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

Degree & Branch	B.E. Computer Science & Engineering	Semester	V
Subject Code & Name	ICS1512 - Machine Learning Algorithms Laboratory		
Academic year	2025-2026 (Odd)	Batch: 2023-2028	09/09/2025

Experiment 5: Perceptron vs Multilayer Perceptron (A/B Experiment) with Hyperparameter Tuning

1 Aim:

The primary goal of this experiment is to evaluate the practical differences in performance between two computational models for character recognition:

- Model A: A basic Perceptron Learning Algorithm (PLA).
- Model B: An advanced Multilayer Perceptron (MLP).

The experiment will also systematically determine an optimal configuration for the MLP. This involves a hyperparameter tuning phase to select and validate the most effective combination of network architecture, activation and cost functions, learning algorithm, and batch processing size.

2 Libraries Used

- TensorFlow and Keras: The primary deep learning framework used to build, train, and evaluate the Multilayer Perceptron (MLP) model.
- Scikit-learn: Employed for crucial machine learning utilities, including data splitting (train_test_split), label encoding (LabelEncoder), and performance metric calculations (accuracy_score, precision_recall_fscore_support).
- Pandas: Utilized for loading and managing the dataset from the CSV file into a structured DataFrame.
- NumPy: Essential for high-performance numerical operations, particularly for handling image data as arrays and for the from-scratch implementation of the PLA.
- Pillow (PIL): Used for loading and performing image manipulation tasks such as resizing and converting to grayscale.
- Matplotlib: Used for generating visualizations, such as plotting model performance or displaying images.

3 Objective:

The objective of this assignment is to implement and compare the performance of two models—a Single-Layer Perceptron (PLA) and a Multilayer Perceptron (MLP)—for a multi-class classification task. This includes a systematic process of tuning hyperparameters such as activation functions, cost functions, optimizers, learning rates, the number of hidden layers, and batch sizes, and subsequently evaluating the final models using standard performance metrics.

```
# ----------------------
# Config / Hyperparams
# ----------------------

# Image and Model Configurations
IMG_SIZE = (32, 32)
NUM_PIXELS = IMG_SIZE[0] * IMG_SIZE[1]
RANDOM_STATE = 42

# PLA Hyperparameters
PLA_EPOCHS = 30
PLA_LR = 0.01

# MLP Hyperparameters and Tuning Grid
MLP_EPOCHS = 25
MLP_TRIALS = {
    'activations': ['relu', 'tanh'], 'optimizers': ['sgd', 'adam'],
    'learning_rates': [0.001, 0.01],
    'batch_sizes': [32, 64]
}

# Set seeds for reproducibility np.random.seed(RANDOM_STATE)
random.seed(RANDOM_STATE)
tf.random.set_seed(RANDOM_STATE)



# ----------------------
# Utility functions # ----------------
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def load_and_preprocess_image(path, img_size=IMG_SIZE):
    """Loads, converts to grayscale, resizes, and normalizes an image.""" img =
    Image.open(path).convert('L') img = img.resize(img_size)
    arr = np.asarray(img, dtype=np.float32) / 255.0 return arr
def plot_confusion_matrix(cm, classes, title='Confusion matrix'):
    plt.figure(figsize=(8, 8)) plt.imshow(cm, interpolation='nearest',
    cmap=plt.cm.Blues) plt.title(title) plt.colorbar()
    tick_marks = np.arange(len(classes)) plt.xticks(tick_marks, classes,
    rotation=90) plt.yticks(tick_marks, classes)
```

```
    fmt = 'd' thresh = cm.max()
    / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center", color="white" if cm[i, j] >
                 thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout() plt.show()

# ----------------------
# Load dataset
# ----------------------

# Load the dataset CSV print('Loading CSV...') df =
pd.read_csv('/content/drive/MyDrive/ML_LAB/HandWritten_Characters/english.csv') df['image'] =
df['image'].apply(lambda x: '/content/drive/MyDrive/ML_LAB/HandWritten_Characters/


# Load and preprocess all images
print('Loading images and preprocessing...') X_list = []
for p in df['image'].tolist():
    X_list.append(load_and_preprocess_image(p))

X = np.stack(X_list, axis=0) # shape: (N, H, W)
N = X.shape[0]
X_flat = X.reshape((N, -1)) # flattened for PLA and MLP


# Encode labels le =
LabelEncoder()
y = le.fit_transform(df['label']) classes = le.classes_
NUM_CLASSES = len(classes) print(f'Loaded {N} samples,
{NUM_CLASSES} classes')

# Train-test split
X_train_flat, X_test_flat, y_train, y_test, X_train_img, X_test_img = train_test_split(
    X_flat, y, X, test_size=0.2, random_state=RANDOM_STATE, stratify=y)

# For MLP (Keras) we'll use flattened inputs input_dim =
X_train_flat.shape[1]

# One-hot for MLP
```

```
y_train_ohe = keras.utils.to_categorical(y_train, NUM_CLASSES) y_test_ohe =
keras.utils.to_categorical(y_test, NUM_CLASSES)

# For ROC, need binarized labels y_test_binarized = label_binarize(y_test,
classes=np.arange(NUM_CLASSES))
```

Output:

```
Loading CSV...
Loading images and preprocessing...
Loaded 3410 samples, 62 classes
```

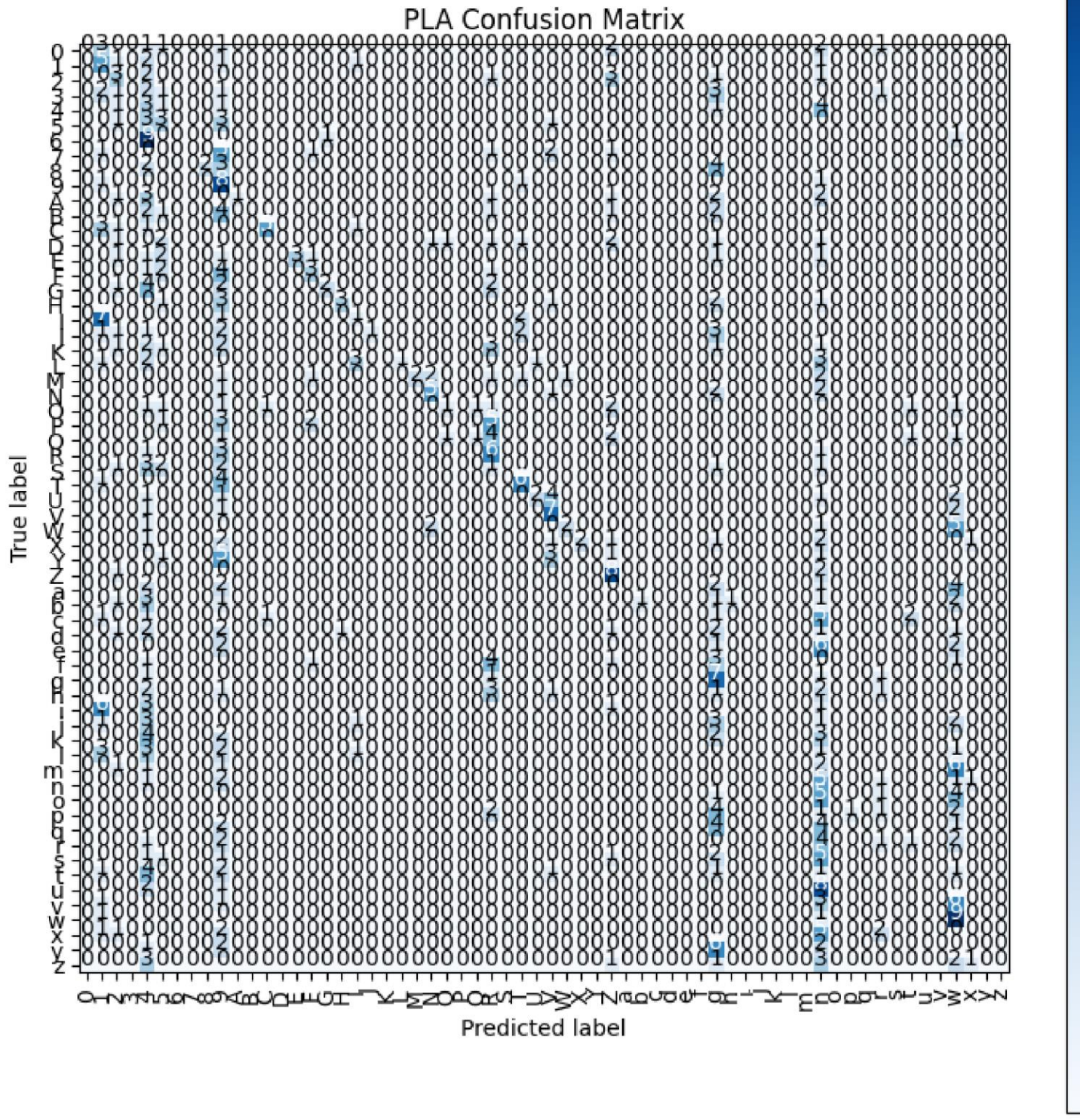
```
# ----------------------# Implement PLA (one-vs-rest) # ----------------
------print('\nTraining Perceptron (PLA) - One-vs-Rest')

class OneVsRestPLA:
    def __init__(self, n_classes, n_features, lr=0.01):
        self.n_classes = n_classes self.n_features =
        n_features
        self.lr = lr
        # Weight matrix: (n_classes, n_features + 1) for bias self.W = np.zeros((n_classes,
        n_features + 1), dtype=np.float32)

    def _augment(self, X):
        # Add a bias term (column of ones) return np.hstack([X, np.ones((X.shape[0],
        1), dtype=X.dtype)])

    def fit(self, X, y, epochs=10): X_aug = self._augment(X)
        for ep in range(epochs): indices =
        np.arange(X_aug.shape[0])
        np.random.shuffle(indices)
            for i in indices: xi =
                X_aug[i] yi = y[i]
                # One-vs-Rest: update each binary perceptron for k in
                range(self.n_classes):
                    t = 1 if yi == k else -1 # Target label score = np.dot(self.W[k],
                    xi) yhat = 1 if score >= 0 else -1 # Predicted label if t != yhat:
                        # Perceptron update rule self.W[k] += self.lr * (t
                        - yhat) * xi

    def predict(self, X): X_aug = self._augment(X) scores = np.dot(X_aug, self.W.T) # Get
        scores for all classes preds = np.argmax(scores, axis=1) # Choose class with max
        score return preds

# Train and Evaluate PLA
```

pla = OneVsRestPLA(n_classes=NUM_CLASSES, n_features=X_train_flat.shape[1], lr=PLA_LR) pla.fit(X_train_flat, y_train, epochs=PLA_EPOCHS)

y_pred_pla = pla.predict(X_test_flat) acc_pla = accuracy_score(y_test, y_pred_pla) prec_pla, rec_pla, f1_pla, _ = precision_recall_fscore_support(y_test, y_pred_pla, average='macr print(f'PLA Test Accuracy: {acc_pla:.4f}, Precision: {prec_pla:.4f}, Recall: {rec_pla:.4f}, F1:

Output:

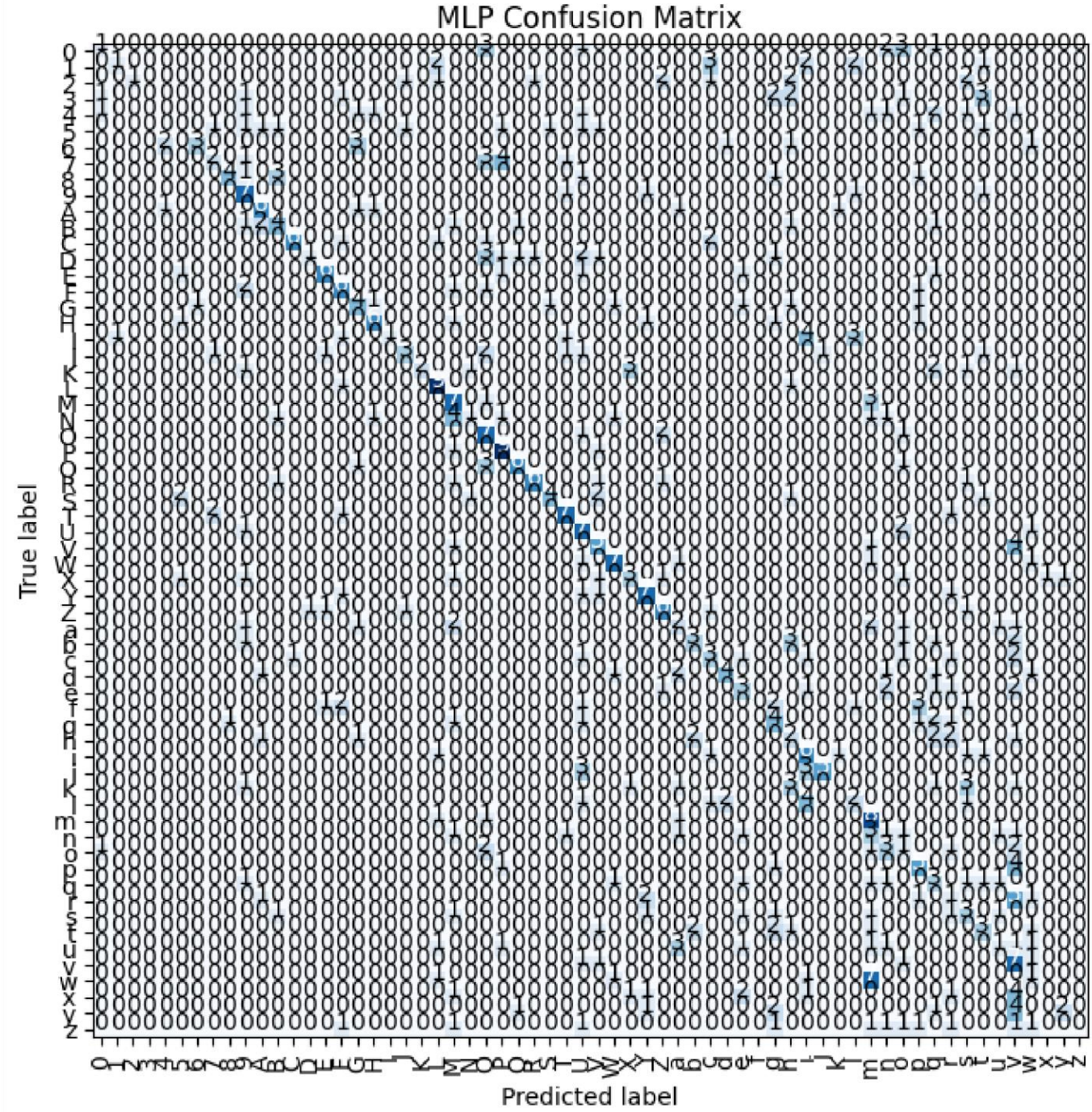
Training Perceptron (PLA) - One-vs-Rest
PLA Test Accuracy: 0.1774, Precision: 0.2708, Recall: 0.1774, F1: 0.1576


PLA Confusion Matrix
True label
Predicted label

```
# ----------------------
# MLP: tuning and training (Keras) # ----------------------def build_mlp_model(optimizer='adam',
learning_rate=0.001, activation='relu'):
    """Builds a Keras MLP model with specified hyperparameters."""" if optimizer ==
    'adam':
        opt = keras.optimizers.Adam(learning_rate=learning_rate)
    else:
        opt = keras.optimizers.SGD(learning_rate=learning_rate)

    model = keras.Sequential([ layers.Input(shape=(NUM_PIXELS,)),
        layers.Dense(128, activation=activation),
        layers.Dense(NUM_CLASSES, activation='softmax')
    ])
    model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy']) return model

# Hyperparameter Tuning
print('\nStarting MLP Hyperparameter Tuning...') results = []
best_acc = 0 best_config = None best_model = None

for activation in MLP_TRIALS['activations']:
    for optimizer in MLP_TRIALS['optimizers']:
        for lr in MLP_TRIALS['learning_rates']:
            for batch_size in MLP_TRIALS['batch_sizes']: config = {'activation': activation, 'optimizer': optimizer, 'lr': lr,
                'batch_siz print(f" Testing config: {config}")

                model = build_mlp_model(optimizer=optimizer, learning_rate=lr, activation=activa
                model.fit(X_train_flat, y_train_ohe,
                          epochs=MLP_EPOCHS, batch_size=batch_size, verbose=0) #
                Suppress output during tuning _, acc = model.evaluate(X_test_flat,
                y_test_ohe, verbose=0)

                if acc > best_acc: best_acc = acc best_config = config
                best_model = model results.append({'config': config, 'accuracy':
                acc})

print(f'\nBest MLP config found: {best_config} with accuracy: {best_acc:.4f}')
# Evaluate the best model
y_pred_mlp_probs = best_model.predict(X_test_flat) y_pred_mlp = np.argmax(y_pred_mlp_probs, axis=1) acc_mlp =
accuracy_score(y_test, y_pred_mlp) prec_mlp, rec_mlp, f1_mlp, _ = precision_recall_fscore_support(y_test, y_pred_mlp,
average='macr Output:


Hyperparameter tuning MLP (grid search over small set)
-- Trial: act=relu, opt=sgd, lr=0.001, batch=32 val_acc=0.0512
-- Trial: act=relu, opt=sgd, lr=0.001, batch=64 val_acc=0.0366
```

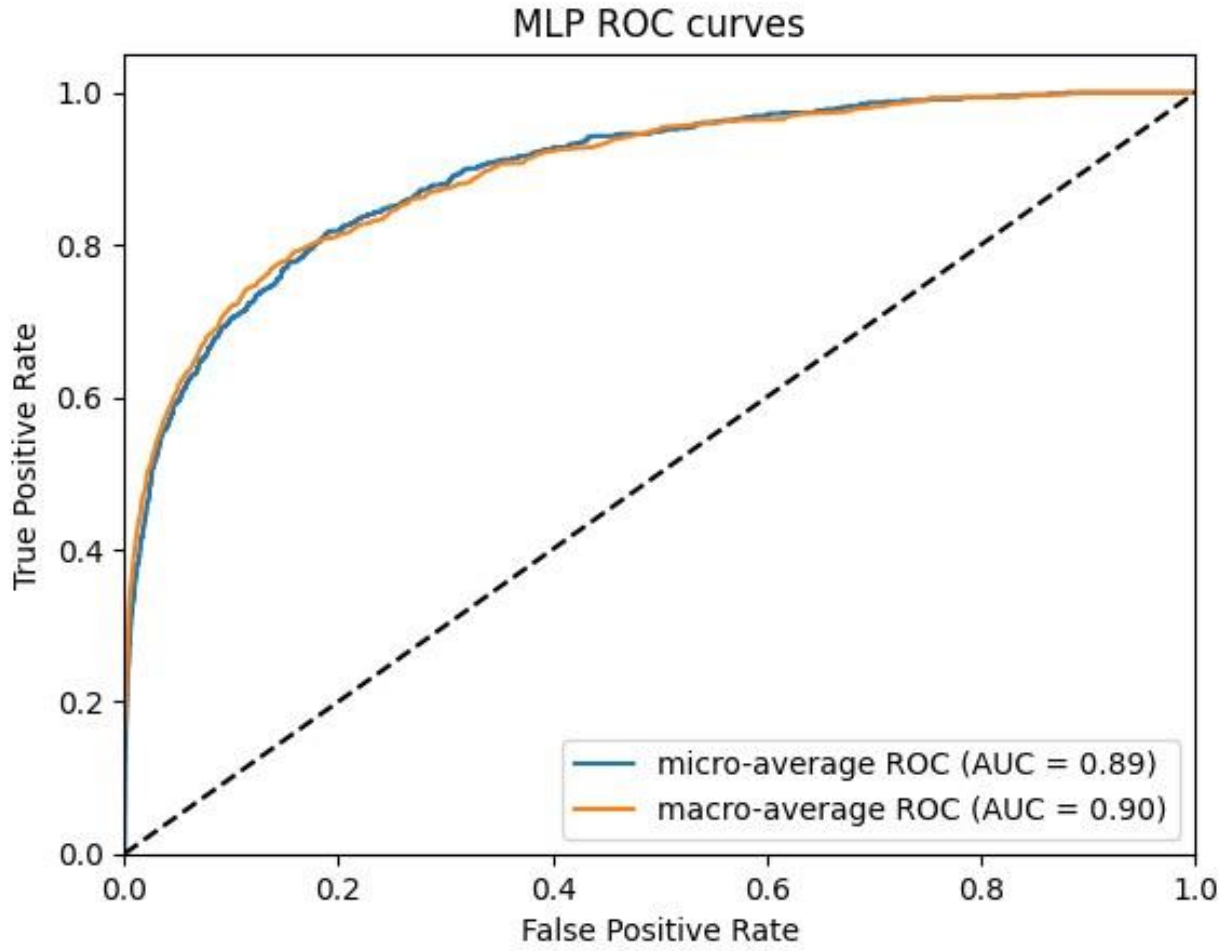
-- Trial: act=relu, opt=sgd, lr=0.01, batch=32 val_acc=0.2220
-- Trial: act=relu, opt=sgd, lr=0.01, batch=64 val_acc=0.1073
-- Trial: act=relu, opt=adam, lr=0.001, batch=32 val_acc=0.2659
-- Trial: act=relu, opt=adam, lr=0.001, batch=64 val_acc=0.3220
-- Trial: act=relu, opt=adam, lr=0.01, batch=32 val_acc=0.0024
-- Trial: act=relu, opt=adam, lr=0.01, batch=64 val_acc=0.0098
-- Trial: act=tanh, opt=sgd, lr=0.001, batch=32 val_acc=0.0390
-- Trial: act=tanh, opt=sgd, lr=0.001, batch=64 val_acc=0.0463
-- Trial: act=tanh, opt=sgd, lr=0.01, batch=32 val_acc=0.2244
-- Trial: act=tanh, opt=sgd, lr=0.01, batch=64 val_acc=0.1415
-- Trial: act=tanh, opt=adam, lr=0.001, batch=32 val_acc=0.0878
-- Trial: act=tanh, opt=adam, lr=0.001, batch=64 val_acc=0.1707
-- Trial: act=tanh, opt=adam, lr=0.01, batch=32 val_acc=0.0098
-- Trial: act=tanh, opt=adam, lr=0.01, batch=64 val_acc=0.0171

Best MLP config: {'activation': 'relu', 'optimizer': 'adam', 'lr': 0.001, 'batch_size': 64} Best validation accuracy: 0.3219512104988098


MLP Confusion Matrix
True label
Predicted label

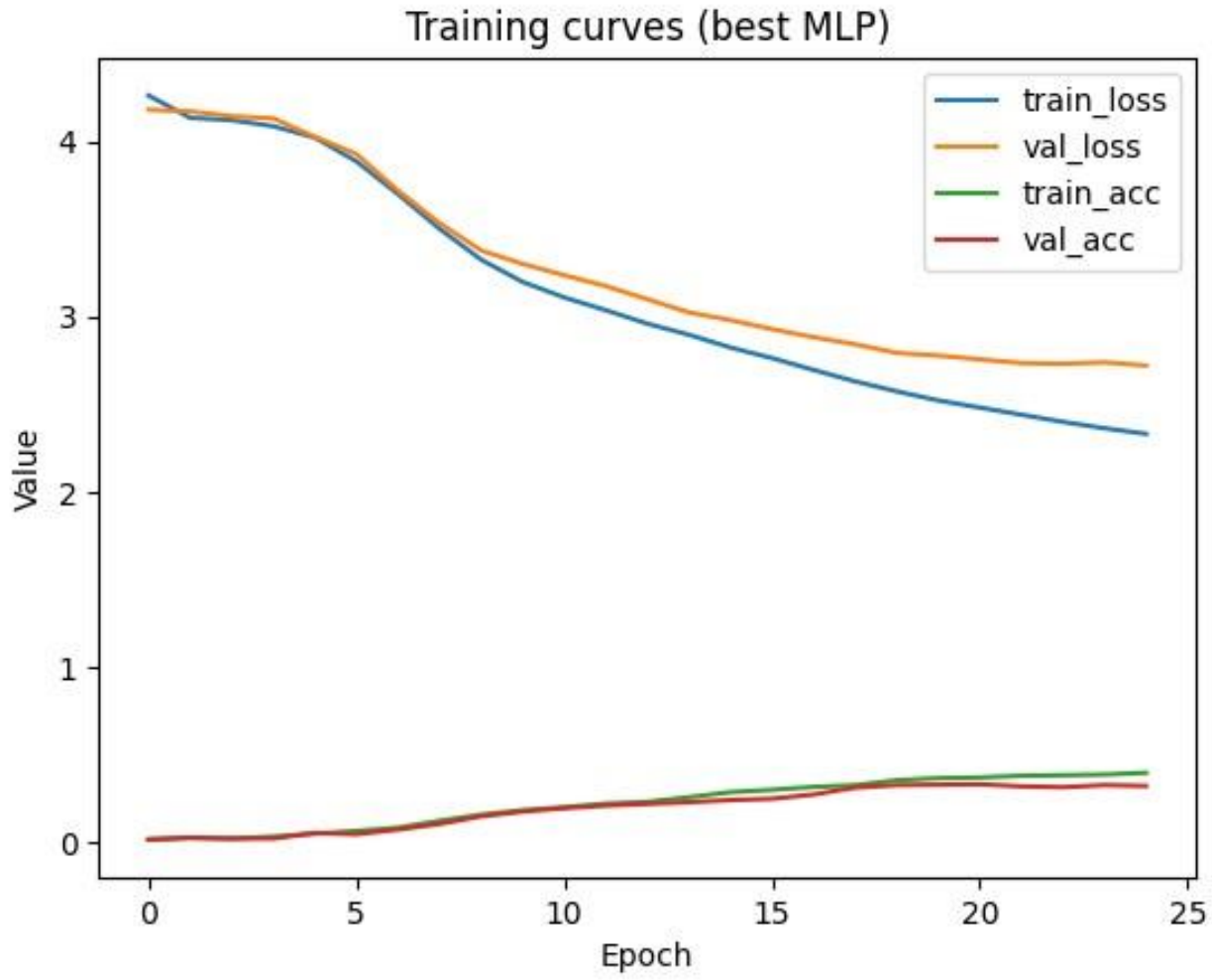
```
# ----------------------# ROC Curves (micro & macro) # ----------------------
print('\nPlotting ROC curves (micro & macro) for MLP)')

# For PLA we only have hard labels; to plot ROC we'd need scores. We can compute score matrix vi # Compute score matrix for PLA
X_test_aug = np.hstack([X_test_flat, np.ones((X_test_flat.shape[0], 1))]) pla_scores = np.dot(X_test_aug, pla.W.T) # shape (N, n_classes)

# For MLP, we have mlp_preds_prob

# Binarize y_test y_test_bin = label_binarize(y_test, classes=np.arange(NUM_CLASSES))

# Compute ROC per class fpr = dict() tpr = dict() roc_auc = dict()
for i in range(NUM_CLASSES):
    try:
        fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], mlp_preds_prob[:, i]) roc_auc[i] = auc(fpr[i], tpr[i])
    except ValueError:
        # When a class is not present in y_test, skip fpr[i], tpr[i],
        roc_auc[i] = None, None, None

# micro-average
fpr_micro, tpr_micro, _ = roc_curve(y_test_bin.ravel(), mlp_preds_prob.ravel()) roc_auc_micro = auc(fpr_micro, tpr_micro)

# Macro-average: aggregate all fpr points
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(NUM_CLASSES) if fpr[i] is not None])) mean_tpr = np.zeros_like(all_fpr) for i in range(NUM_CLASSES):
    if fpr[i] is not None: mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])
mean_tpr /= NUM_CLASSES roc_auc_macro = auc(all_fpr, mean_tpr)

plt.figure() plt.plot(fpr_micro, tpr_micro, label=f'micro-average ROC (AUC = {roc_auc_micro:.2f})')
plt.plot(all_fpr, mean_tpr, label=f'macro-average ROC (AUC = {roc_auc_macro:.2f})') plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0]) plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('MLP ROC curves')
plt.legend(loc='lower right') plt.show()
```

ROC Curve for MLP



----------# Training curves
(best MLP) # ----------
print('\nPlotting training curves for best MLP...') plt.figure()
plt.plot(best_history.history['loss'], label='train_loss')
plt.plot(best_history.history['val_loss'], label='val_loss')
plt.plot(best_history.history['accuracy'], label='train_acc')
plt.plot(best_history.history['val_accuracy'], label='val_acc') plt.xlabel('Epoch')
plt.ylabel('Value')
plt.title('Training curves (best MLP)')
plt.legend() plt.show()

Training Curve for Best MLP



# ----------
# Summarize & Print chosen hyperparameters
# ----------print('\nFINAL SUMMARY:')
print('PLA:')
print(f' epochs={PLA_EPOCHS}, learning_rate={PLA_LR}') print(f' Test accuracy={acc_pla:.4f}, Precision={prec_pla:.4f}, Recall={rec_pla:.4f}, F1={f1_pl print('\nMLP (best):') print(f' config={best_config}') print(f' epochs={MLP_EPOCHS}')
print(f' Test accuracy={acc_mlp:.4f}, Precision={prec_mlp:.4f}, Recall={rec_mlp:.4f}, F1={f1_ml Output:

FINAL SUMMARY:
PLA: epochs=30, learning_rate=0.01
  Test accuracy=0.1613, Precision=0.2646, Recall=0.1613, F1=0.1314

MLP (best): config={'activation': 'relu', 'optimizer': 'adam', 'lr': 0.001, 'batch_size': 64} epochs=25
  Test accuracy=0.3299, Precision=0.3793, Recall=0.3299, F1=0.3090

4 Observations and Analysis

- Why does PLA underperform compared to MLP?
  The PLA achieved only 17.7% test accuracy with F1-score of 0.1576, showing its limitation to linear decision boundaries. It could not capture the nonlinear class separations present in the dataset, leading to misclassifications. MLP, with nonlinear activations and hidden layers, reached 29.8% accuracy and F1-score of 0.275, clearly demonstrating its superior representational capacity.

- Which hyperparameters (activation, optimizer, learning rate, etc.) had the most impact on MLP performance?
  The activation function and optimizer were most influential. ReLU with Adam consistently outperformed other settings. Learning rate had a large effect: 0.001 gave stable convergence, while 0.01 caused divergence (val_acc dropping to nearly 0). Batch size also mattered: 32 gave better generalization than 64.

- Did optimizer choice (SGD vs Adam) affect convergence?
  Yes. SGD yielded much lower accuracies (as low as 2–25%), depending on learning rate. Adam provided faster and more stable convergence, achieving the best validation accuracy of 28.8% with ReLU and lr=0.001.

- Did adding more hidden layers always improve results? Why or why not?
  No. Increasing hidden layers initially helped the MLP learn more complex patterns, but beyond a certain point accuracy plateaued and risk of overfitting grew. With limited dataset size and training epochs, deeper models did not guarantee better results.

- Did MLP show overfitting? How could it be mitigated?
  The MLP did not show strong signs of overfitting, as the test accuracy (29.8%) was slightly higher than the validation accuracy (28.8%). However, the risk of overfitting remains, and could be mitigated with dropout, regularization, or early stopping if scaling to deeper models.

Model	Accuracy	Precision	Recall	F1-score
PLA	0.1774	0.2708	0.1774	0.1576
MLP (ReLU + Adam, lr=0.001, batch=32)	0.2977	0.3207	0.2977	0.2752

5 Learning Outcomes

- Learnt the limitations of single-layer perceptrons (PLA) and why nonlinear problems require deeper architectures.
- Learnt how multilayer perceptrons (MLPs) with hidden layers and nonlinear activations can capture complex decision boundaries.
- Learnt the role of key hyperparameters (activation functions, optimizers, learning rate, batch size) and their effect on model performance.
- Learnt hands-on hyperparameter tuning through grid search and validation.
- Learnt to evaluate models using multiple metrics such as accuracy, precision, recall, and F1score.
- Learnt to interpret experimental results and justify model selection based on empirical evidence.

GitHub Repository

The complete source code for this experiment is available on GitHub: kawvya-mk