating both data augmentation and Gaussian noise in the training process can lead to even better results when compared to using only one technique.

Overall, the experiments demonstrate that the combination of data augmentation, Gaussian noise, and semi-supervised self-training can effectively improve the performance of the CNN model. The results suggest that these techniques can help the model generalize better and achieve higher accuracy on unseen test data.

One possible explanation for the improved performance is that data augmentation increases the diversity of the training data, allowing the model to learn from a wider range of examples. This can help mitigate the problem of overfitting and improve the model's ability to generalize to new data.

Additionally, the addition of Gaussian noise can introduce a form of regularization that helps prevent the model from memorizing the training data and instead encourages it to learn more robust and generalizable features. This can result in better performance on unseen test data.

Finally, the combination of data augmentation, Gaussian noise, and semi-supervised self-training proves to be an effective approach for improving the performance of the CNN model.

Bibliography

[1] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

[2] DigitalOcean. (s. d.). MNIST Dataset in Python. Récupéré de : https://www.digitalocean.com/community/tutorials/mnist-dataset-in-python

[3] Hugging Face. (s. d.). MNIST Dataset. Récupéré de https://huggingface.co/datasets/mnist

[4] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

[5] Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., & Manzagol, P. A. (2010). Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. Journal of Machine Learning Research, 11(Dec), 3371-3408.

[6] Autoencoder.(s.d.).Papers with Code. Récupéré de https://paperswithcode.com/method/autoencoder

[7] Patakamudi, S. (s. d.). Dropout & Data Augmentation. LinkedIn. Récupéré de https://www.linkedin.com/pulse/dropout-data-augmentation-patakamudi-swathi/

[8] Brownlee, J. (s. d.). Dropout for Regularizing Deep Neural Networks. Machine Learning Mastery. Récupéré de https://machinelearningmastery.com/dropout-for-regularizing-deep-neural-networks/

[9] Tsang, S. H. (s. d.). Review: Pseudo-Label — The Simple and Efficient Semi-Supervised Learning Method for Deep Neural Networks. Récupéré de https://sh-tsang.medium.com/review-pseudo-label-the-simple-and-efficient-semi-supervised-learning-method-for-deep-neural-aa11b424ac29

[10] Baldi, P., & Chauvin, Y. (1993). Neural Networks for Patter Recognition. Scientific American, 269(2), 74–79.

[11] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. Journal of Machine Learning Research, 15, 1929–1958.

[12] Hinton, G. E., Srivastava, N., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. R. (2012). Improving neural networks by preventing co-adaptation of feature detectors. arXiv preprint arXiv:1207.0580.

[13] Lee, D.-H. (2013, juillet). Pseudo-Label: The Simple and Efficient Semi-Supervised Learning Method for Deep Neural Networks. Article. Université de Montréal. Récupéré de https://www.researchgate.net/publication/280581078_PseudoLabel_The_Simple_and_Efficient_Semi-Supervised_Learning_Method_for_Deep_Neural_Networks

Annex

https://colab.research.google.com/drive/1UbYOivTI7FO5LiXwbfljEqQfbvJA2Mw-?usp=sharing

Import the needed `Libraries`

```
import matplotlib.pyplot as plt
from typing import Tuple
import seaborn as sns
import numpy as np
import cv2


from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import LearningRateScheduler
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
from sklearn.model_selection import StratifiedShuffleSplit
from tensorflow.keras.datasets import mnist
from tensorflow.keras import layers,models
from keras.callbacks import EarlyStopping
from sklearn.utils import shuffle
from tensorflow import keras
```

Load the `MNIST degit` data from `keras`

```
def load_mnist():
    """
    Load the MNIST dataset.

    Returns:
        Tuple of NumPy arrays : (x_train_full, y_train_full, x_test, y_test)
    """
    (x_train_full, y_train_full), (x_test, y_test) = mnist.load_data()
    return x_train_full, y_train_full, x_test, y_test

# Separate the train/test data
x_train_full, y_train_full, x_test, y_test = load_mnist()

# Print the length of the loaded data
print(f"Number of training samples: {len(x_train_full)}")
print(f"Number of testing samples: {len(x_test)}")
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 0s 0us/step
Number of training samples: 60000
Number of testing samples: 10000
```

We're using a dataset of **60,000 images** to train a semi-supervised model. Out of these, **100 images are labeled**, and the remaining **59,900 are unlabeled**. After training, we'll assess the model's performance on **10,000 test images**.

> **Note:** The 100 labeled images might not be sufficient (we'll explain later). To address this, we'll employ `data augmentation` on the labeled set. Afterward, we'll retrain the model and compare performances.
> Simultaneously, we'll experiment with **different models** to identify which one learns the most from our data.

Selecting `Train/Test Data` with Respect to Data Balance

```
def get_class_indices(y, class_label, count):
    """
    Get random indices for a specific class.

    Args:
        y (np.ndarray): Labels.
        class_label (int): Class label.
        count (int): Number of indices to select.

    Returns:
        NumPy array of indices.
    """
    class_indices = np.where(y == class_label)[0]
    return np.random.choice(class_indices, size=count, replace=False)
```

```
def select_labeled_and_unlabeled_data_with_validation(x_train_full, y_train_full, labeled_count_per_class, validation_count, test_unlabeled_count):
    """
    Select a small subset for labeled data, use the rest as unlabeled,
    and select a fixed number of samples for validation and unlabeled for testing.

    Args:
        x_train_full (np.ndarray): Full set of input images.
        y_train_full (np.ndarray): Full set of labels.
        labeled_count_per_class (int): Number of labeled examples per class.
        validation_count (int): Number of samples for the validation set.
        test_unlabeled_count (int): Number of samples for the unlabeled test set.

    Returns:
        Tuple of NumPy arrays: (x_labeled, y_labeled, x_unlabeled, x_validation, y_validation)
    """
    # Get unique classes in the training set
    classes = np.unique(y_train_full)

    # Select a small subset for labeled data
    labeled_indices = np.concatenate([get_class_indices(y_train_full, label, labeled_count_per_class) for label in classes])
    x_labeled = x_train_full[labeled_indices]
    y_labeled = y_train_full[labeled_indices]

    # Use the rest of the data as unlabeled
    x_unlabeled = np.delete(x_train_full, labeled_indices, axis=0)
    y_unlabeled = np.delete(y_train_full, labeled_indices, axis=0)

    # Use StratifiedShuffleSplit to split the remaining data into training and validation sets
    sss = StratifiedShuffleSplit(n_splits=1, test_size=validation_count, random_state=42)

    for train_index, validation_index in sss.split(x_unlabeled, y_unlabeled):
        x_validation = x_unlabeled[validation_index]
        y_validation = y_unlabeled[validation_index]
        x_unlabeled = x_unlabeled[train_index]
        y_unlabeled = y_unlabeled[train_index]

    # Take the remaining samples as unlabeled for testing
    x_unlabeled_test = x_unlabeled[:test_unlabeled_count]
    y_unlabeled_test = y_unlabeled[:test_unlabeled_count]

    # Shuffle x_labeled, x_validation, and x_unlabeled in the same way
    shuffle_indices = np.random.permutation(len(x_labeled))
    x_labeled = x_labeled[shuffle_indices]
    y_labeled = y_labeled[shuffle_indices]

    shuffle_indices = np.random.permutation(len(x_validation))
    x_validation = x_validation[shuffle_indices]
    y_validation = y_validation[shuffle_indices]

    shuffle_indices = np.random.permutation(len(x_unlabeled))
    x_unlabeled = x_unlabeled[shuffle_indices]
    y_unlabeled_test = y_unlabeled_test[shuffle_indices]

    return x_labeled, y_labeled, x_unlabeled, x_validation, y_validation

# Example of using the function
x_labeled, y_labeled, x_unlabeled, x_validation, y_validation = select_labeled_and_unlabeled_data_with_validation(
    x_train_full, y_train_full, labeled_count_per_class=10, validation_count=100, test_unlabeled_count=59800
)

# Print information about labeled, unlabeled, and validation sets
print(f"Number of labeled samples in the train set: {len(x_labeled)}")
print(f"Number of unique classes in labeled data: {len(np.unique(y_labeled))}")
for class_label in np.unique(y_labeled):
    class_count = np.sum(y_labeled == class_label)
    print(f"-> Number of samples for class {class_label}: {class_count}")

print(f"Number of unlabeled samples in the test set: {len(x_unlabeled)}")

print(f"\nNumber of samples in the validation set: {len(x_validation)}")
print(f"Number of unique classes in the validation set: {len(np.unique(y_validation))}")
for class_label in np.unique(y_validation):
    class_count = np.sum(y_validation == class_label)
    print(f"-> Number of samples for class {class_label}: {class_count}")
```

```
Number of labeled samples in the train set: 100
Number of unique classes in labeled data: 10
-> Number of samples for class 0: 10
-> Number of samples for class 1: 10
-> Number of samples for class 2: 10
-> Number of samples for class 3: 10
-> Number of samples for class 4: 10
-> Number of samples for class 5: 10
-> Number of samples for class 6: 10
-> Number of samples for class 7: 10
-> Number of samples for class 8: 10
-> Number of samples for class 9: 10
Number of unlabeled samples in the test set: 59800

Number of samples in the validation set: 100
Number of unique classes in the validation set: 10
-> Number of samples for class 0: 10
-> Number of samples for class 1: 11
-> Number of samples for class 2: 10
-> Number of samples for class 3: 10
-> Number of samples for class 4: 10
-> Number of samples for class 5: 9
-> Number of samples for class 6: 10
-> Number of samples for class 7: 10
-> Number of samples for class 8: 10
-> Number of samples for class 9: 10
```

Note: We kept the `data balanced` in the **target column** by randomly picking 100 images, 10 from each class.

- `Exploring the Data`: Visualizing 10 Random Samples from the Training Dataset

```python
def display_random_images(x_data, y_data, num_images=10):
    # Generate random indices
    random_indices = np.random.choice(len(x_data), num_images, replace=False)

    # Create subplots
    fig, axs = plt.subplots(1, num_images, figsize=(18, 2))

    for i, index in enumerate(random_indices):
        # Print the label
        print(f"Image {i + 1}, Label:", y_data[index])

        # Reshape the image and display it
        img = x_data[index].reshape(28, 28)
        axs[i].imshow(img, cmap='gray')
        axs[i].axis('off')  # Turn off axis for cleaner display

    # Display the plot
    plt.show()

# Assuming y_labeled and x_labeled are defined somewhere before calling the function
display_random_images(x_validation, y_validation, num_images=10)
```

```
Image 1, Label: 1
Image 2, Label: 0
Image 3, Label: 6
Image 4, Label: 9
Image 5, Label: 3
Image 6, Label: 0
Image 7, Label: 8
Image 8, Label: 2
Image 9, Label: 1
Image 10, Label: 5
```

Here, we **displayed 10 randomly** selected images from the training set with the aim of **visually understanding the nature of the data**.

- `Normalize` the data

```python
def normalize_data_with_validation(x_labeled,
                                   x_unlabeled,
                                   x_validation,
                                   x_test):
    """
    Normalize pixel values of input images to the range [0, 1].

    Args:
        x_labeled (np.ndarray): Labeled input images.
        x_unlabeled (np.ndarray): Unlabeled input images.
        x_validation (np.ndarray): Validation input images.
        x_test (np.ndarray): Test input images.

    Returns:
        Tuple of normalized NumPy arrays: (x_labeled, x_unlabeled, x_validation, x_test)
    """
    x_labeled = x_labeled / 255.0
    x_unlabeled = x_unlabeled / 255.0
    x_validation = x_validation / 255.0
    x_test = x_test / 255.0

    return x_labeled, x_unlabeled, x_validation, x_test

# Normalize the pixel values of the images to the range [0, 1], including validation set
x_labeled, x_unlabeled, x_validation, x_test = normalize_data_with_validation(
    x_labeled, x_unlabeled, x_validation, x_test
)
```

This code **normalizes** MNIST digits data by scaling pixel values to the range [0, 1], `aiding faster model training and ensuring consistency`.

- `Semi-Supervised` self-training CNN

- Defining the `Models` and Setting Up the Data

```python
model_CNN = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),  # Convolutional layer with 32 filters
    layers.MaxPooling2D((2, 2)),                                            # Max pooling layer
    layers.Flatten(),                                                       # Flatten for fully connected layers
    layers.Dense(128, activation='relu'),                                   # Fully connected layer with 128 units and ReLU activation
    layers.Dense(10, activation='softmax')                                  # Output layer with 10 units and softmax activation
])

# Display the model summary
model_CNN.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2  (None, 13, 13, 32)        0
 D)

 flatten (Flatten)           (None, 5408)              0

 dense (Dense)               (None, 128)               692352

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 693962 (2.65 MB)
Trainable params: 693962 (2.65 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

▸ Training and Testing the Model

```python
def pseudo_labeling(model, x_unlabeled, confidence_threshold=0.8):
    """
    Perform pseudo-labeling on unlabeled data using the given model.

    Parameters:
        model: Trained model for pseudo-labeling.
        x_unlabeled: Unlabeled input images.
        confidence_threshold: Confidence threshold for pseudo-labeling.

    Returns:
        Tuple of numpy arrays: (pseudo_labeled_images, pseudo_labels, x_unlabeled_unused)
    """
    # Predict pseudo-labels for the unlabeled data using the provided model
    pseudo_labels = model.predict(x_unlabeled)

    # Create a mask to identify instances with confidence above the threshold
    confident_mask = np.max(pseudo_labels, axis=1) > confidence_threshold

    # Check if there are instances with confidence above the threshold
    num_confident_instances = np.sum(confident_mask)
    total_instances = len(x_unlabeled)
    print(f"\n\nNumber of instances with confidence > {confidence_threshold}: {num_confident_instances} out of {total_instances}\n\n")

    # Check if there are instances with confidence above the threshold
    if num_confident_instances > 0:
        # Extract pseudo-labeled images and their corresponding labels
        pseudo_labeled_images = x_unlabeled[confident_mask]
        pseudo_labels = np.argmax(pseudo_labels[confident_mask], axis=1)

        # Extract unused unlabeled images
        x_unlabeled_unused = x_unlabeled[~confident_mask]

        return pseudo_labeled_images, pseudo_labels, x_unlabeled_unused
    else:
        # Return None if no instances meet the confidence threshold
        return None, None, x_unlabeled
```

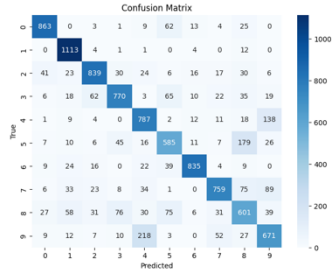
```python
# Selecting the model and hyperparameters
classifier1, classifier2 = model_CNN, model_CNN
epochs_classifier1, batch_size_classifier1= 150, 32
epochs_classifier2, batch_size_classifier2= 100, 2000

# Compile the classifier1 and classifier2
classifier1.compile(optimizer=Adam(learning_rate=0.001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])
classifier2.compile(optimizer=Adam(learning_rate=0.001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Use EarlyStopping to avoid wasting time
early_stop = EarlyStopping(monitor='loss', patience=3, verbose=1)

# Learning rate schedule
def lr_schedule(epoch):
    return 0.001 * 0.9**epoch

lr_scheduler = LearningRateScheduler(lr_schedule)


# Print the number of elements used to train the first classifier
print(f">>>> Number of elements used to train the first classifier: {len(x_labeled)}")

# Train the model with the original labeled data and validation set, and save the history
history_classifier1 = classifier1.fit(
    x_labeled,
    y_labeled,
    epochs=epochs_classifier1,
    batch_size=batch_size_classifier1,
    validation_data=(x_validation, y_validation),
    callbacks=[early_stop, lr_scheduler]
)

# Pseudo-labeling
pseudo_labeled_images, pseudo_labels, x_unlabeled_unused = pseudo_labeling(classifier1,
                                                                           x_unlabeled,
                                                                           confidence_threshold=0.95)

if pseudo_labeled_images is not None:
    # Update labeled data with pseudo-labeled data
    x_labeled_and_pseudo_labeled_images = np.concatenate([x_labeled, pseudo_labeled_images])
    y_labeled_and_pseudo_labeled_images = np.concatenate([y_labeled, pseudo_labels])

    # Print the number of elements used to train the first classifier and pseudo-labeled data
    print(f">>>> Number of elements used to train the second classifier : {len(x_labeled_and_pseudo_labeled_images)+len(x_unlabeled_unused)}")

    # Train the classifier2 on the full dataset (original + pseudo-labeled) with validation set, and save the history
    history_classifier2 = classifier2.fit(
        np.concatenate([x_labeled_and_pseudo_labeled_images, x_unlabeled_unused]),
        np.concatenate([y_labeled_and_pseudo_labeled_images, np.argmax(classifier2.predict(x_unlabeled_unused), axis=1)]),
        epochs=epochs_classifier2,
        batch_size=batch_size_classifier2,
        validation_data=(x_validation, y_validation),
        callbacks=[early_stop, lr_scheduler]
    )

# Evaluate the classifier2 Performance on Test Data
test_loss, test_acc = classifier2.evaluate(x_test, y_test)
print(f"classifier2 - Test Loss: {test_loss}, Test Accuracy: {test_acc}\n")
```

```
Epoch 92/100
30/30 [==============================] - 1s 20ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0294 - val_accuracy: 0.7400 - lr: 6.8560e-08
Epoch 93/100
30/30 [==============================] - 1s 21ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0294 - val_accuracy: 0.7400 - lr: 6.1704e-08
Epoch 94/100
30/30 [==============================] - 1s 21ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0294 - val_accuracy: 0.7400 - lr: 5.5533e-08
Epoch 95/100
30/30 [==============================] - 1s 21ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0294 - val_accuracy: 0.7400 - lr: 4.9980e-08
Epoch 96/100
30/30 [==============================] - 1s 20ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0295 - val_accuracy: 0.7400 - lr: 4.4982e-08
Epoch 97/100
30/30 [==============================] - 1s 19ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0295 - val_accuracy: 0.7400 - lr: 4.0484e-08
Epoch 98/100
30/30 [==============================] - 1s 19ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0295 - val_accuracy: 0.7400 - lr: 3.6435e-08
Epoch 99/100
30/30 [==============================] - 1s 18ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0295 - val_accuracy: 0.7400 - lr: 3.2792e-08
Epoch 100/100
30/30 [==============================] - 1s 19ms/step - loss: 0.0462 - accuracy: 0.9914 - val_loss: 2.0295 - val_accuracy: 0.7400 - lr: 2.9513e-08
313/313 [==============================] - 1s 3ms/step - loss: 2.0836 - accuracy: 0.7823
classifier2 - Test Loss: 2.083629608154297, Test Accuracy: 0.7822999954223633
```

```python
def plot_and_print_classification_metrics(y_true, y_pred):
    # Create a confusion matrix
    conf_mat = confusion_matrix(y_true, y_pred)

    # Plot the confusion matrix
    plt.figure(figsize=(8, 6))
    sns.heatmap(conf_mat, annot=True, fmt="d", cmap="Blues", xticklabels=np.arange(10), yticklabels=np.arange(10))
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()

    # Accuracy
    accuracy = accuracy_score(y_true, y_pred)
    print(f"Test Accuracy: {accuracy:.4f}")

    # Classification report
    class_report = classification_report(y_true, y_pred, target_names=[str(i) for i in range(10)])
    print("Classification Report:\n", class_report)
```

```python
# Predictions on the test set using classifier2
y_pred = np.argmax(classifier2.predict(x_test), axis=1)

# Use the function to plot and print metrics
plot_and_print_classification_metrics(y_test, y_pred)
```

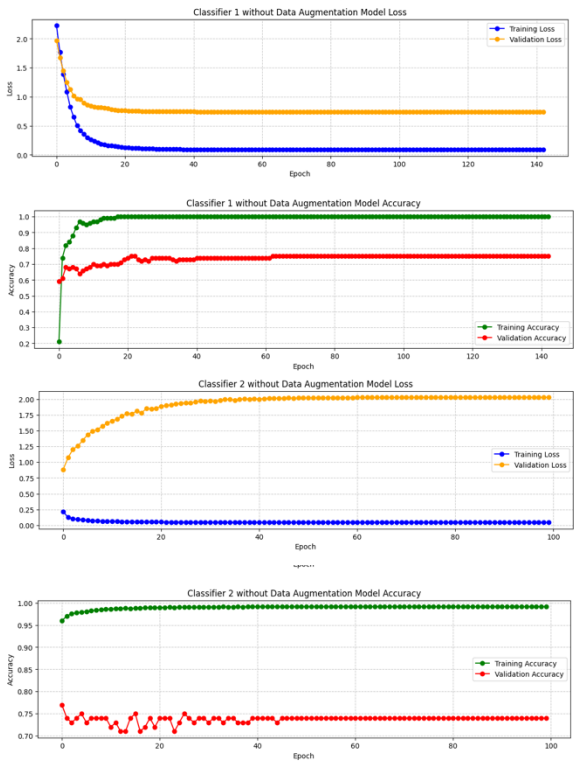
```
313/313 [==============================] - 1s 2ms/step
```




```
Test Accuracy: 0.7823
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.88      0.89       980
           1       0.86      0.98      0.91      1135
           2       0.84      0.81      0.83      1032
           3       0.82      0.76      0.79      1010
           4       0.69      0.80      0.74       982
           5       0.70      0.66      0.68       892
           6       0.92      0.87      0.90       958
           7       0.84      0.74      0.78      1028
           8       0.59      0.62      0.61       974
           9       0.68      0.67      0.67      1009

    accuracy                           0.78     10000
   macro avg       0.78      0.78      0.78     10000
weighted avg       0.78      0.78      0.78     10000
```

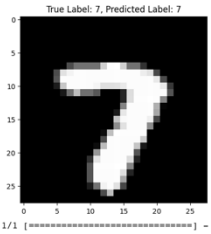
```python
# Plot the training loss and validation accuracy for both classifiers with improved aesthetics
def plot_metrics(history, title):
    plt.figure(figsize=(12, 8))

    # Plot training and validation loss
    plt.subplot(2, 1, 1)
    plt.plot(history.history['loss'], label='Training Loss', color='blue', marker='o')
    plt.plot(history.history['val_loss'], label='Validation Loss', color='orange', marker='o')
    plt.title(f'{title} Model Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.grid(True, linestyle='--', alpha=0.7)

    # Plot training and validation accuracy
    plt.subplot(2, 1, 2)
    plt.plot(history.history['accuracy'], label='Training Accuracy', color='green', marker='o')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red', marker='o')
    plt.title(f'{title} Model Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.grid(True, linestyle='--', alpha=0.7)

    plt.tight_layout(pad=3.0)
    plt.show()

# Plot the training loss and validation accuracy for each classifier
plot_metrics(history_classifier1, 'Classifier 1 without Data Augmentation')
plot_metrics(history_classifier2, 'Classifier 2 without Data Augmentation')
```



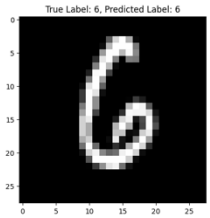
Testing the Model on a Random MNIST Image

```python
def visualize_predictions(model, x_test, y_test, num_samples):
    """
    Visualize predictions on a few test images.

    Args:
        model (keras.Model): Trained neural network model.
        x_test (np.ndarray): Test input images.
        y_test (np.ndarray): Test labels.
        num_samples (int): Number of test samples to visualize. Default is 5.
    """
    # Randomly select test samples
    test_indices = np.random.choice(range(len(x_test)), size=num_samples, replace=False)

    # Iterate over selected test samples
    for index in test_indices:
        test_image = x_test[index].reshape(1, 28, 28)  # Reshape for prediction
        prediction = model.predict(test_image)

        # Display the test image along with true and predicted labels
        plt.figure()
        plt.imshow(test_image.squeeze(), cmap='gray')
        plt.title(f"True Label: {y_test[index]}, Predicted Label: {np.argmax(prediction)}")
        plt.show()

num_samples = 5
visualize_predictions(classifier2, x_test, y_test, num_samples)
```

```
1/1 [==============================] - 0s 39ms/step
```




```
1/1 [==============================] - 0s 17ms/step
```




```
1/1 [==============================] - 0s 17ms/step
```

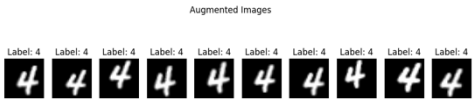

Data Augmentation

Data Augmentation function for an image

```python
def augment_data(image, augment_factor=8):
    """
    Apply diverse data augmentation to a given image.

    Parameters:
        image (numpy.ndarray): Input image to be augmented.
        augment_factor (int): Number of augmented images to generate.

    Returns:
        numpy.ndarray: Array of augmented images.
    """
    augmented_images = []
    for _ in range(augment_factor):
        # Random rotation (between -10 and 10 degrees)
        angle = np.random.uniform(-10, 10)
        # Random translation (between -3 and 3 pixels in both x and y directions)
        tx = np.random.uniform(-3, 3)
        ty = np.random.uniform(-3, 3)
        # Random zoom (between 0.9 and 1.1)
        zoom = np.random.uniform(0.9, 1.1)
        # Random brightness adjustment
        brightness_factor = np.random.uniform(0.7, 1.3)
        # Random contrast adjustment
        contrast_factor = np.random.uniform(0.7, 1.3)
        # Apply transformations
        transform_matrix = cv2.getRotationMatrix2D((14, 14), angle, zoom)
        transform_matrix[:, 2] += (tx, ty)
        augmented_image = cv2.warpAffine(image[0], transform_matrix, (28, 28), flags=cv2.INTER_LINEAR)
        # Adjust brightness and contrast
        augmented_image = cv2.convertScaleAbs(augmented_image, alpha=brightness_factor, beta=contrast_factor)
        augmented_images.append(augmented_image.reshape(1, 28, 28, 1))
    augmented_images = np.vstack(augmented_images)
    return augmented_images

# Utility function to test the Data Augmentation on sample images
def visualize_images(images, title, labels):
    """
    Display images with their corresponding labels.

    Parameters:
        images (List[numpy.ndarray]): List of images to be visualized.
        title (str): Title for the visualization.
        labels (numpy.ndarray): Array of labels corresponding to the images.
    """
    plt.figure(figsize=(12, 3))
    for i in range(len(images)):
        plt.subplot(1, len(images), i + 1)
        plt.imshow(images[i].reshape(28, 28), cmap='gray')
        plt.title(f"Label: {labels[i]}")
        plt.axis('off')
    plt.suptitle(title)
    plt.show()
```

Testing Data Augmentation on a random MNIST image

```python
# Select one image for demonstration
demo_index = np.random.choice(range(len(x_train_full)), size=1, replace=False)
demo_image = x_train_full[demo_index]
demo_label = y_train_full[demo_index]

# Display original image
visualize_images([demo_image], "", demo_label)

# Data augmentation for demonstration
augmented_images = augment_data(demo_image, augment_factor=10)

# Display augmented images
augmented_labels = np.full(len(augmented_images), demo_label[0])
visualize_images(augmented_images, "Augmented Images", augmented_labels)
```



Semi-Supervised self-training CNN with `Data Augmentation`

Applying `Data Augmentation` on Labeled Images

```
# Function to generate augmented labeled data
def augment_labeled_data(x, y, augmentation_factor):
    """
    Apply data augmentation to labeled data.

    Parameters:
        x (numpy.ndarray): Labeled input images.
        y (numpy.ndarray): Corresponding labels.
        augmentation_factor (int): Number of augmented images to generate for each labeled image.

    Returns:
        (numpy.ndarray, numpy.ndarray): Tuple of augmented labeled images and their corresponding labels.
    """
    augmented_labeled_images = []
    augmented_labels = []

    for i in range(len(x)):
        augmented_images = augment_data(x[i:i+1], augmentation_factor)
        augmented_labeled_images.append(augmented_images)
        augmented_labels.extend([y[i]] * augmentation_factor)

    # Reshape augmented images to match the dimensions of x
    augmented_labeled_images = np.vstack(augmented_labeled_images).reshape(-1, 28, 28)

    return augmented_labeled_images, np.array(augmented_labels)

# Data Augmentation
augmentation_factor = 150
augmented_x_labeled, augmented_y_labeled = augment_labeled_data(x=x_labeled,
                                                                y=y_labeled,
                                                                augmentation_factor=augmentation_factor)
```

```
# Create the full training data after we have done the data augmentation
full_x_labeled = np.concatenate([x_labeled, augmented_x_labeled])
full_y_labeled = np.concatenate([y_labeled, augmented_y_labeled])

# Shuffle full_x_labeled and full_y_labeled in the same way
shuffle_indices = np.random.permutation(len(augmented_x_labeled))
full_x_labeled = full_x_labeled[shuffle_indices]
full_y_labeled = full_y_labeled[shuffle_indices]

# Print details about the data used for training
print(f"Number of original labeled samples: {len(x_labeled)}")
print(f"Number of augmented samples per original labeled sample: {augmentation_factor}")
print(f"Total number of labeled samples after augmentation: {len(full_x_labeled)}")

# Print details about the unlabeled data
print(f"Number of unlabeled samples: {len(x_unlabeled)}")
```

```
Number of original labeled samples: 100
Number of augmented samples per original labeled sample: 150
Total number of labeled samples after augmentation: 15000
Number of unlabeled samples: 59800
```

```
display_random_images(full_x_labeled, full_y_labeled, num_images=10)
```

```
Image 1, Label: 2
Image 2, Label: 9
Image 3, Label: 1
Image 4, Label: 2
Image 5, Label: 0
Image 6, Label: 6
Image 7, Label: 4
Image 8, Label: 1
Image 9, Label: 2
Image 10, Label: 7
```

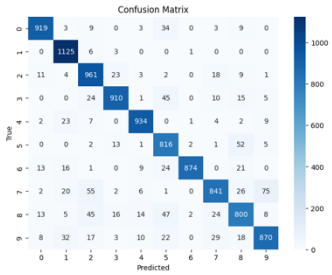
Training and Testing the Model

```
# Selecting the model and hyperparameters
classifier1_augmented, classifier2_augmented = model_CNN, model_CNN
epochs_classifier1_augmented, batch_size_classifier1_augmented= 150, 32
epochs_classifier2_augmented, batch_size_classifier2_augmented= 100, 2000

# Compile the classifier1_augmented and classifier2_augmented
classifier1_augmented.compile(optimizer=Adam(learning_rate=0.001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])
classifier2_augmented.compile(optimizer=Adam(learning_rate=0.001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Use EarlyStopping to avoid wasting time
early_stop = EarlyStopping(monitor='loss', patience=3, verbose=1)

# Print the number of elements used to train the first classifier
print(f">>>> Number of elements used to train the first classifier: {len(full_x_labeled)}")

# Train the model with the original labeled data and validation set, and save the history
history_classifier1_augmented = classifier1_augmented.fit(
    full_x_labeled,  # x_labeled and augmented_x_labeled
    full_y_labeled,  # y_labeled and augmented_y_labeled
    epochs=epochs_classifier1_augmented,
    batch_size=batch_size_classifier1_augmented,
    validation_data=(x_validation, y_validation),
    callbacks=[early_stop, lr_scheduler]
)

# Pseudo-labeling
pseudo_labeled_images, pseudo_labels, x_unlabeled_unused = pseudo_labeling(classifier1_augmented,
                                                                           x_unlabeled,
                                                                           confidence_threshold=0.95)

if pseudo_labeled_images is not None:
    # Update labeled data with pseudo-labeled data
    x_labeled_and_pseudo_labeled_images = np.concatenate([full_x_labeled, pseudo_labeled_images])
    y_labeled_and_pseudo_labeled_images = np.concatenate([full_y_labeled, pseudo_labels])

    # Print the number of elements used to train the first classifier and pseudo-labeled data
    print(
        f">>>> Number of elements used to train the second classifier : {len(x_labeled_and_pseudo_labeled_images) + len(x_unlabeled_unused)} ( number of augmented elements: {len(augmented_x_labeled)} )")

    # Train the classifier2 on the full dataset (original + pseudo-labeled) with validation set, and save the history
    history_classifier2_augmented = classifier2_augmented.fit(
        np.concatenate([x_labeled_and_pseudo_labeled_images, x_unlabeled_unused]),
        np.concatenate([y_labeled_and_pseudo_labeled_images,
                        np.argmax(classifier2_augmented.predict(x_unlabeled_unused), axis=1)]),
        epochs=epochs_classifier2_augmented,
        batch_size=batch_size_classifier2_augmented,
        validation_data=(x_validation, y_validation),
        callbacks=[early_stop, lr_scheduler]
    )

# Evaluate the classifier2 Performance on Test Data
test_loss, test_acc = classifier2_augmented.evaluate(x_test, y_test)
print(f"classifier2 - Test Loss: {test_loss}, Test Accuracy: {test_acc}\n")
```

```
Epoch 91/100
38/38 [==============================] - 1s 19ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 7.6177e-08
Epoch 92/100
38/38 [==============================] - 1s 18ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 6.8560e-08
Epoch 93/100
38/38 [==============================] - 1s 19ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 6.1704e-08
Epoch 94/100
38/38 [==============================] - 1s 19ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 5.5533e-08
Epoch 95/100
38/38 [==============================] - 1s 18ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 4.9980e-08
Epoch 96/100
38/38 [==============================] - 1s 19ms/step - loss: 0.0216 - accuracy: 0.9970 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 4.4982e-08
Epoch 97/100
38/38 [==============================] - 1s 20ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 4.0484e-08
Epoch 98/100
38/38 [==============================] - 1s 20ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 3.6435e-08
Epoch 99/100
38/38 [==============================] - 1s 21ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 3.2792e-08
Epoch 100/100
38/38 [==============================] - 1s 21ms/step - loss: 0.0216 - accuracy: 0.9971 - val_loss: 0.7482 - val_accuracy: 0.8700 - lr: 2.9513e-08
313/313 [==============================] - 1s 3ms/step - loss: 0.6137 - accuracy: 0.9050
classifier2 - Test Loss: 0.6137354969978333, Test Accuracy: 0.9049999713897705
```

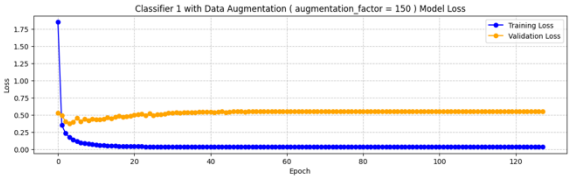
```
# Predictions on the test set using classifier2
y_pred_augmented = np.argmax(classifier2_augmented.predict(x_test), axis=1)

# Use the function to plot and print metrics
plot_and_print_classification_metrics(y_test, y_pred_augmented)
```

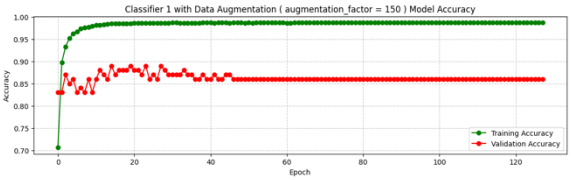
```
313/313 [==============================] - 1s 2ms/step
```

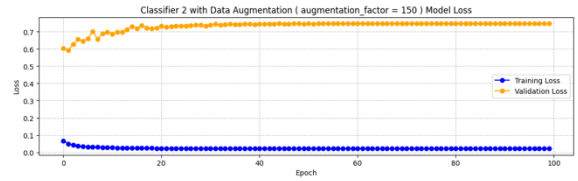


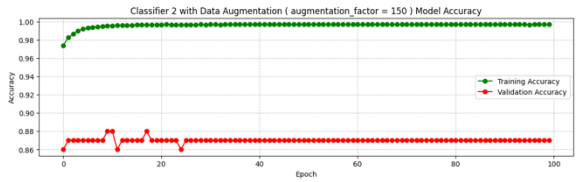

```
Test Accuracy: 0.9050
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.94      0.94       980
           1       0.92      0.99      0.95      1135
           2       0.85      0.93      0.89      1032
           3       0.94      0.90      0.92      1010
           4       0.95      0.95      0.95       982
           5       0.82      0.91      0.87       892
           6       0.99      0.91      0.95       958
           7       0.90      0.82      0.86      1028
           8       0.84      0.82      0.83       974
           9       0.89      0.86      0.88      1009

    accuracy                           0.91     10000
   macro avg       0.91      0.90      0.90     10000
weighted avg       0.91      0.91      0.90     10000
```

```
# Plot the training loss and validation accuracy for each classifier with data augmentation
plot_metrics(history_classifier1_augmented, f'Classifier 1 with Data Augmentation ( augmentation_factor = {augmentation_factor} )')
plot_metrics(history_classifier2_augmented, f'Classifier 2 with Data Augmentation ( augmentation_factor = {augmentation_factor} )')
```





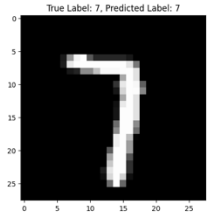




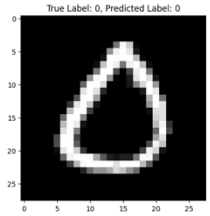
▸ Testing the Model on an MNIST Image

```
num_samples = 5
visualize_predictions(classifier2_augmented, x_test, y_test, num_samples)
```

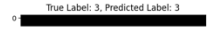
```
1/1 [==============================] - 0s 21ms/step
```




```
1/1 [==============================] - 0s 20ms/step
```




```
1/1 [==============================] - 0s 19ms/step
```



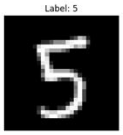
- Data Augmentation function for an image with added Gaussian noise

```
[ ] def augment_data_with_noise(image, augment_factor, noise_factor):
        """
        Apply diverse data augmentation, including random noise, to a given image.

        Parameters:
            image (numpy.ndarray): Input image to be augmented.
            augment_factor (int, optional): Number of augmented images to generate. Defaults to 8.
            noise_factor (float, optional): Intensity of random noise to be added. Defaults to 0.1.

        Returns:
            numpy.ndarray: Array of augmented images.
        """
        augmented_images = []

        # Convert the image to float32 to allow for addition with floating-point noise
        image_float = image.astype(np.float32)

        for _ in range(augment_factor):
            # Random rotation (between -10 and 10 degrees)
            angle = np.random.uniform(-10, 10)
            # Random translation (between -3 and 3 pixels in both x and y directions)
            tx = np.random.uniform(-3, 3)
            ty = np.random.uniform(-3, 3)
            # Random zoom (between 0.9 and 1.1)
            zoom = np.random.uniform(0.9, 1.1)
            # Random brightness adjustment
            brightness_factor = np.random.uniform(0.7, 1.3)
            # Random contrast adjustment
            contrast_factor = np.random.uniform(0.7, 1.3)

            # Apply transformations
            transform_matrix = cv2.getRotationMatrix2D((14, 14), angle, zoom)
            transform_matrix[:, 2] += (tx, ty)
            augmented_image = cv2.warpAffine(image[0], transform_matrix, (28, 28), flags=cv2.INTER_LINEAR)

            # Adjust brightness and contrast
            augmented_image = cv2.convertScaleAbs(augmented_image, alpha=brightness_factor, beta=contrast_factor)

            # Add random noise
            noise = np.random.normal(scale=noise_factor, size=augmented_image.shape).astype(np.float32)
            augmented_image = image_float + noise

            # Clip the values to the valid uint8 range [0, 255]
            augmented_image = np.clip(augmented_image, 0, 255).astype(np.uint8)

            augmented_images.append(augmented_image.reshape(1, 28, 28, 1))

        augmented_images = np.vstack(augmented_images)
        return augmented_images
```

- Testing Data Augmentation with Gaussian noise on a random MNIST image

```
[ ] # Select one image for demonstration
    demo_index = np.random.choice(range(len(x_train_full)), size=1, replace=False)
    demo_image = x_train_full[demo_index]
    demo_label = y_train_full[demo_index]

    # Display original image
    visualize_images([demo_image], "", demo_label)

    # Data augmentation for demonstration
    augmented_images = augment_data_with_noise(demo_image, augment_factor=10, noise_factor=0.08)

    # Display augmented images
    noise_factor = 10
    augmented_labels = np.full(len(augmented_images), demo_label[0])
    visualize_images(augmented_images, f"Augmented Images with a noise factor of {noise_factor}", augmented_labels)
```

Label: 5



Augmented Images with a noise factor of 0.08

- Semi-Supervised self-training with Data Augmentation with Gaussian noise

Applying Data Augmentation with Gaussian noise on Labeled Images

```
# Function to generate augmented labeled data with noise
def augment_labeled_data_with_noise(x, y, augmentation_factor, noise_factor):
    """
    Apply data augmentation with noise to labeled data.

    Parameters:
        x (numpy.ndarray): Labeled input images.
        y (numpy.ndarray): Corresponding labels.
        augmentation_factor (int): Number of augmented images to generate for each labeled image.
        noise_factor (float): Factor to control the amount of noise to be added.

    Returns:
        (numpy.ndarray, numpy.ndarray): Tuple of augmented labeled images with noise and their corresponding labels.
    """
    augmented_labeled_images = []
    augmented_labels = []

    for i in range(len(x)):
        augmented_images = augment_data_with_noise(x[i:i+1], augmentation_factor, noise_factor)
        augmented_labeled_images.append(augmented_images)
        augmented_labels.extend([y[i]] * augmentation_factor)

    # Reshape augmented images to match the dimensions of x
    augmented_labeled_images = np.vstack(augmented_labeled_images).reshape(-1, 28, 28)

    return augmented_labeled_images, np.array(augmented_labels)

# Data Augmentation with Noise
def augment_data_with_noise(image, augment_factor=8, noise_factor=0.1):
    """
    Apply diverse data augmentation with noise to a given image.

    Parameters:
        image (numpy.ndarray): Input image to be augmented.
        augment_factor (int): Number of augmented images to generate.
        noise_factor (float): Factor to control the amount of noise to be added.

    Returns:
        numpy.ndarray: Array of augmented images with noise.
    """
    augmented_images = []
    for _ in range(augment_factor):
        # Call the existing augment_data function for transformations
        transformed_images = augment_data(image, 1)
        # Add noise to the transformed images without clipping
        noisy_images = add_noise(transformed_images, noise_factor)
        augmented_images.append(noisy_images)

    augmented_images = np.vstack(augmented_images)
    return augmented_images
```

```python
# Function to add noise to images
def add_noise(images, noise_factor=0.1):
    """
    Add random noise to a given set of images.

    Parameters:
        images (numpy.ndarray): Input images.
        noise_factor (float): Factor to control the amount of noise to be added.

    Returns:
        numpy.ndarray: Array of images with added noise.
    """
    noisy_images = images + noise_factor * np.random.normal(0, 1, images.shape)
    return noisy_images

# Usage example
augmentation_factor = 400
noise_factor = 0.08
augmented_x_labeled_with_noise, augmented_y_labeled_with_noise = augment_labeled_data_with_noise(x=x_labeled,
                                                                                                 y=y_labeled,
                                                                                                 augmentation_factor=augmentation_factor,
                                                                                                 noise_factor=noise_factor)
```

```python
# Create the full training data after we have done the data augmentation with noise
full_x_labeled_with_noise = np.concatenate([x_labeled, augmented_x_labeled_with_noise])
full_y_labeled_with_noise = np.concatenate([y_labeled, augmented_y_labeled_with_noise])

# Shuffle full_x_labeled_with_noise and full_y_labeled_with_noise in the same way
shuffle_indices = np.random.permutation(len(full_x_labeled_with_noise))
full_x_labeled_with_noise = full_x_labeled_with_noise[shuffle_indices]
full_y_labeled_with_noise = full_y_labeled_with_noise[shuffle_indices]

# Print details about the data used for training
print(f"Number of original labeled samples: {len(x_labeled)}")
print(f"Number of augmented samples per original labeled sample: {augmentation_factor}")
print(f"Total number of labeled samples after augmentation with noise: {len(full_x_labeled)}")

# Print details about the unlabeled data
print(f"Number of unlabeled samples: {len(x_unlabeled)}")
```

```
Number of original labeled samples: 100
Number of augmented samples per original labeled sample: 400
Total number of labeled samples after augmentation with noise: 15000
Number of unlabeled samples: 59800
```

```python
display_random_images(full_x_labeled_with_noise, full_y_labeled_with_noise, num_images=10)
```

```
Image 1, Label: 1
Image 2, Label: 2
Image 3, Label: 3
Image 4, Label: 9
Image 5, Label: 9
Image 6, Label: 9
Image 7, Label: 5
Image 8, Label: 1
Image 9, Label: 7
Image 10, Label: 9
```

Training and Testing the Model

```python
# Selecting the model and hyperparameters
classifier1_augmented_with_noise, classifier2_augmented_with_noise = model_CNN, model_CNN
epochs_classifier1_augmented_with_noise, batch_size_classifier1_augmented_with_noise= 150, 32
epochs_classifier2_augmented_with_noise, batch_size_classifier2_augmented_with_noise= 100, 2000

# Compile the classifier1_augmented and classifier2_augmented
classifier1_augmented_with_noise.compile(optimizer=Adam(learning_rate=0.001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])
classifier2_augmented_with_noise.compile(optimizer=Adam(learning_rate=0.001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Use EarlyStopping to avoid wasting time
early_stop = EarlyStopping(monitor='loss', patience=3, verbose=1)

# Print the number of elements used to train the first classifier
print(f">>>> Number of elements used to train the first classifier: {len(full_x_labeled_with_noise)}")

# Train the model with the original labeled data and validation set, and save the history
history_classifier1_augmented_with_noise = classifier1_augmented.fit(
    full_x_labeled_with_noise,  # x_labeled and augmented_x_labeled_with_noise
    full_y_labeled_with_noise,  # y_labeled and augmented_y_labeled_with_noise
    epochs=epochs_classifier1_augmented_with_noise,
    batch_size=batch_size_classifier1_augmented_with_noise,
    validation_data=(x_validation, y_validation),
    callbacks=[early_stop, lr_scheduler]
)

# Pseudo-labeling
pseudo_labeled_images, pseudo_labels, x_unlabeled_unused = pseudo_labeling(classifier1_augmented_with_noise,
                                                                           x_unlabeled,
                                                                           confidence_threshold=0.95)


if pseudo_labeled_images is not None:
    # Update labeled data with pseudo-labeled data
    x_labeled_and_pseudo_labeled_images = np.concatenate([full_x_labeled, pseudo_labeled_images])
    y_labeled_and_pseudo_labeled_images = np.concatenate([full_y_labeled, pseudo_labels])

    # Print the number of elements used to train the first classifier and pseudo-labeled data
    print(
        f">>>> Number of elements used to train the second classifier : {len(x_labeled_and_pseudo_labeled_images) + len(x_unlabeled_unused)} ( number of augmented elements: {len(augmented_x_labeled)} )")

    # Train the classifier2 on the full dataset (original + pseudo-labeled) with validation set, and save the history
    history_classifier2_augmented_with_noise = classifier2_augmented_with_noise.fit(
        np.concatenate([x_labeled_and_pseudo_labeled_images, x_unlabeled_unused]),
        np.concatenate([y_labeled_and_pseudo_labeled_images,
                        np.argmax(classifier2_augmented_with_noise.predict(x_unlabeled_unused), axis=1)]),
        epochs=epochs_classifier2_augmented_with_noise,
        batch_size=batch_size_classifier2_augmented_with_noise,
        validation_data=(x_validation, y_validation),
        callbacks=[early_stop, lr_scheduler]
    )

# Evaluate the classifier2 Performance on Test Data
test_loss, test_acc = classifier2_augmented_with_noise.evaluate(x_test, y_test)
print(f"classifier2 - Test Loss: {test_loss}, Test Accuracy: {test_acc}\n")
```

```
>>>> Number of elements used to train the first classifier: 40100
Epoch 1/150
1254/1254 [==============================] - 6s 4ms/step - loss: 0.0999 - accuracy: 0.9658 - val_loss: 0.7596 - val_accuracy: 0.8500 - lr: 0.0010
Epoch 2/150
1254/1254 [==============================] - 4s 3ms/step - loss: 0.0590 - accuracy: 0.9795 - val_loss: 0.6685 - val_accuracy: 0.8800 - lr: 9.0000e-04
Epoch 3/150
1254/1254 [==============================] - 4s 3ms/step - loss: 0.0483 - accuracy: 0.9829 - val_loss: 0.8639 - val_accuracy: 0.8500 - lr: 8.1000e-04
Epoch 4/150
```

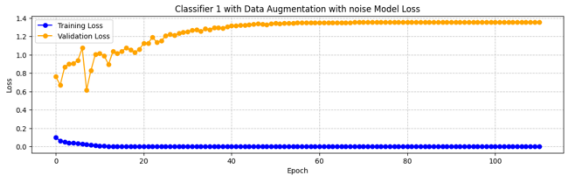
...

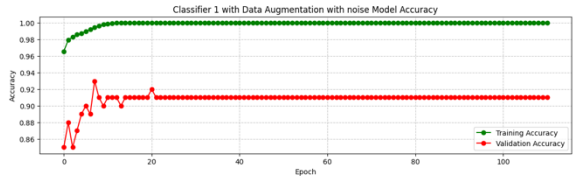
```
Number of instances with confidence > 0.95: 57028 out of 59800


>>>> Number of elements used to train the second classifier : 74800 ( number of augmented elements: 15000 )
87/87 [==============================] - 0s 2ms/step
Epoch 1/100
38/38 [==============================] - 1s 24ms/step - loss: 0.1499 - accuracy: 0.9641 - val_loss: 1.0234 - val_accuracy: 0.9100 - lr: 0.0010
Epoch 2/100
38/38 [==============================] - 1s 21ms/step - loss: 0.0462 - accuracy: 0.9821 - val_loss: 1.0614 - val_accuracy: 0.9100 - lr: 9.0000e-04
Epoch 3/100
38/38 [==============================] - 1s 21ms/step - loss: 0.0257 - accuracy: 0.9903 - val_loss: 1.0958 - val_accuracy: 0.9100 - lr: 8.1000e-04
Epoch 4/100
38/38 [==============================] - 1s 18ms/step - loss: 0.0191 - accuracy: 0.9936 - val_loss: 1.1527 - val_accuracy: 0.9100 - lr: 7.2900e-04
Epoch 5/100
38/38 [==============================] - 1s 18ms/step - loss: 0.0157 - accuracy: 0.9955 - val_loss: 1.1786 - val_accuracy: 0.9100 - lr: 6.5610e-04
```

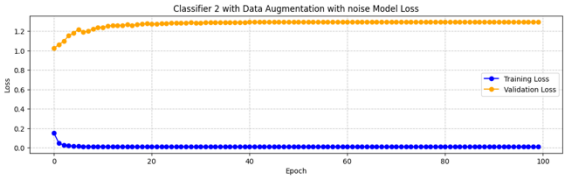
...

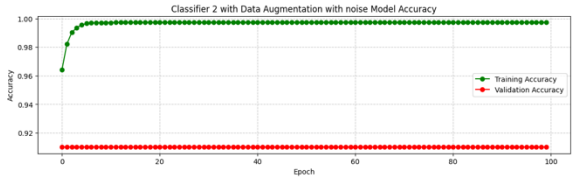
```
Epoch 97/100
38/38 [==============================] - 1s 21ms/step - loss: 0.0092 - accuracy: 0.9974 - val_loss: 1.2943 - val_accuracy: 0.9100 - lr: 4.0484e-08
Epoch 98/100
38/38 [==============================] - 1s 21ms/step - loss: 0.0092 - accuracy: 0.9974 - val_loss: 1.2943 - val_accuracy: 0.9100 - lr: 3.6435e-08
Epoch 99/100
38/38 [==============================] - 1s 21ms/step - loss: 0.0092 - accuracy: 0.9974 - val_loss: 1.2943 - val_accuracy: 0.9100 - lr: 3.2792e-08
Epoch 100/100
38/38 [==============================] - 1s 20ms/step - loss: 0.0092 - accuracy: 0.9974 - val_loss: 1.2943 - val_accuracy: 0.9100 - lr: 2.9513e-08
313/313 [==============================] - 1s 3ms/step - loss: 0.9929 - accuracy: 0.9153
classifier2 - Test Loss: 0.992854893207550, Test Accuracy: 0.9153000116348267
```

```
# Plot the training loss and validation accuracy for each classifier
plot_metrics(history_classifier1_augmented_with_noise, 'Classifier 1 with Data Augmentation with noise')
plot_metrics(history_classifier2_augmented_with_noise, 'Classifier 2 with Data Augmentation with noise')
```



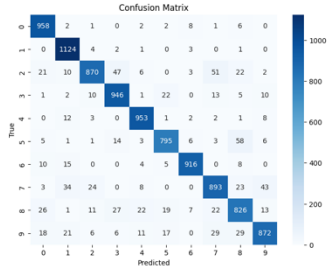







```
[ ] # Predictions on the test set using classifier2
    y_pred_augmented_with_noise = np.argmax(classifier2_augmented_with_noise.predict(x_test), axis=1)

    # Use the function to plot and print metrics
    plot_and_print_classification_metrics(y_test, y_pred_augmented_with_noise)
```

```
313/313 [==============================] - 1s 2ms/step
```

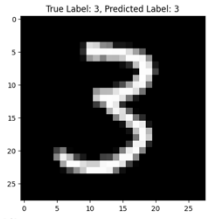



```
Test Accuracy: 0.9153
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.98      0.95       980
           1       0.92      0.99      0.95      1135
           2       0.94      0.84      0.89      1032
           3       0.91      0.94      0.92      1010
           4       0.94      0.97      0.96       982
           5       0.92      0.89      0.91       892
           6       0.97      0.96      0.96       958
           7       0.88      0.87      0.87      1028
           8       0.84      0.85      0.85       974
           9       0.91      0.86      0.89      1009

    accuracy                           0.92     10000
   macro avg       0.92      0.91      0.91     10000
weighted avg       0.92      0.92      0.91     10000
```

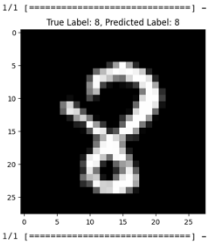
▸ Testing the Model on an MNIST Image

```
[ ] num_samples = 5
    visualize_predictions(classifier2_augmented_with_noise, x_test, y_test, num_samples)
```

```
1/1 [==============================] - 0s 19ms/step
```




```
1/1 [==============================] - 0s 19ms/step
```




```
1/1 [==============================] - 0s 19ms/step
```