

Sri Sivasubramaniya Nadar College of Engineering, Chennai
(An Autonomous Institution affiliated to Anna University)

Degree & Branch	B.E Computer Science & Engineering	Semester	VI
Subject Code & Name	UCS2612 – Machine Learning Laboratory		
Academic Year	2025–2026 (Even)	Batch	2023–2027

Experiment 5

Perceptron vs Multilayer Perceptron with Hyperparameter Tuning

Objective

To implement and compare the performance of:

- **Model A:** Single-Layer Perceptron Learning Algorithm (PLA)
- **Model B:** Multilayer Perceptron (MLP) with hidden layers and nonlinear activation functions

Students must select, tune, and justify hyperparameters such as learning rate, activation function, optimizer, batch size, and number of hidden layers.

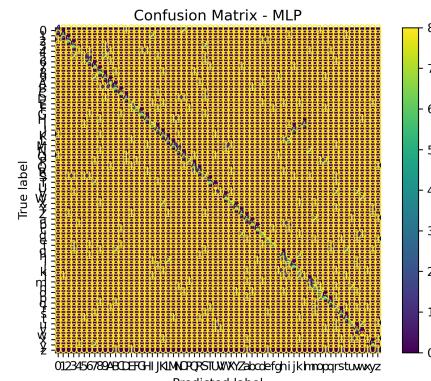
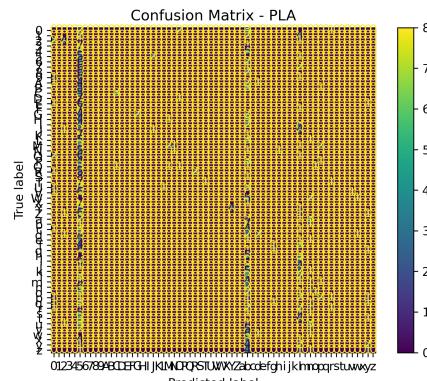
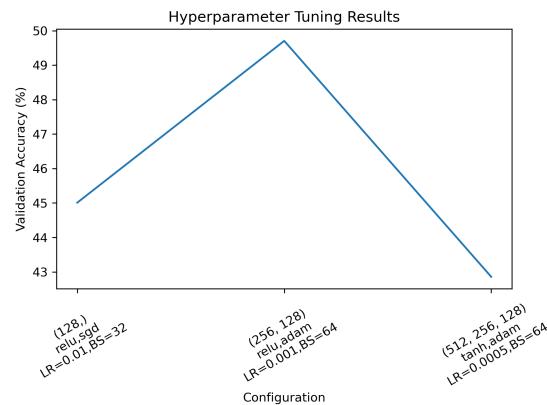
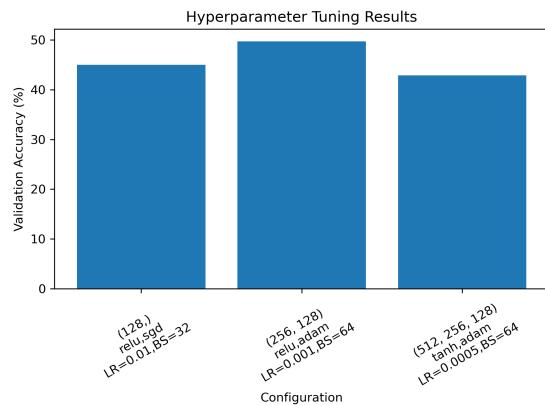
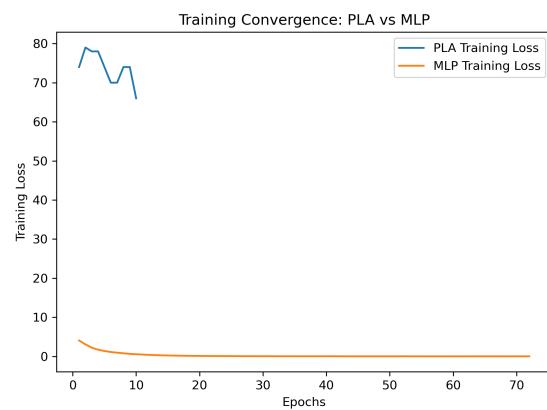
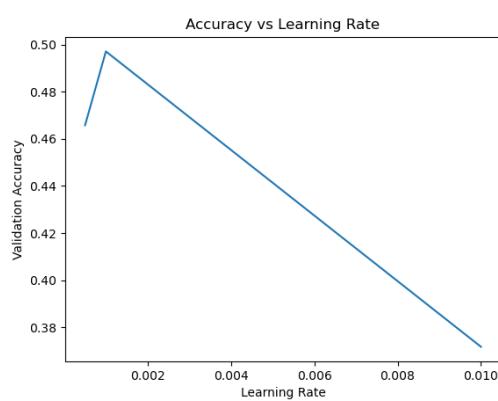
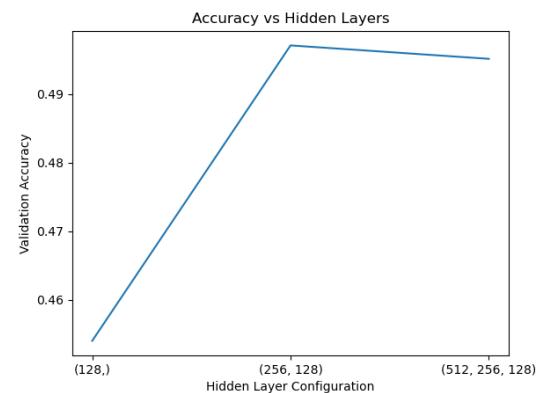
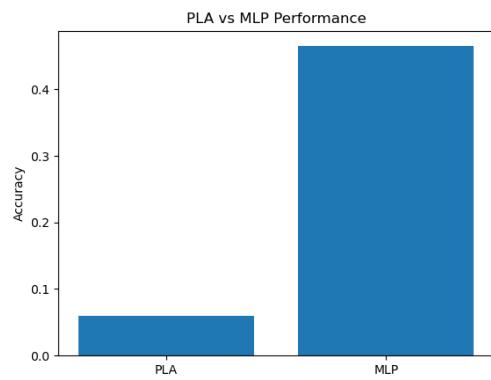
Dataset

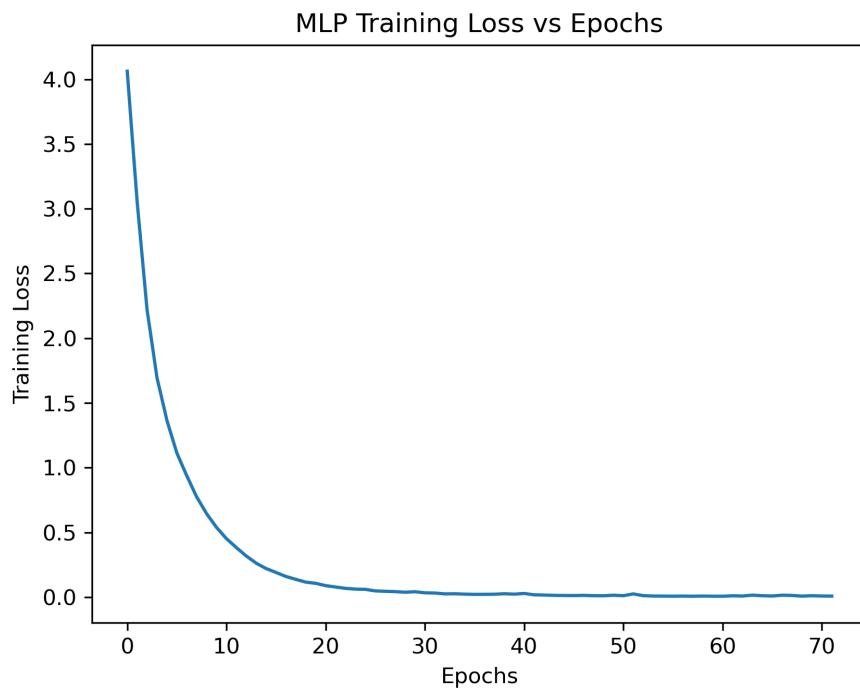
English Handwritten Characters Dataset

Download Link: <https://www.kaggle.com/datasets/dhruvildave/english-handwritten-characters-dataset>

- Total samples: 3,410
- Number of classes: 62 (0–9, A–Z, a–z)
- Image type: Grayscale

Graphs





Performance Evaluation

Table 1: Overall Performance Comparison between PLA and MLP

Model	Accuracy (%)	Precision	Recall	F1-score
PLA (OvR)	8.5937	0.1425	0.0851	0.0802
MLP (Tuned)	46.4843	0.4770	0.4650	0.4583

Table 2: Hyperparameter Tuning Results for MLP

Hidden Layers	Activation	Optimizer	Learning Rate	Batch Size	Accuracy (%)
1 (128)	ReLU	SGD	0.01	32	45.0097
2 (256–128)	ReLU	Adam	0.001	64	49.7064
3 (512–256–128)	Tanh	Adam	0.0005	64	42.8571

A/B Experiment Comparison

Students must clearly highlight:

- Final tuned hyperparameters for MLP

Table 3: Training Convergence Comparison

Model	Epochs	Final Training Loss	Convergence Behavior
PLA	10	66	Non-convergent
MLP (Tuned)	72	0.007658	Stable convergence

- Strengths and weaknesses of PLA vs MLP
- Effect of hyperparameter tuning on convergence and accuracy

Observation Questions

- Why does PLA underperform compared to MLP?
- Which hyperparameter had the most impact on MLP performance?
- How does optimizer choice affect convergence?
- Does increasing hidden layers always improve performance?
- How can overfitting be detected and mitigated?

Report Checklist

- Aim and Objective
- Dataset Description and Preprocessing
- PLA Implementation and Results
- MLP Implementation and Results
- Hyperparameter Tuning Analysis
- Performance Comparison Tables
- Observations and Conclusion

Conclusion

The Multilayer Perceptron achieved the best performance with tuned hyperparameters: two hidden layers (256–128), ReLU activation, Adam optimizer, learning rate 0.001, and batch size 64. Compared to the Perceptron Learning Algorithm, the MLP showed significantly higher accuracy and stable convergence, as PLA is limited to linear decision boundaries and failed to converge effectively on the nonlinear character dataset. Hyperparameter tuning improved the MLP’s convergence speed and validation accuracy by selecting optimal learning rate, network depth, and optimizer. Overall, the experiment demonstrates that MLP is more suitable than PLA for complex multiclass image classification tasks.