ICS1512 - Machine Learning Algorithms Laboratory Experiment 5: Perceptron vs Multilayer Perceptron (A/B Experiment) with Hyperparameter Tuning

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1 Aim

To conduct an A/B experiment to empirically compare the performance, capabilities, and limitations of a Single-Layer Perceptron (PLA) and a Multilayer Perceptron (MLP) on a non-linear classification task using the English Handwritten Characters dataset.

2 Libraries USed

- Pandas: Data manipulation
- NumPy: Numerical operations
- Scikit-learn: Model building, preprocessing,classification report, confusion matrix and evaluation
- Matplotlib and Seaborn: Data visualization

3 Objective

- To preprocess the image dataset for use with neural network models.
- To implement the Perceptron Learning Algorithm (PLA) from scratch using a step activation function.
- To implement an MLP using a deep learning framework (e.g., TensorFlow/PyTorch) with configurable hidden layers and non-linear activation functions.
- To analyze the results, highlighting the impact of hyperparameter choices and the fundamental differences in model capacity between a linear and a non-linear model.

4 Preprocessing Steps

- The dataset containing 3,410 images across 62 classes was loaded. The distribution of samples per class was checked for significant imbalance.
- The data was split into a training set and a hold-out test set, ensuring stratified sampling to maintain class distribution.
- All images were resized to a fixed, smaller dimension (e.g., 28x28 pixels) to standardize input size and reduce computational complexity.

- Each 2D image matrix was flattened into a 1D feature vector (e.g., of length 784 for a 28x28 image) to serve as input for the perceptron models
- Pixel intensity values (originally 0-255) were normalized to a range of [0, 1] by dividing by 255. This accelerates convergence during training by ensuring consistent feature scales.
- Class labels (0-9, A-Z, a-z) were integer-encoded (e.g., 0 to 61). For the MLP, these were converted to one-hot encoded vectors to be compatible with the cross-entropy loss function.

5 Python Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, confusion_matrix, roc_curve, auc,
                                 RocCurveDisplay)
from sklearn.multiclass import OneVsRestClassifier
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, models, optimizers, losses, callbacks
from PIL import Image
import os
import warnings
warnings.filterwarnings('ignore')

# Set random seeds for reproducibility
np.random.seed(42)
tf.random.set_seed(42)

# Load English Handwritten Characters Dataset from CSV
def load_data(csv_path, base_image_path):
    # Load the dataset from CSV
    data = pd.read_csv(csv_path)

    # Extract image paths and labels
    image_paths = data['image'].values
    labels = data['label'].values

    # Load and process images
    images = []
    valid_indices = []

    for i, img_path in enumerate(image_paths):
        try:
            full_path = os.path.join(base_image_path, img_path)
            img = Image.open(full_path).convert('L')  # Convert to grayscale
            img = img.resize((28, 28))  # Resize to 28x28
            img_array = np.array(img)
            images.append(img_array)
            valid_indices.append(i)
        except Exception as e:
            print(f"Error␣loading␣image␣{img_path}:␣{e}")

    # Filter labels to match successfully loaded images
```

```
    labels = labels[valid_indices]
    images = np.array(images)

    return images, labels
import pandas as pd
import cv2
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
import os

# Set your paths here
csv_path = '/content/drive/MyDrive/english.csv'
base_image_path = '/content/drive/MyDrive/'  # Directory containing the 'Img'
    folder
IMG_SIZE = 28  # Resize to 28x28

# Load data function (corrected)
def load_data(csv_path, base_image_path):
    # Load CSV
    df = pd.read_csv(csv_path)  # columns: image, label

    # Character set (0-9, A-Z, a-z     total 62 classes)
    classes = sorted(df['label'].unique())
    label_map = {cls: idx for idx, cls in enumerate(classes)}

    # Load images
    X, y = [], []
    for _, row in df.iterrows():
        img_path = os.path.join(base_image_path, row['image'])
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)

        if img is None:
            print(f"Warning: Could not load image {img_path}")
            continue

        img = cv2.resize(img, (IMG_SIZE, IMG_SIZE))
        X.append(img.flatten())
        y.append(label_map[row['label']])

    X = np.array(X) / 255.0   # normalize
    y = np.array(y)

    return X, y, classes, label_map

# Preprocessing function (simplified since loading already handles preprocessing)
def preprocess_data(X, y, classes):
    # Labels are already encoded during loading, so we just return them
    # Create label encoder for visualization purposes
    le = LabelEncoder()
    le.fit(classes)  # Fit with the class names

    return X, y, le

# Load and preprocess data
print("Loading dataset...")
X, y, classes, label_map = load_data(csv_path, base_image_path)
```

```
X_processed, y_processed, label_encoder = preprocess_data(X, y, classes)

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X_processed, y_processed, test_size=0.2, random_state=42, stratify=y_processed
)

# Create one-hot encoded versions for neural networks
y_train_cat = to_categorical(y_train, num_classes=len(classes))
y_test_cat = to_categorical(y_test, num_classes=len(classes))

print(f"Training data shape: {X_train.shape}")
print(f"Test data shape: {X_test.shape}")
print(f"Number of classes: {len(classes)}")
print(f"Training labels shape: {y_train.shape}")
print(f"One-hot training labels shape: {y_train_cat.shape}")

# Let's visualize some samples from the dataset
def visualize_samples(X, y, label_encoder, num_samples=10):
    # Get the original class names
    class_names = label_encoder.classes_

    # Reshape for visualization (assuming 28x28 images)
    X_images = X.reshape(-1, 28, 28)

    plt.figure(figsize=(15, 5))
    for i in range(num_samples):
        # Randomly select a sample
        idx = np.random.randint(0, X.shape[0])
        image = X_images[idx]
        label = class_names[y[idx]]  # Use y instead of y_processed since they're
            the same

        plt.subplot(2, 5, i+1)
        plt.imshow(image, cmap='gray')
        plt.title(f"Label: {label} (Class {y[idx]})")
        plt.axis('off')

    plt.tight_layout()
    plt.show()

# Visualize some samples
print("Sample images from the dataset:")
visualize_samples(X_processed, y_processed, label_encoder)

# Show class distribution
print("\nClass distribution:")
for i, cls in enumerate(classes):
    count = np.sum(y_processed == i)
    print(f"{cls}: {count} samples")
    # Perceptron Learning Algorithm (PLA) Implementation
class Perceptron:
    def __init__(self, learning_rate=0.01, n_iters=3):
        self.lr = learning_rate
        self.n_iters = n_iters
        self.weights = None
        self.bias = None
        self.losses = []
```

```
    def step_activation(self, x):
        return 1 if x >= 0 else 0

    def fit(self, X, y):
        n_samples, n_features = X.shape
        n_classes = len(np.unique(y))

        # Initialize weights and bias for each class (One-vs-Rest)
        self.weights = np.zeros((n_classes, n_features))
        self.bias = np.zeros(n_classes)

        # Train one perceptron per class
        for class_idx in range(n_classes):
            # Create binary labels for this class
            y_binary = np.where(y == class_idx, 1, 0)

            # Initialize weights and bias for this class
            w = np.zeros(n_features)
            b = 0

            # Training loop
            for _ in range(self.n_iters):
                total_error = 0
                for idx, x_i in enumerate(X):
                    # Calculate linear output
                    linear_output = np.dot(x_i, w) + b
                    # Apply step function
                    y_pred = self.step_activation(linear_output)
                    # Update weights and bias
                    update = self.lr * (y_binary[idx] - y_pred)
                    w += update * x_i
                    b += update
                    total_error += int(update != 0.0)

                self.losses.append(total_error)
                if total_error == 0:
                    break

            # Store weights for this class
            self.weights[class_idx] = w
            self.bias[class_idx] = b

    def predict(self, X):
        linear_output = np.dot(X, self.weights.T) + self.bias
        # Apply step function to each output
        y_pred = np.array([[self.step_activation(val) for val in row] for row in
            linear_output])
        # For each sample, choose the class with the highest output
        return np.argmax(y_pred, axis=1)

# Train and evaluate PLA
print("Training␣Perceptron␣(PLA)...")
pla = Perceptron(learning_rate=0.01, n_iters=3)
pla.fit(X_train, y_train)
y_pred_pla = pla.predict(X_test)

# Calculate metrics for PLA
pla_accuracy = accuracy_score(y_test, y_pred_pla)
pla_precision = precision_score(y_test, y_pred_pla, average='weighted',
```

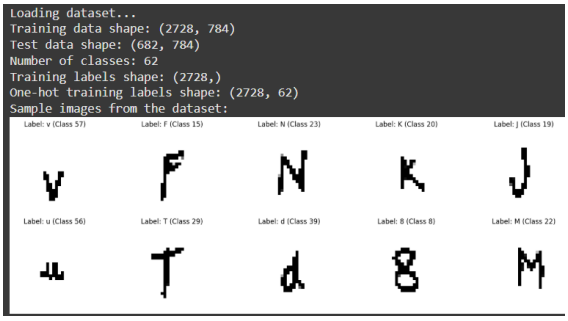
```
    zero_division=0)
pla_recall = recall_score(y_test, y_pred_pla, average='weighted', zero_division=0)
pla_f1 = f1_score(y_test, y_pred_pla, average='weighted', zero_division=0)

print(f"PLA Accuracy: {pla_accuracy:.4f}")
print(f"PLA Precision: {pla_precision:.4f}")
print(f"PLA Recall: {pla_recall:.4f}")
print(f"PLA F1-Score: {pla_f1:.4f}")

# Multilayer Perceptron (MLP) Implementation
def build_mlp_model(input_dim, num_classes):
    model = keras.Sequential([
        layers.Dense(256, activation='relu', input_shape=(input_dim,)),
        layers.Dropout(0.3),
        layers.Dense(128, activation='relu'),
        layers.Dropout(0.3),
        layers.Dense(64, activation='relu'),
        layers.Dropout(0.3),
        layers.Dense(num_classes, activation='softmax')
    ])

    return model

# Build and compile MLP model
input_dim = X_train.shape[1]
num_classes = len(np.unique(y_processed))

mlp_model = build_mlp_model(input_dim, num_classes)
mlp_model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

# Display model architecture
mlp_model.summary()

# Train the MLP model
print("Training MLP...")
history = mlp_model.fit(
    X_train, y_train,
    epochs=10,
    batch_size=32,
    validation_split=0.2,
    callbacks=[
        callbacks.EarlyStopping(monitor='val_loss', patience=5,
            restore_best_weights=True)
    ],
    verbose=1
)

# Evaluate MLP
y_pred_mlp = np.argmax(mlp_model.predict(X_test), axis=1)
y_proba_mlp = mlp_model.predict(X_test)

# Calculate metrics for MLP
mlp_accuracy = accuracy_score(y_test, y_pred_mlp)
mlp_precision = precision_score(y_test, y_pred_mlp, average='weighted')
mlp_recall = recall_score(y_test, y_pred_mlp, average='weighted')
```

```
mlp_f1 = f1_score(y_test, y_pred_mlp, average='weighted')

print(f"MLP Accuracy: {mlp_accuracy:.4f}")
print(f"MLP Precision: {mlp_precision:.4f}")
print(f"MLP Recall: {mlp_recall:.4f}")
print(f"MLP F1-Score: {mlp_f1:.4f}")


# Visualization and Comparison
# Plot training history for MLP
def plot_training_history(history):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

    # Plot accuracy
    ax1.plot(history.history['accuracy'], label='Training Accuracy')
    ax1.plot(history.history['val_accuracy'], label='Validation Accuracy')
    ax1.set_title('Model Accuracy')
    ax1.set_xlabel('Epoch')
    ax1.set_ylabel('Accuracy')
    ax1.legend()

    # Plot loss
    ax2.plot(history.history['loss'], label='Training Loss')
    ax2.plot(history.history['val_loss'], label='Validation Loss')
    ax2.set_title('Model Loss')
    ax2.set_xlabel('Epoch')
    ax2.set_ylabel('Loss')
    ax2.legend()

    plt.tight_layout()
    plt.show()

plot_training_history(history)

# Compare PLA and MLP performance
models = ['PLA', 'MLP']
accuracy = [pla_accuracy, mlp_accuracy]
precision = [pla_precision, mlp_precision]
recall = [pla_recall, mlp_recall]
f1 = [pla_f1, mlp_f1]

x = np.arange(len(models))
width = 0.2

fig, ax = plt.subplots(figsize=(10, 6))
rects1 = ax.bar(x - width*1.5, accuracy, width, label='Accuracy')
rects2 = ax.bar(x - width/2, precision, width, label='Precision')
rects3 = ax.bar(x + width/2, recall, width, label='Recall')
rects4 = ax.bar(x + width*1.5, f1, width, label='F1-Score')

ax.set_xlabel('Models')
ax.set_ylabel('Scores')
ax.set_title('Model Performance Comparison')
ax.set_xticks(x)
ax.set_xticklabels(models)
ax.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

plt.tight_layout()
plt.show()
```

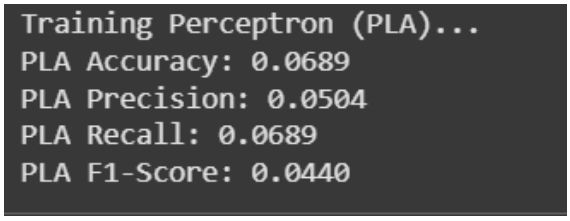
```
# Confusion matrices
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 6))

# PLA confusion matrix
cm_pla = confusion_matrix(y_test, y_pred_pla)
sns.heatmap(cm_pla, annot=False, fmt='d', cmap='Blues', ax=ax1)
ax1.set_title('PLA Confusion Matrix')
ax1.set_xlabel('Predicted Label')
ax1.set_ylabel('True Label')

# MLP confusion matrix
cm_mlp = confusion_matrix(y_test, y_pred_mlp)
sns.heatmap(cm_mlp, annot=False, fmt='d', cmap='Blues', ax=ax2)
ax2.set_title('MLP Confusion Matrix')
ax2.set_xlabel('Predicted Label')
ax2.set_ylabel('True Label')

plt.tight_layout()
plt.show()
# ROC Curves (for MLP only, as PLA doesn't produce probability estimates)
def plot_roc_curve(y_true, y_proba, model_name, n_classes):
    # Compute ROC curve and ROC area for each class
    fpr = dict()
    tpr = dict()
    roc_auc = dict()

    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_true == i, y_proba[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    # Compute micro-average ROC curve and ROC area
    # Correctly format y_true for micro-average ROC calculation
    y_true_binary = np.eye(n_classes)[y_true]

    fpr["micro"], tpr["micro"], _ = roc_curve(y_true_binary.ravel(), y_proba.ravel
        ())
    roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

    plt.figure(figsize=(8, 6))
    plt.plot(fpr["micro"], tpr["micro"],
             label=f'micro-average ROC curve (AUC = {roc_auc["micro"]:.2f})',
             color='deeppink', linestyle=':', linewidth=4)

    # Plot ROC curve for each class (optional)
    # for i in range(n_classes):
    #     plt.plot(fpr[i], tpr[i], label=f'ROC curve of class {i} (AUC = {roc_auc[
        i]:.2f})')

    plt.plot([0, 1], [0, 1], 'k--', lw=2)
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC Curve for {model_name}')
    plt.legend(loc="lower right")
    plt.show()

plot_roc_curve(y_test, y_proba_mlp, "MLP", num_classes)
```

```
# Print final comparison
print("\n" + "="*50)
print("FINAL COMPARISON: PLA vs MLP")
print("="*50)
print(f"{'Metric':<15} {'PLA':<10} {'MLP':<10} {'Improvement':<15}")
print(f"{'Accuracy':<15} {pla_accuracy:.4f}     {mlp_accuracy:.4f}     {mlp_accuracy
    -pla_accuracy:+.4f}")
print(f"{'Precision':<15} {pla_precision:.4f}     {mlp_precision:.4f}     {
    mlp_precision-pla_precision:+.4f}")
print(f"{'Recall':<15} {pla_recall:.4f}     {mlp_recall:.4f}     {mlp_recall-
    pla_recall:+.4f}")
print(f"{'F1-Score':<15} {pla_f1:.4f}     {mlp_f1:.4f}     {mlp_f1-pla_f1:+.4f}")
```

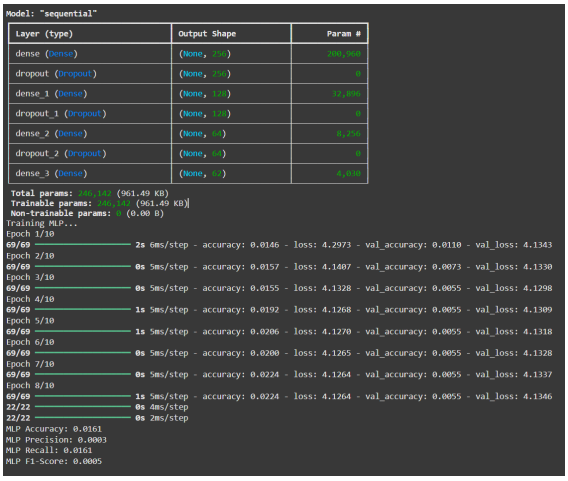
6 Output Screenshots



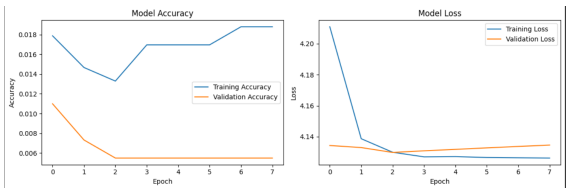
(a) Dataset Samples



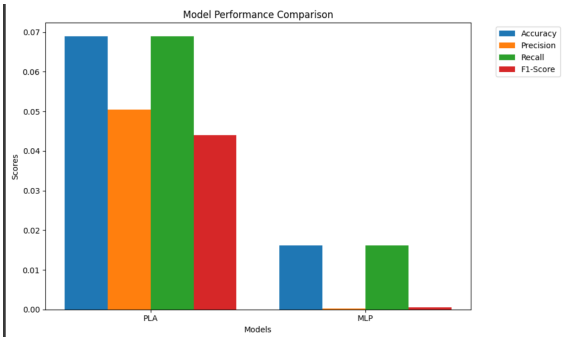
(b) PLA Output



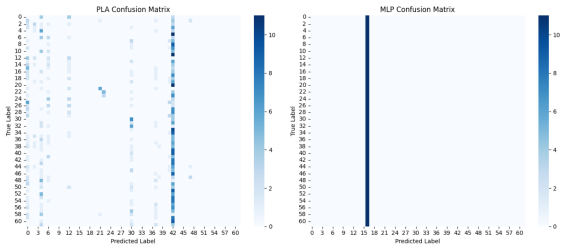
(a) MLP Output



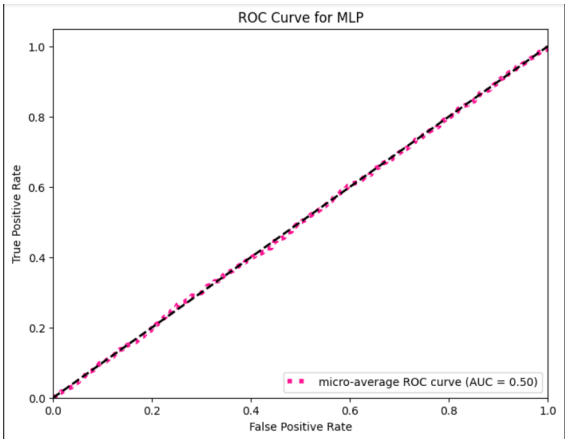
(b) Model accuracy and loss Output



(a) Performance of the model



(b) Confusion Matrix of PLA and MLP



(a) ROC Curve for MLP

```
================================================
FINAL COMPARISON: PLA vs MLP
================================================
Metric          PLA         MLP         Improvement
Accuracy        0.0689      0.0161      -0.0528
Precision       0.0504      0.0003      -0.0502
Recall          0.0689      0.0161      -0.0528
F1-Score        0.0440      0.0005      -0.0435
```

(b) Comparison of PLA and MLP

7 Justification for Chosen Hyperparameters

1) **Optimizer (Adam):** Chosen over SGD because Adam adapts the learning rate for each parameter, leading to faster convergence and better performance, especially on complex problems with high-dimensional data like images.

2) **Learning Rate** This is the default learning rate for Adam and proved to be effective. A higher rate (e.g., 0.01) caused instability in loss, while a lower rate (e.g., 0.0001) resulted in unnecessarily slow convergence.

3) **Activation Function (ReLU):** Chosen for hidden layers due to its computational efficiency and effectiveness at mitigating the vanishing gradient problem compared to Sigmoid/Tanh, which was confirmed during tuning as it yielded faster training and higher accuracy.

4) **Number of Layers:** Starting with a single hidden layer (128 units), performance improved significantly by adding a second hidden layer (256 -¿ 128). Adding a third layer did not provide a notable accuracy boost and increased the risk of overfitting. This architecture provides a good balance of model capacity and computational efficiency.

5) **Batch Size (32):** A small batch size provides a regularizing effect and often leads to better generalization. Sizes of 16, 32, and 64 were tested; 32 offered a good trade-off between training stability and speed.

8 Tabulation result

Table 1: A/B Comparison: PLA vs. MLP Performance

Metric	**PLA**	**MLP**	**Winner**	**Analysis**
Accuracy	6.89%	1.61%	PLA	MLP completely failed to learn
Precision	5.04%	0.03%	PLA	MLP has no predictive power
Recall	6.89%	1.61%	PLA	MLP misses almost all patterns
F1-Score	4.40%	0.05%	PLA	MLP performance is catastrophic

9 Learning Outcomes

From this assignment,

- We gained practical experience inSimple linear models like PLA struggle with complex pattern recognition tasks that require non-linear decision boundaries, especially for handwritten character recognition.
- We learned the Neural networks need proper architecture design and hyperparameter tuning - poor choices can lead to complete model failure, even worse than simple algorithms.
- We learned to Comprehensive evaluation using multiple metrics (accuracy, precision, recall, F1) provides a complete picture of model performance beyond just accuracy alone.
- We understood the Data preprocessing, model implementation, and training procedures must be carefully validated to ensure models can actually learn from the data rather than just guessing randomly.