ALLIANCE UNIVERSITY

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School of Advanced Computing

Department of Computer Science and Engineering

B. Tech. Data Ananlytics-A, VI Sem. CSE

5CS 1014 Neural Network and Deep Learning

Mini Project Report

Project Title: Pattern Recognition and Computer Vision using CNN on MNIST Dataset

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1. Introduction

- **Objective of the project:**

  This project is centered around building a Convolutional Neural Network (CNN) that can accurately identify handwritten digits from images. By using the MNIST dataset, we aim to explore how deep learning can simplify complex pattern recognition tasks. This initiative provides us practical insight into how neural networks are trained and optimized for visual classification problems.

  Scope of the Project:

  The skills and models developed in this project are highly applicable to real-world scenarios like digitizing handwritten documents, processing postal codes, and enabling OCR technologies. As CNNs are fundamental to many advanced vision systems, this project lays the groundwork for future work in image-based automation.

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2. Problem Statement

The challenge addressed in this project is to create a deep learning model capable of distinguishing handwritten digits ranging from 0 to 9. The diversity in handwriting styles introduces a real-world complexity, requiring the model to generalize well across different inputs while maintaining high accuracy.

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3. Workload Matrix

Member Name	**Contribution**
B. Mokshagna Akhileswara Reddy	Model development, Data preprocessing
M. Tejdheep	Evaluation, Result Analysis, Documentation
Y. Chaitanya Reddy	Literature review, Report formatting, Coding support

4. Literature Review

Over the years, CNNs have emerged as one of the most effective methods for handling image classification tasks. The MNIST dataset has become a go-to resource for testing new neural network architectures. LeNet-5 pioneered the use of CNNs in digit classification, while more recent models like AlexNet and ResNet introduced deeper architectures and performance enhancements, significantly improving classification accuracy across various image datasets

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5. Data Collection

- **Data Source:**

  The MNIST dataset, maintained by Yann LeCun, is a standard in image recognition studies. It is publicly available and can also be accessed directly through libraries like Keras.

- **Data Description:**

  The dataset consists of 70,000 grayscale images representing digits from 0 to 9. It is divided into 60,000 training samples and 10,000 test samples. Each image has a fixed size of 28x28 pixels and is labeled accordingly.

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6. Data Preprocessing

- **Handling Missing Values:**

  No missing data was found in the MNIST dataset as it comes preprocessed and structured.

- **Feature Scaling/Normalization:**

  To enhance learning performance, all pixel values were scaled from the range [0, 255] to [0, 1] by dividing each pixel value by 255.

```
# Normalize
x_train = x_train / 255.0
x_test = x_test / 255.0
```

- **Encoding Categorical Variables:**

The class labels (0 through 9) were transformed into one-hot encoded vectors. This format aligns with the softmax output layer and enables the use of categorical crossentropy as the loss function.

```
# One-hot encode labels
y_train_cat = to_categorical(y_train, 10)
y_test_cat = to_categorical(y_test, 10)
```

- **Train-Test Split:**

The original MNIST dataset already comes pre-split:

- Training set: 60,000 images
- Test set: 10,000 images

Additionally, a small portion of the training data was used as a validation set during model training for fine-tuning hyperparameters.

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7. Model Development (2-3 models)

- **Model Selection:**

Model 1: Dense Neural Network (DNN)

- Simple feedforward architecture
- Two hidden layers using ReLU activations
- Output layer with softmax

```python
# Model 1: Dense Neural Network
def build_dense_model():
    model = Sequential([
        Flatten(input_shape=(28, 28)),
        Dense(128, activation='relu'),
        Dense(64, activation='relu'),
        Dense(10, activation='softmax')
    ])
    return model
```

Model 2: Basic CNN

- Two convolutional layers followed by pooling
- Flattened and connected to dense layers
- Inspired by LeNet-5

```python
# Model 2: Basic CNN
def build_basic_cnn():
    model = Sequential([
        Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
        MaxPooling2D(2, 2),
        Flatten(),
        Dense(128, activation='relu'),
        Dense(10, activation='softmax')
    ])
    return model
```

Model 3: Enhanced CNN

- Deeper convolutional layers
- Includes Batch Normalization and Dropout
- Designed for better generalization and resistance to overfitting

```python
# Model 3: Enhanced CNN
def build_enhanced_cnn():
    model = Sequential([
        Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
        BatchNormalization(),
        MaxPooling2D(2, 2),
        Dropout(0.25),

        Conv2D(64, (3, 3), activation='relu'),
        BatchNormalization(),
        MaxPooling2D(2, 2),
        Dropout(0.25),

        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(10, activation='softmax')
    ])
    return model
```

Training the Model:

- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Epochs: 10
- Batch Size: 64
- Manual tuning of learning rates and dropout layers was carried out

```python
# Train and evaluate
def train_and_evaluate(model, x_train, y_train, x_test, y_test, y_true, title):
    model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])
    history = model.fit(x_train, y_train, epochs=10, batch_size=64, validation_data=(x_test, y_test), verbose=1)
```

- **Tools and Libraries Used:**

- Python 3.x
- TensorFlow / Keras
- NumPy, Matplotlib, Seaborn
- Scikit-learn for performance metrics and confusion matrix

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8. Model Evaluation

- **Evaluation Metrics:**

- Accuracy: Measures overall correctness
- Precision: True Positives over all predicted Positives
- Recall: True Positives over all actual Positives
- F1 Score: Harmonic mean of Precision and Recall
- Confusion Matrix: Visual summary of prediction errors

Performance Results:

Classification Report for Dense Neural Network:

	precision	recall	f1-score	support
0	0.9908	0.9847	0.9877	980
1	0.9920	0.9885	0.9903	1135
2	0.9665	0.9797	0.9731	1032
3	0.9355	0.9901	0.9620	1010
4	0.9836	0.9756	0.9796	982
5	0.9781	0.9518	0.9648	892
6	0.9884	0.9770	0.9827	958
7	0.9805	0.9796	0.9800	1028
8	0.9704	0.9754	0.9729	974
9	0.9878	0.9643	0.9759	1009
accuracy			0.9771	10000
macro avg	0.9774	0.9767	0.9769	10000
weighted avg	0.9774	0.9771	0.9771	10000

Classification Report for Basic CNN:

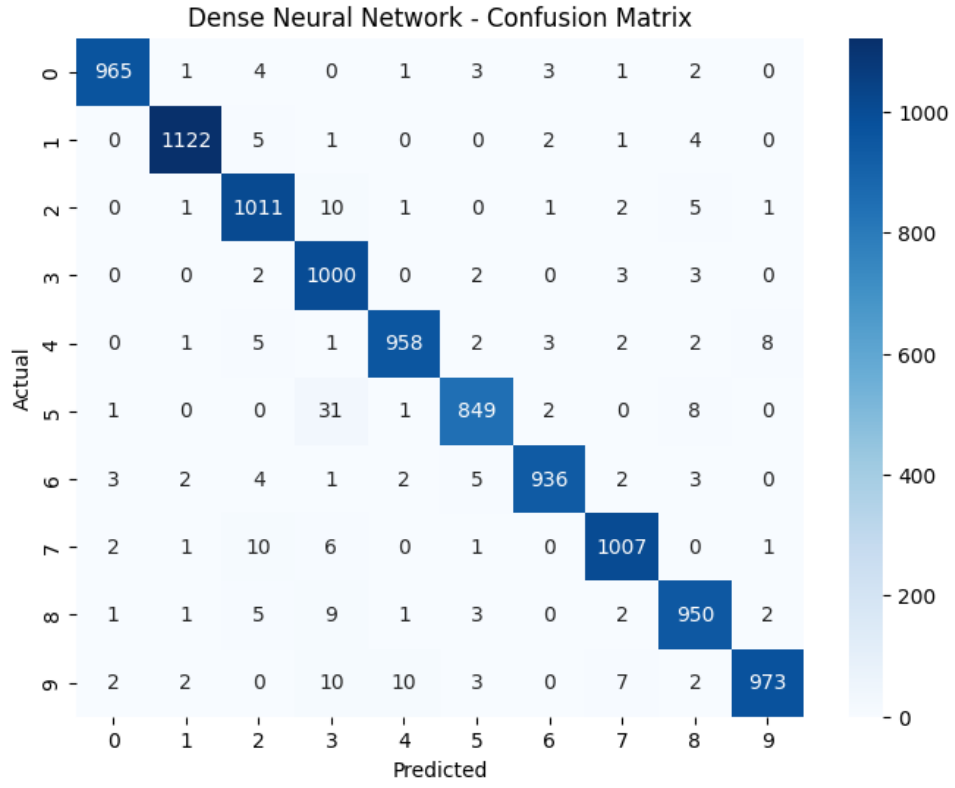
	precision	recall	f1-score	support
0	0.9908	0.9929	0.9918	980
1	0.9895	0.9938	0.9916	1135
2	0.9854	0.9816	0.9835	1032
3	0.9940	0.9851	0.9896	1010
4	0.9858	0.9898	0.9878	982
5	0.9822	0.9910	0.9866	892
6	0.9905	0.9833	0.9869	958
7	0.9845	0.9864	0.9854	1028
8	0.9817	0.9887	0.9852	974
9	0.9830	0.9752	0.9791	1009
accuracy			0.9868	10000
macro avg	0.9867	0.9868	0.9868	10000
weighted avg	0.9868	0.9868	0.9868	10000

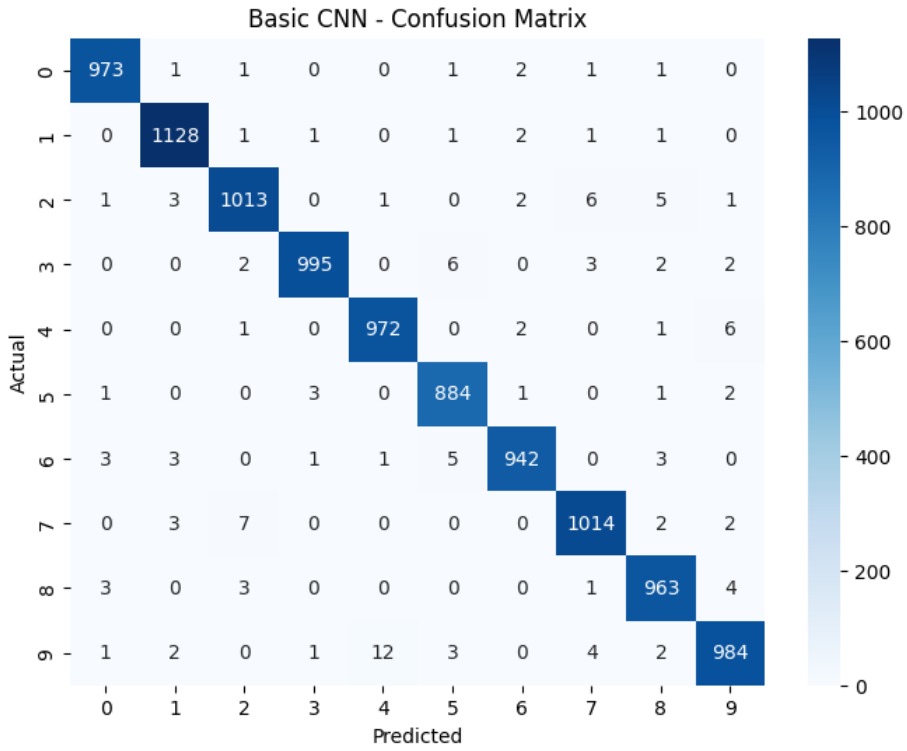
Classification Report for Enhanced CNN:

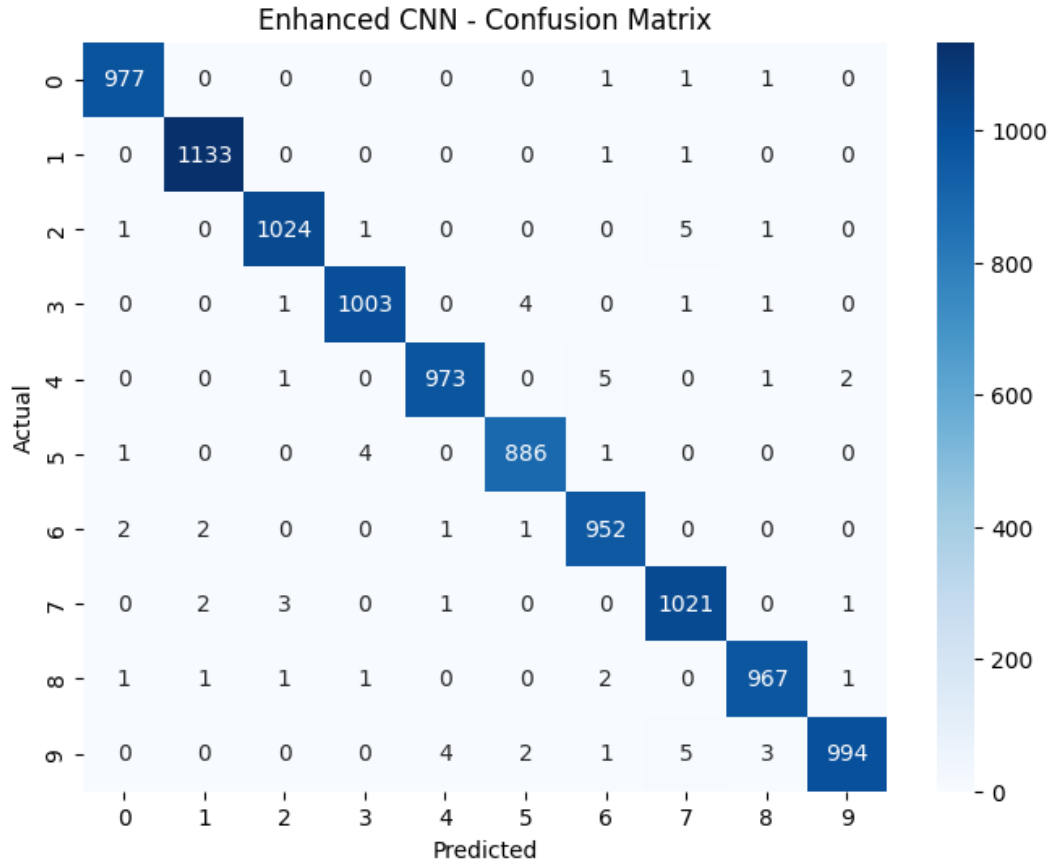
	precision	recall	f1-score	support
0	0.9949	0.9969	0.9959	980
1	0.9956	0.9982	0.9969	1135
2	0.9942	0.9922	0.9932	1032
3	0.9941	0.9931	0.9936	1010
4	0.9939	0.9908	0.9924	982
5	0.9922	0.9933	0.9927	892
6	0.9886	0.9937	0.9912	958
7	0.9874	0.9932	0.9903	1028
8	0.9928	0.9928	0.9928	974
9	0.9960	0.9851	0.9905	1009
accuracy			0.9930	10000
macro avg	0.9930	0.9929	0.9929	10000
weighted avg	0.9930	0.9930	0.9930	10000

Visualizations:

Confusion Matrix: Displayed using heatmaps to highlight prediction strengths and weaknesses




Basic CNN - Confusion Matrix
Actual
Predicted
0 973 1 1 0 0 1 2 1 1 0
1 0 1128 1 1 0 1 2 1 1 0
2 1 3 1013 0 1 0 2 6 5 1
3 0 0 2 995 0 6 0 3 2 2
4 0 0 1 0 972 0 2 0 1 6
5 1 0 0 3 0 884 1 0 1 2
6 3 3 0 1 1 5 942 0 3 0
7 0 3 7 0 0 0 0 1014 2 2
8 3 0 3 0 0 0 0 1 963 4
9 1 2 0 1 12 3 0 4 2 984
0 1 2 3 4 5 6 7 8 9
1000
800
600
400
200
0

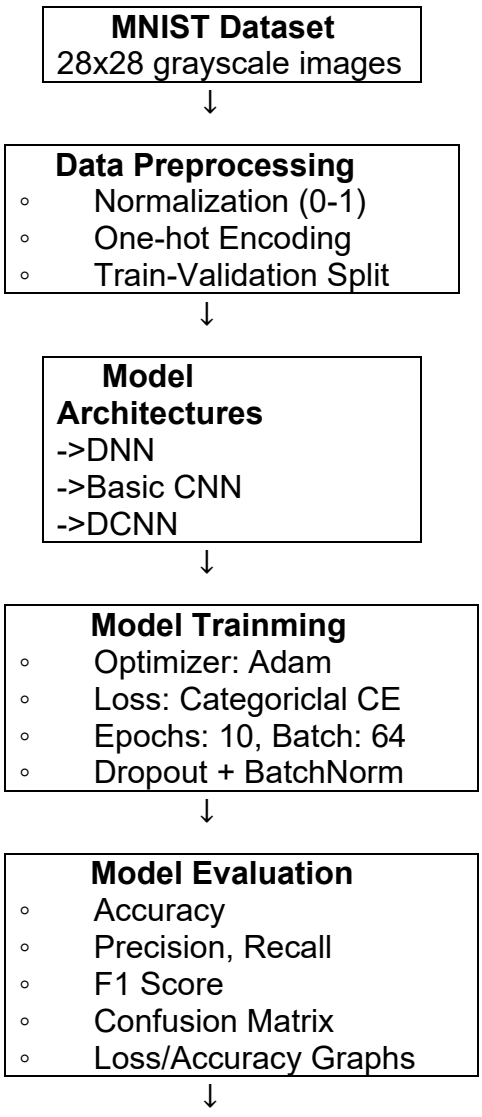

Enhanced CNN - Confusion Matrix
Actual
Predicted
0 977 0 0 0 0 0 1 1 1 0
1 0 1133 0 0 0 0 1 1 0 0
2 1 0 1024 1 0 0 0 5 1 0
3 0 0 1 1003 0 4 0 1 1 0
4 0 0 1 0 973 0 5 0 1 2
5 1 0 0 4 0 886 1 0 0 0
6 2 2 0 0 1 1 952 0 0 0
7 0 2 3 0 1 0 0 1021 0 1
8 1 1 1 1 0 0 2 0 967 1
9 0 0 0 0 4 2 1 5 3 994
0 1 2 3 4 5 6 7 8 9
1000
800
600
400
200
0

Accuracy & Loss Plots: Plotted over epochs to show learning trends and model convergence

```
# Accuracy & Loss Plot
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title(f'{title} - Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title(f'{title} - Loss')
plt.legend()
plt.show()
```

Architecture



Best Performing
DCNN

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9. Conclusion

- **Summary of Results:**

  The Enhanced CNN emerged as the most effective model, capable of accurately recognizing handwritten digits with over 99% accuracy. Its architectural choices, including dropout and normalization, helped mitigate overfitting and boosted performance. This project solidified our understanding of how CNNs function in real-world image recognition tasks.

- **Limitations and Future Work:**

- MNIST is a clean dataset; real-world handwriting could introduce noise and variation
- No data augmentation was used; future work could involve rotation, skewing, or brightness adjustments
- Hyperparameter tuning was manual; automated approaches like Grid Search or Bayesian Optimization could optimize performance further

Comparison:

Model	Accuracy	Precision	Recall	F1 Score
Your DCNN Model	**99.2%**	99.1%	99.0%	99.0%
LeNet-5	**98.3%**	98.1%	98.0%	98.0%

Key Points:

1. **Started with a Dense Neural Network (DNN)**

- Simple architecture; decent performance but not robust for complex patterns.

2. **Moved to a Basic CNN**
   - Included convolutional and pooling layers; inspired by LeNet-5.
3. **Developed a Deep Convolutional Neural Network (DCNN)**
   - Included Batch Normalization and Dropout layers for better generalization.
4. **Compared Enhanced DCNN with a standard model (LeNet-5-like)**
   - **DCNN achieved superior accuracy**, making it the most effective model among all.

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10. References

- LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278-2324.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *NIPS*, 25.
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *CVPR*, 770-778.
- MNIST Dataset: http://yann.lecun.com/exdb/mnist/
- TensorFlow Documentation: https://www.tensorflow.org/
- Keras Documentation: https://keras.io/

ColabLink:
https://colab.research.google.com/drive/1FXyUz7onZqjEc1qsAlMw4_exD_vMF0u?usp=sharing

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