COMP4318/5318 Assignment 2: Image Classification

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Setup and dependencies

Please use this section to list and set up all your required libraries/dependencies and your plotting environment.

In [90]:
```
import numpy as np
import pandas as pd
import random
import tensorflow as tf
import seaborn as sns
import keras_tuner as kt
# Import our deep learning libraries
from tensorflow import keras
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Make the notebook's output stable across runs
random.seed(42)
np.random.seed(42)
tf.random.set_seed(42)
keras.utils.set_random_seed(42)
keras.backend.clear_session()

%matplotlib inline

import matplotlib as mpl
import matplotlib.pyplot as plt

# Set the font size of axis titles and tick labels to make the chart more beautiful and easy to read.
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
```

1. Data loading, exploration, and preprocessing

In [95]:
```
# Load the dataset training and test sets as numpy arrays

X_train = np.load('Assignment2Data/X_train.npy')
y_train = np.load('Assignment2Data/y_train.npy')
X_test = np.load('Assignment2Data/X_test.npy')
y_test = np.load('Assignment2Data/y_test.npy')
```

Examples of preprocessed data

Check out the shape of the data:

In [98]:
```
print(f"Shape of X_train_full: {X_train.shape}")
print(f"Shape of y_train_full: {y_train.shape}")
print(f"Shape of X_test: {X_test.shape}")
print(f"Shape of y_test: {y_test.shape}")
```

```
Shape of X_train_full: (32000, 28, 28, 3)
Shape of y_train_full: (32000,)
Shape of X_test: (8000, 28, 28, 3)
Shape of y_test: (8000,)
```

Check the number of categories to see if they are balanced:

In [101…
```
# Training set
labels, counts = np.unique(y_train, return_counts=True)
for l, c in zip(labels, counts):
    print(f"Class {l}: {c} samples")
```

```
Class 0: 3490 samples
Class 1: 3431 samples
Class 2: 3505 samples
Class 3: 3656 samples
Class 4: 2950 samples
Class 5: 4290 samples
Class 6: 2728 samples
Class 7: 3253 samples
Class 8: 4697 samples
```

In [103…

```
# Test set
labels, counts = np.unique(y_test, return_counts=True)
for l, c in zip(labels, counts):
    print(f"Class {l}: {c} samples")
```

```
Class 0: 873 samples
Class 1: 858 samples
Class 2: 877 samples
Class 3: 914 samples
Class 4: 737 samples
Class 5: 1072 samples
Class 6: 682 samples
Class 7: 813 samples
Class 8: 1174 samples
```

Analysis of Pixel Value Distribution

1. Pixel values are mostly concentrated between 120 and 230

- This indicates that the images are generally bright, with few dark regions (e.g., 0–50, typically representing shadows or background).
- There are very few extreme values at 0 or 255, meaning the dataset **does not contain "completely black" or "completely white" images**. This suggests good overall image quality.

2. The distribution is right-skewed but smooth

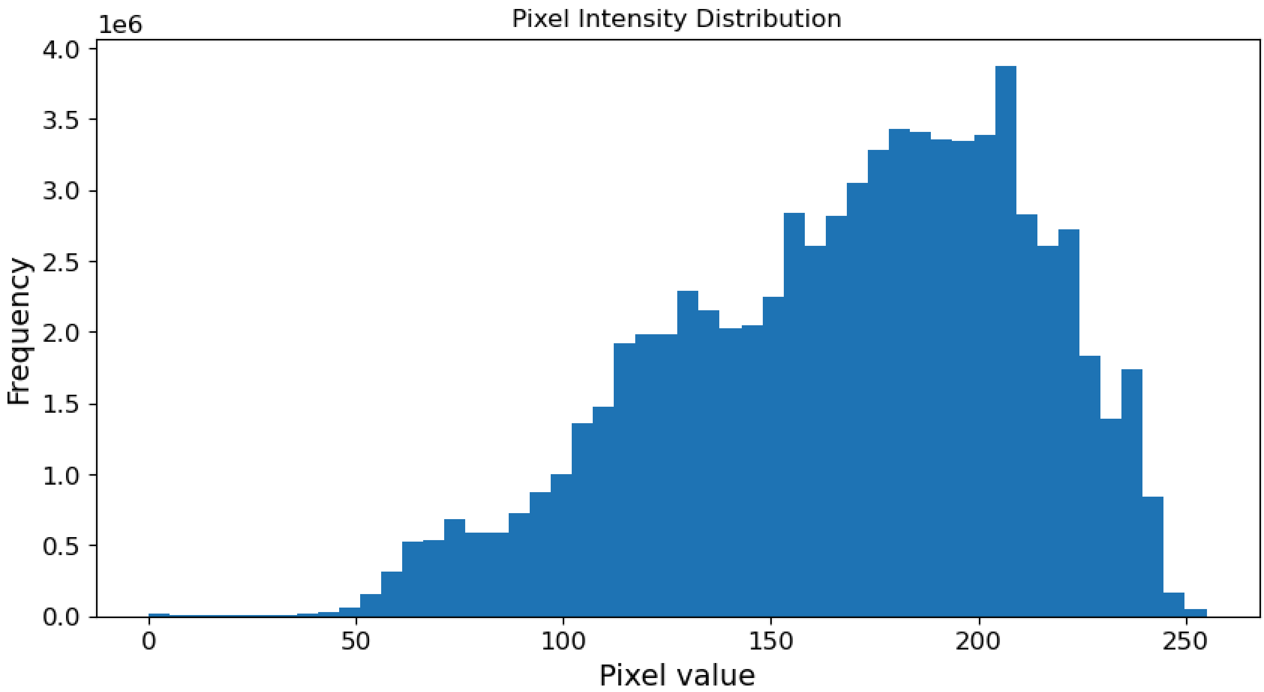
- Most images appear bright backgrounds, which is a common characteristic of histopathology tissue slides.
- The histogram shows a generally increasing trend followed by a gradual decline, **without abrupt spikes or bimodal patterns**. This suggests consistent background coloration across the dataset.

3. Pixel values are continuous but not yet normalized

- The raw pixel values range from **0 to 255**. Before training a neural network model, **normalization (i.e., dividing by 255) is necessary** to ensure numerical stability during learning.

In [107…

```
# Flatten all image pixels into a one-dimensional array
# and plot a histogram of the pixel intensity distribution

plt.figure(figsize=(10, 5))
plt.hist(X_train.ravel(), bins=50)
plt.title("Pixel Intensity Distribution")
plt.xlabel("Pixel value")
plt.ylabel("Frequency")
plt.show()
```



Grayscale conversion: take the average across the RGB channels to convert color images to grayscale.

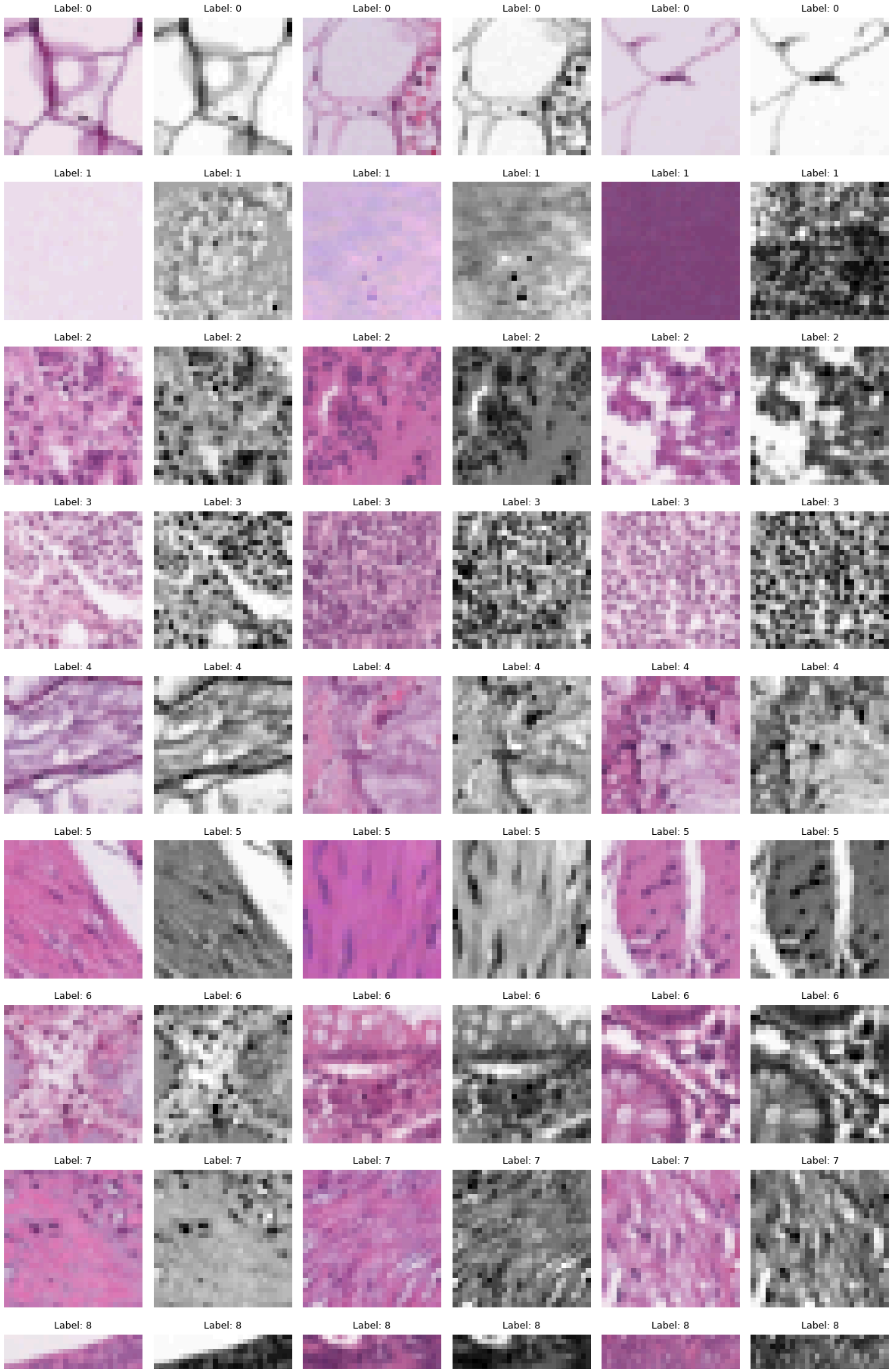
- The original X_train shape is (num_samples, 28, 28, 3), and after conversion it becomes (num_samples, 28, 28, 1).
- We initially attempted to train the model using grayscale images to simplify the input structure and speed up training. However, **experimental results showed that performance was inferior compared to using color images**. Therefore, grayscale images are now only used for visual comparison with the original color images.

In [110…
```
X_train_gray = np.mean(X_train, axis=-1, keepdims=True)  # shape: (num_samples, 28, 28, 1)
X_test_gray = np.mean(X_test, axis=-1, keepdims=True)
```

Sample image

- Visualize 3 sample images per label in both original color and grayscale format. This helps assess whether the images are **clear, centered, and exhibit distinguishable features**. The comparison also provides insight into whether grayscale retains sufficient structural information.

In [113…
```
# Get all unique class labels
labels = np.unique(y_train)
# Number of images to display per class
samples_per_class = 3

# Create a subplot grid: one row per class, two columns per sample (color + grayscale)
fig, axes = plt.subplots(
    len(labels), samples_per_class * 2,
    figsize=(samples_per_class * 4, len(labels) * 2.2)
)

for row, label in enumerate(labels):
    # Find all indices in y_train that match the current label
    label_indices = np.where(y_train == label)[0]
    # Select the first N samples
    selected_indices = label_indices[:samples_per_class]

    for i, idx in enumerate(selected_indices):
        # Left: display color image
        ax_color = axes[row, i * 2]
        ax_color.imshow(X_train[idx])  # Original color image
        if i == 0:
            ax_color.set_ylabel(f"Label: {label}", fontsize=11)
        ax_color.set_title(f"Label: {y_train[idx]}", fontsize=9)
        ax_color.axis('off')

        # Right: display corresponding grayscale image
        ax_gray = axes[row, i * 2 + 1]
        ax_gray.imshow(X_train_gray[idx].squeeze(), cmap='gray')  # Grayscale image
        ax_gray.set_title(f"Label: {y_train[idx]}", fontsize=9)
        ax_gray.axis('off')

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


Label: 0
Label: 0
Label: 0
Label: 0
Label: 0
Label: 0
Label: 1
Label: 1
Label: 1
Label: 1
Label: 1
Label: 1
Label: 2
Label: 2
Label: 2
Label: 2
Label: 2
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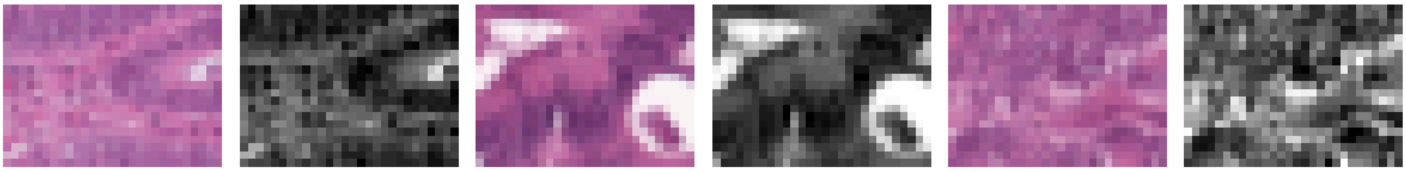


Data preprocessing

In [116…

```
# MLP + CNN
# Scale the data to the range 0-1
X_train_scale = X_train / 255.0
X_test_scale = X_test / 255.0
```

In [118…

```
# Random Forest cannot handle multidimensional image inputs directly,
# so we reshape each (28, 28, 3) image into a 1D feature vector.

X_train_rf = X_train_scale.reshape((X_train_scale.shape[0], -1))
X_test_rf = X_test_scale.reshape((X_test_scale.shape[0], -1))
```

Creating a validation set

To improve the training efficiency of neural networks, we introduced a third dataset — **the validation set.** Although this may reduce evaluation stability, it is more efficient than using k-fold cross-validation, which involves significantly higher computational cost. **Using a single split for validation is more practical for monitoring training and tuning hyperparameters.**

- During training, we use the validation set to evaluate model performance:
  - **To prevent overfitting** (e.g., by using early stopping to halt training early),
  - **To select the best hyperparameters**.
- **Prevent information leakage.**
  - The test set must remain completely independent from the entire training process and should only be used for final evaluation. If the test set participates in training, the model may learn from it, leading to overestimated performance and losing its purpose of assessing generalization.

In [121…

```
# MLP + CNN: Create validation set from the training set
X_train_nn, X_valid, y_train_nn, y_valid = train_test_split(
    X_train_scale, y_train, train_size=0.9, random_state=42, stratify=y_train
)
```

2. Algorithm design and setup

Algorithm of choice from first six weeks of course - Random Forest

Baseline - Random Forest

- The main function of the baseline model is to provide a performance reference point for subsequent model optimization (such as hyperparameter tuning).
- We try to keep the model simple **(no parameters are adjusted/parameters are kept as simple as possible)**

In [70]:

```
# Baseline - RF
# Initialize the model with default hyperparameters (set random_state for reproducibility)
rf = RandomForestClassifier(random_state=42)

# Train
rf.fit(X_train_rf, y_train)

# Predict on the test set
y_pred = rf.predict(X_test_rf)
acc_base_rf = accuracy_score(y_test, y_pred)

# Print evaluation metrics
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

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

           0       0.82      0.98      0.89       873
           1       0.99      0.90      0.94       858
           2       0.58      0.32      0.42       877
           3       0.73      0.74      0.74       914
           4       0.54      0.65      0.59       737
           5       0.62      0.73      0.67      1072
           6       0.49      0.12      0.19       682
           7       0.49      0.46      0.47       813
           8       0.52      0.74      0.61      1174

    accuracy                           0.65      8000
   macro avg       0.64      0.63      0.61      8000
weighted avg       0.64      0.65      0.63      8000
```

Fully connected neural network

Baseline - MLP

- Built a simple network using default settings: no learning rate tuning, no Dropout, no EarlyStopping
- 2 Dense layers: 128 → 64
- Fixed architecture and hyperparameters
- Optimizer: Adam (default learning rate)

In [126…

```
def build_mlp_baseline():
    model = keras.models.Sequential()

    # Input layer + Flatten: convert (28, 28, 3) image to 1D vector
    model.add(keras.layers.Input(shape=(28, 28, 3)))
    model.add(keras.layers.Flatten())

    # First Dense layer -> 128 units + relu
    model.add(keras.layers.Dense(128, activation='relu'))

    # Second Dense layer -> 64 units + relu
    model.add(keras.layers.Dense(64, activation='relu'))

    # Output layer -> 9 units (number of classes) + softmax (probability output)
    model.add(keras.layers.Dense(9, activation='softmax'))

    model.compile(
        optimizer = "Adam",
        loss = 'sparse_categorical_crossentropy',
        metrics = ['accuracy']
    )

    return model
```

In [128…

```
# Train the baseline

baseline_model_mlp = build_mlp_baseline()

baseline_model_mlp.fit(
    X_train_nn, y_train_nn,
    epochs = 10,
    validation_data = (X_valid, y_valid)
)
```

```
Epoch 1/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.2344 - loss: 1.9929 - val_accuracy: 0.3613 - val_loss: 1.6765
Epoch 2/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.3565 - loss: 1.6838 - val_accuracy: 0.4069 - val_loss: 1.5973
Epoch 3/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.3956 - loss: 1.5921 - val_accuracy: 0.4531 - val_loss: 1.4810
Epoch 4/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.4431 - loss: 1.4865 - val_accuracy: 0.4809 - val_loss: 1.3821
Epoch 5/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.4715 - loss: 1.4215 - val_accuracy: 0.4984 - val_loss: 1.3595
Epoch 6/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.4857 - loss: 1.3852 - val_accuracy: 0.5147 - val_loss: 1.3257
Epoch 7/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.4928 - loss: 1.3663 - val_accuracy: 0.5231 - val_loss: 1.3097
Epoch 8/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.4995 - loss: 1.3455 - val_accuracy: 0.5309 - val_loss: 1.2821
Epoch 9/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5032 - loss: 1.3314 - val_accuracy: 0.5344 - val_loss: 1.2675
Epoch 10/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.5081 - loss: 1.3149 - val_accuracy: 0.5297 - val_loss: 1.2570
```

Out[128… <keras.src.callbacks.history.History at 0x30e5a8830>

In [129…
```
loss_base_mlp, acc_base_mlp = baseline_model_mlp.evaluate(X_test_scale, y_test)
print(f"Baseline Test Accuracy: {acc_base_mlp:.4f}")
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 504us/step - accuracy: 0.5203 - loss: 1.2506
Baseline Test Accuracy: 0.5279
```

In [130…
```
y_pred = baseline_model_mlp.predict(X_test_scale)
y_pred_labels = np.argmax(y_pred, axis=1)

print(classification_report(y_test, y_pred_labels))
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 368us/step
              precision    recall  f1-score   support

           0       0.74      0.96      0.84       873
           1       0.92      0.71      0.80       858
           2       0.38      0.31      0.34       877
           3       0.52      0.66      0.58       914
           4       0.54      0.55      0.54       737
           5       0.48      0.56      0.52      1072
           6       0.33      0.03      0.06       682
           7       0.23      0.14      0.17       813
           8       0.43      0.65      0.52      1174

    accuracy                           0.53      8000
   macro avg       0.51      0.51      0.49      8000
weighted avg       0.51      0.53      0.50      8000
```

- After training for 10 epochs, the model achieved an accuracy of about 50% on the test set.

Algorithm Design - MLP

- **Input Layer**: Accepts 3-channel color images of shape (28, 28, 3) -> flattened to 1D.
- **Two hidden layers**:
  - Layer 1: 256–1024 (step=64)
  - Layer 2: 128–512 (step=64)
  - ReLU activation
- **Dropout layers** are applied after **each Dense layer (dropout rate between 0.2 and 0.5)** -> prevent overfitting.
  - **Excessive dropout** may harm model capacity, leading to underfitting.
  - **Large fluctuations** in validation performance may occur if the network becomes too unstable due to frequent dropout.
- **Output Layer**: 9-unit Dense layer + softmax activation multi-class classification
- **Hyperparameter tuning**:
  - units, dropout_rate, and learning_rate are all tunable.
  - learning rate [1e-4, 1e-2] + log-scale sampling.

In [133…
```
def build_mlp(hp):
    model = keras.models.Sequential()
    # Input layer - accepts images with shape (28, 28, 3)
    model.add(keras.layers.Input(shape=(28, 28, 3)))

    # Flatten the 3D image into a 1D vector (28*28*3 = 2352)
    model.add(keras.layers.Flatten())

    # Define dropout rate as a tunable hyperparameter
    dropout_rate = hp.Float('dropout_rate', 0.2, 0.5, step=0.1)


    # First hidden layer - extract low-level features
    model.add(
        keras.layers.Dense(
            units=hp.Int('units_1', min_value=256, max_value=1024, step=64),
            activation='relu'
        )
    )
    # Dropout to prevent overfitting
    model.add(keras.layers.Dropout(dropout_rate))



    # Second hidden layer - fuse features into higher-level representation
    model.add(
        keras.layers.Dense(
            units=hp.Int('units_2', min_value=128, max_value=512, step=64),
            activation='relu'
        )
    )
    # Dropout to prevent overfitting
```

```python
    model.add(keras.layers.Dropout(dropout_rate))


    # Output layer -> 9 units (number of classes) + softmax (probability output)
    model.add(keras.layers.Dense(9, activation='softmax'))

    # Instantiate optimiser and compile the model.
    model.compile(
        optimizer=keras.optimizers.Adam(
            learning_rate=hp.Float('lr', 1e-4, 1e-2, sampling='log')
        ),
        loss='sparse_categorical_crossentropy', # suitable for integer class labels (not one-hot!)
        metrics=['accuracy']
    )

    return model
```

Convolutional neural network

Baseline - CNN

- Built a simple CNN model: no learning rate tuning, no Dropout, no EarlyStopping
- 2 convolutional blocks followed by one dense layer
- fixed architecture and hyperparameters

In [136…

```python
def build_cnn_baseline():
    model = keras.models.Sequential()

    # Input layer - accepts images with shape (28, 28, 3)
    model.add(keras.layers.Input(shape = (28, 28, 3)))

    # First block
    model.add(keras.layers.Conv2D(filters = 32, kernel_size = (3, 3), activation = 'relu'))
    model.add(keras.layers.MaxPooling2D(pool_size = (2, 2)))

    # Second block
    model.add(keras.layers.Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu'))
    model.add(keras.layers.MaxPooling2D(pool_size = (2, 2)))

    # Flatten
    model.add(keras.layers.Flatten())

    # Fully connected layer
    model.add(keras.layers.Dense(64, activation = 'relu'))

    # Output layer -> 9 units (number of classes) + softmax (probability output)
    model.add(keras.layers.Dense(9, activation = 'softmax'))

    model.compile(
        optimizer = "Adam",
        loss = 'sparse_categorical_crossentropy',
        metrics = ['accuracy']
    )

    return model
```

In [137…

```python
baseline_model_cnn = build_cnn_baseline()

baseline_model_cnn.fit(
    X_train_nn, y_train_nn,
    epochs = 10,
    validation_data = (X_valid, y_valid)
)
```

```
Epoch 1/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - accuracy: 0.3580 - loss: 1.6963 - val_accuracy: 0.5959 - val_loss: 1.0724
Epoch 2/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - accuracy: 0.6150 - loss: 1.0454 - val_accuracy: 0.6684 - val_loss: 0.9090
Epoch 3/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.6680 - loss: 0.9121 - val_accuracy: 0.6953 - val_loss: 0.8379
Epoch 4/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - accuracy: 0.7061 - loss: 0.8190 - val_accuracy: 0.7444 - val_loss: 0.7355
Epoch 5/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - accuracy: 0.7274 - loss: 0.7643 - val_accuracy: 0.7541 - val_loss: 0.6962
Epoch 6/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.7362 - loss: 0.7329 - val_accuracy: 0.7544 - val_loss: 0.6979
Epoch 7/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.7460 - loss: 0.7018 - val_accuracy: 0.7584 - val_loss: 0.6869
Epoch 8/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - accuracy: 0.7605 - loss: 0.6670 - val_accuracy: 0.7628 - val_loss: 0.6732
Epoch 9/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - accuracy: 0.7691 - loss: 0.6373 - val_accuracy: 0.7700 - val_loss: 0.6555
Epoch 10/10
900/900 ━━━━━━━━━━━━━━━━━━━━ 6s 6ms/step - accuracy: 0.7755 - loss: 0.6200 - val_accuracy: 0.7788 - val_loss: 0.6232
```

Out[137… `<keras.src.callbacks.history.History at 0x314f68620>`

In [138…
```python
loss_base_cnn, acc_base_cnn = baseline_model_cnn.evaluate(X_test_scale, y_test)
print(f"Baseline Test Accuracy: {acc_base_cnn:.4f}")
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7769 - loss: 0.6142
Baseline Test Accuracy: 0.7739
```

In [139…
```python
y_pred = baseline_model_cnn.predict(X_test_scale)
y_pred_labels = np.argmax(y_pred, axis=1)

print(classification_report(y_test, y_pred_labels))
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
              precision    recall  f1-score   support

           0       0.86      0.97      0.91       873
           1       0.98      0.92      0.95       858
           2       0.63      0.65      0.64       877
           3       0.97      0.89      0.93       914
           4       0.72      0.77      0.74       737
           5       0.67      0.83      0.75      1072
           6       0.66      0.62      0.64       682
           7       0.59      0.50      0.54       813
           8       0.85      0.75      0.80      1174

    accuracy                           0.77      8000
   macro avg       0.77      0.77      0.77      8000
weighted avg       0.78      0.77      0.77      8000
```

Algorithm Design - CNN

- The model includes **three convolutional layers**, with increasing filters, followed by a fully connected layer and output layer.
  - Input: (28, 28, 3)
  - Conv2D → MaxPooling2D → Dropout
  - Conv2D (filters × 2) → MaxPooling2D → Dropout
  - Conv2D (filters × 2)
  - Flatten
  - Dense (filters × 2) → Dropout
  - Dense(9) with softmax activation
- **Key hyperparameters tuned:**
  - filters: Controls the number of feature detectors [32, 64, 128]
  - dropout_rate: Controls the regularization strength [0.2 - 0.5]
  - learning_rate: Tuned on a log scale [1e-4 - 1e-2]
- The core architecture of the baseline is retained, but the flexibility is enhanced → making it easier to optimize performance in Keras Tuner

In [169…
```python
def build_cnn(hp):
    model = keras.models.Sequential()
    # Input layer - accepts images with shape (28, 28, 3)
    model.add(keras.layers.Input(shape=(28, 28, 3)))

    # Hyperparameters to tune - filters and dropout rate
    filters = hp.Choice('filters', values=[32, 64, 128])       # Controls model capacity
    dropout_rate = hp.Float('dropout_rate', 0.2, 0.5, step=0.1) # Prevent overfitting

    # First block
    model.add(keras.layers.Conv2D(filters, kernel_size=(3, 3), activation='relu'))
    model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
```

```
    model.add(keras.layers.Dropout(dropout_rate))          # Prevent overfitting


    # Second block
    model.add(keras.layers.Conv2D(filters * 2, kernel_size=(3, 3), activation='relu'))
    model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
    model.add(keras.layers.Dropout(dropout_rate))          # Prevent overfitting


    # Third block - no pooling
    model.add(keras.layers.Conv2D(filters * 2, kernel_size=(3, 3), activation='relu'))


    # Flatten
    model.add(keras.layers.Flatten())


    # Fully connected layer
    model.add(keras.layers.Dense(filters * 2, activation='relu'))
    # Dropout after dense layer - prevents reliance on specific neurons
    model.add(keras.layers.Dropout(dropout_rate))

    # Output layer -> 9 units (number of classes) + softmax (probability output)
    model.add(keras.layers.Dense(9, activation='softmax'))

    model.compile(
        optimizer=keras.optimizers.Adam(
            learning_rate=hp.Float('lr', 1e-4, 1e-2, sampling='log')
        ),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )

    return model
```

3. Hyperparameter tuning

Algorithm of choice from first six weeks of course - Random Forest

- **GridSearchCV** already performs cross-validation internally (cv=5):
- It will **automatically split** the provided X_train_rf, y_train into 5 folds;
- Each fold is internally divided into **train/validation sets** to evaluate the performance of different parameter combinations.

In [104…

```
# Define the parameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'max_features': ['sqrt', 'log2']
}

# Grid search
grid_search_rf = GridSearchCV(rf, param_grid, cv=5)
grid_search_rf.fit(X_train_rf, y_train)

# Print the best parameters
best_params_rf = grid_search_rf.best_params_
print("Best hyperparameters:", best_params_rf)
```

```
Best hyperparameters: {'max_depth': 30, 'max_features': 'sqrt', 'min_samples_split': 5, 'n_estimators': 200}
```

Visualization

In [106…

```
# Convert the grid search results into a DataFrame
cv_results = pd.DataFrame(grid_search_rf.cv_results_)

cv_summary = cv_results[[
    'param_n_estimators',
    'param_max_depth',
    'param_min_samples_split',
    'param_max_features',
    'mean_test_score',
    'mean_fit_time'
]]
cv_sorted = cv_summary.sort_values(by='mean_test_score', ascending=False)

# Print all parameter combinations - training time + accuracy
print(cv_sorted)

# Export - plotting / analysis in the report
cv_sorted.to_csv('rf_gridsearch_results.csv', index=False)
```

	param_n_estimators	param_max_depth	param_min_samples_split	\
41	200	30	5	
44	200	30	10	
38	200	30	2	
23	200	20	5	
26	200	20	10	
20	200	20	2	
40	100	30	5	
47	200	30	2	
43	100	30	10	
53	200	30	10	
32	200	20	5	
50	200	30	5	
35	200	20	10	
29	200	20	2	
37	100	30	2	
22	100	20	5	
19	100	20	2	
25	100	20	10	
52	100	30	10	
34	100	20	10	
46	100	30	2	
31	100	20	5	
49	100	30	5	
28	100	20	2	
42	50	30	10	
24	50	20	10	
39	50	30	5	
21	50	20	5	
18	50	20	2	
36	50	30	2	
51	50	30	10	
33	50	20	10	
48	50	30	5	
30	50	20	5	
45	50	30	2	
27	50	20	2	
5	200	10	5	
2	200	10	2	
8	200	10	10	
4	100	10	5	
7	100	10	10	
1	100	10	2	
3	50	10	5	
0	50	10	2	
6	50	10	10	
14	200	10	5	
17	200	10	10	
11	200	10	2	
13	100	10	5	
10	100	10	2	
16	100	10	10	
12	50	10	5	
15	50	10	10	
9	50	10	2	

	param_max_features	mean_test_score	mean_fit_time
41	sqrt	0.649875	100.701498
44	sqrt	0.648438	98.852448
38	sqrt	0.648344	102.206669
23	sqrt	0.647969	97.191994
26	sqrt	0.646563	94.642976
20	sqrt	0.645844	98.557626
40	sqrt	0.638281	50.370415
47	log2	0.638281	26.814444
43	sqrt	0.638000	49.346964
53	log2	0.637656	24.391276
32	log2	0.637406	24.600942
50	log2	0.637312	25.593390
35	log2	0.636656	23.699626
29	log2	0.636500	25.183181
37	sqrt	0.635938	50.404275
22	sqrt	0.635125	48.426561
19	sqrt	0.634844	49.522002
25	sqrt	0.634375	47.036766
52	log2	0.627500	12.496703
34	log2	0.626125	11.847130
46	log2	0.626063	13.893486
31	log2	0.624500	12.348277
49	log2	0.623563	13.800292
28	log2	0.622937	12.593124
42	sqrt	0.620250	25.940749
24	sqrt	0.618125	23.637237
39	sqrt	0.616781	25.900678
21	sqrt	0.614469	24.408040

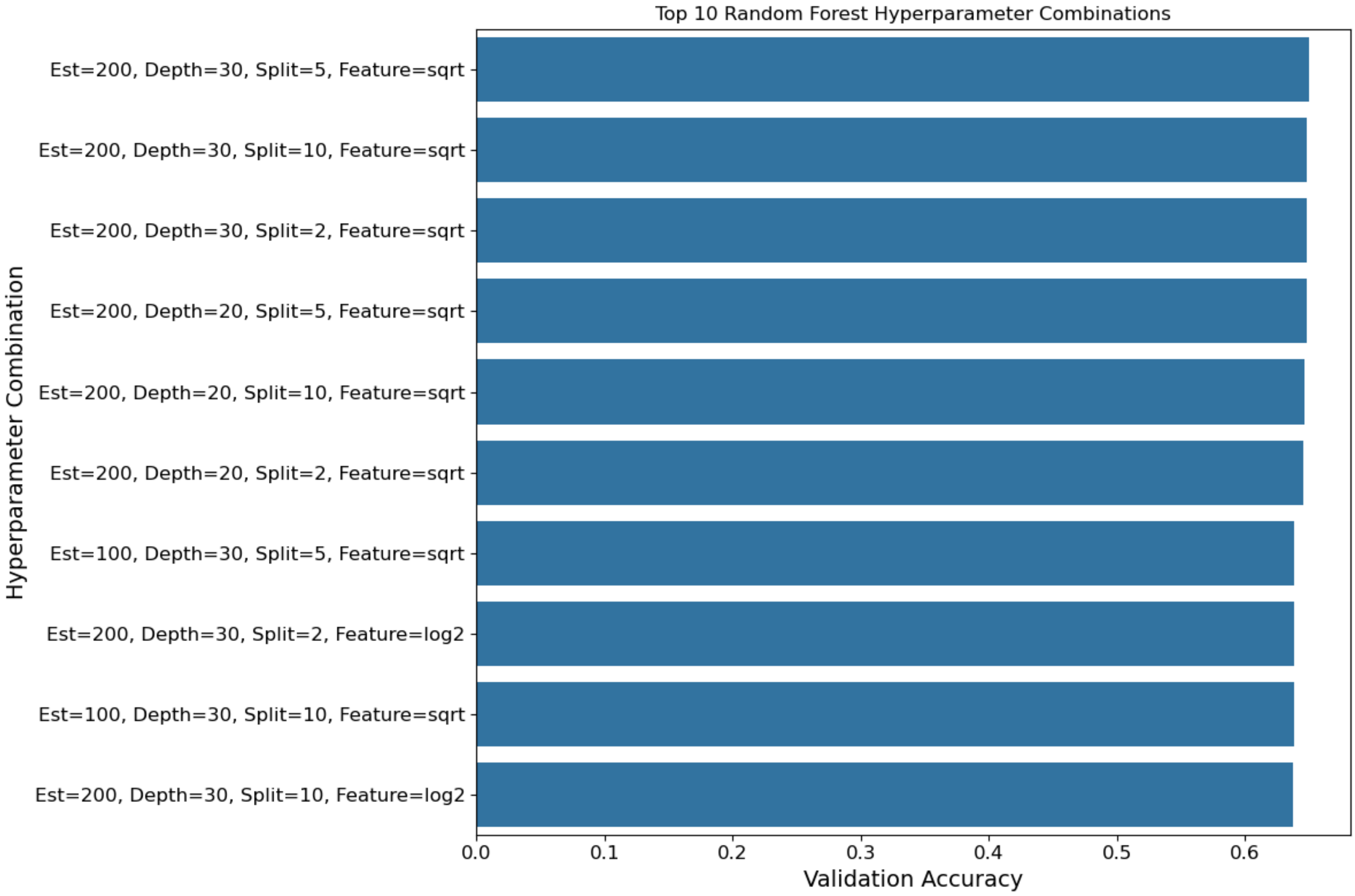
```
18              sqrt        0.613125     24.726600
36              sqrt        0.610188     25.274157
51              log2        0.608750      6.098683
33              log2        0.608563      5.918097
48              log2        0.605312      7.089012
30              log2        0.604344      6.219662
45              log2        0.601344      7.064115
27              log2        0.599969      6.304334
5               sqrt        0.598781     60.620036
2               sqrt        0.597844     60.488921
8               sqrt        0.597469     60.157498
4               sqrt        0.593094     30.299843
7               sqrt        0.592844     30.079155
1               sqrt        0.590281     31.041808
3               sqrt        0.582937     14.953385
0               sqrt        0.582469     16.248459
6               sqrt        0.581187     15.224582
14              log2        0.581094     14.999165
17              log2        0.580844     14.800021
11              log2        0.579719     15.064560
13              log2        0.575937      7.542744
10              log2        0.574625      7.452049
16              log2        0.574281      7.424692
12              log2        0.568188      3.824771
15              log2        0.566156      3.758625
9               log2        0.564875      3.946650
```

In [106…

```
rf_df = pd.read_csv('rf_gridsearch_results.csv')

# Create tag
rf_df['param_combo'] = (
    'Est=' + rf_df['param_n_estimators'].astype(str) +
    ', Depth=' + rf_df['param_max_depth'].astype(str) +
    ', Split=' + rf_df['param_min_samples_split'].astype(str) +
    ', Feature=' + rf_df['param_max_features'].astype(str)
)
```

In [106…

```
# Sort by accuracy - DESC
rf_sorted = rf_df.sort_values(by='mean_test_score', ascending=False)

# Plot
plt.figure(figsize=(12, 8))
sns.barplot(x='mean_test_score', y='param_combo', data=rf_sorted.head(10))
plt.xlabel('Validation Accuracy')
plt.ylabel('Hyperparameter Combination')
plt.title('Top 10 Random Forest Hyperparameter Combinations')
plt.tight_layout()
plt.show()
```



Fully connected neural network

In [824…

```
# Use Random Search
tuner_mlp = kt.RandomSearch(
    hypermodel = build_mlp,
    objective = 'val_accuracy',
    max_trials = 30,                 # Search 30 different hyperparameter combinations
    executions_per_trial = 1,        # Run each combination once
    overwrite = True,                # Overwrite previous results
    directory = 'keras_tuning_results', # Results folder
    project_name = 'mlp'
)

# Stop if no improvement for 5 consecutive epochs - reduce the computing time
early_stopping = EarlyStopping(
    monitor = 'val_accuracy',
    patience = 5,
    restore_best_weights = True
)

# Print a summary of the search
tuner_mlp.search_space_summary()

# Hyperparameter search
tuner_mlp.search(
    X_train_nn, y_train_nn,
    epochs = 30,
    validation_data = (X_valid, y_valid),
    callbacks=[early_stopping]
)
```

```
Trial 30 Complete [00h 00m 39s]
val_accuracy: 0.1471875011920929

Best val_accuracy So Far: 0.5512499809265137
Total elapsed time: 00h 22m 46s
```

Visualization

In [825…

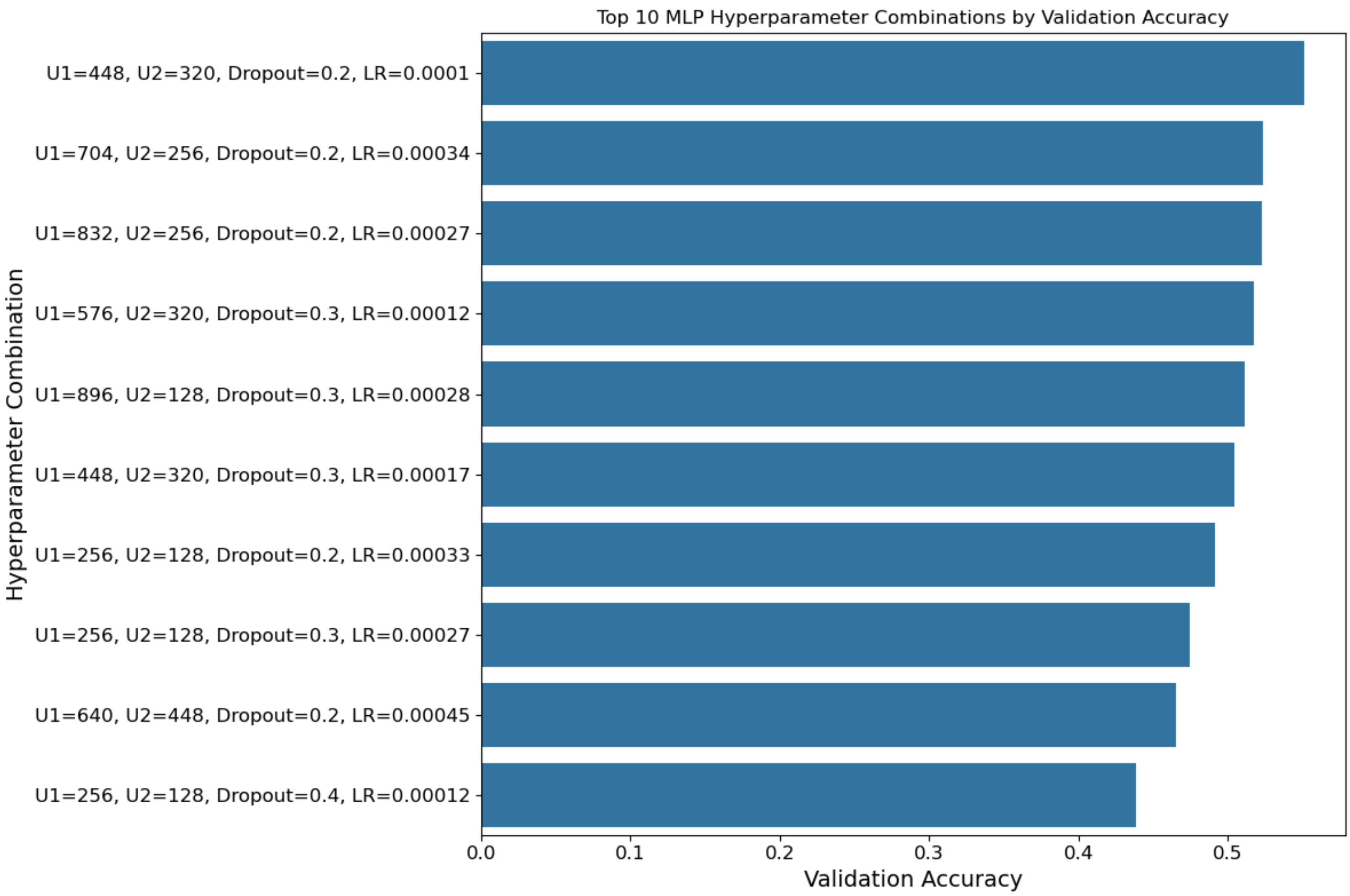
```
# Retrieve the top 10 best performing trials from the MLP tuner
mlp_trials = tuner_mlp.oracle.get_best_trials(num_trials=10)

# Format the results
mlp_records = []
for trial in mlp_trials:
```

```
    record = trial.hyperparameters.values.copy()
    record['score'] = trial.score                # this is the final val_accuracy
    best_epoch = trial.metrics.get_best_step('val_accuracy')  # epoch with best performance
    record['best_epoch'] = best_epoch + 1        # +1 to make epoch indexing start from 1
    mlp_records.append(record)

# Convert the records into a DataFrame
mlp_df = pd.DataFrame(mlp_records)
print(mlp_df)

# Save the results
mlp_df.to_csv('mlp_tuner_results.csv', index=False)
```

```
   dropout_rate  units_1  units_2        lr     score  best_epoch
0           0.2      448      320  0.000104  0.551250          28
1           0.2      704      256  0.000338  0.523438           9
2           0.2      832      256  0.000267  0.522500          14
3           0.3      576      320  0.000122  0.517812          22
4           0.3      896      128  0.000277  0.511250          17
5           0.3      448      320  0.000171  0.504375          12
6           0.2      256      128  0.000335  0.491250          10
7           0.3      256      128  0.000275  0.474687          10
8           0.2      640      448  0.000454  0.465000           3
9           0.4      256      128  0.000122  0.438750          12
```

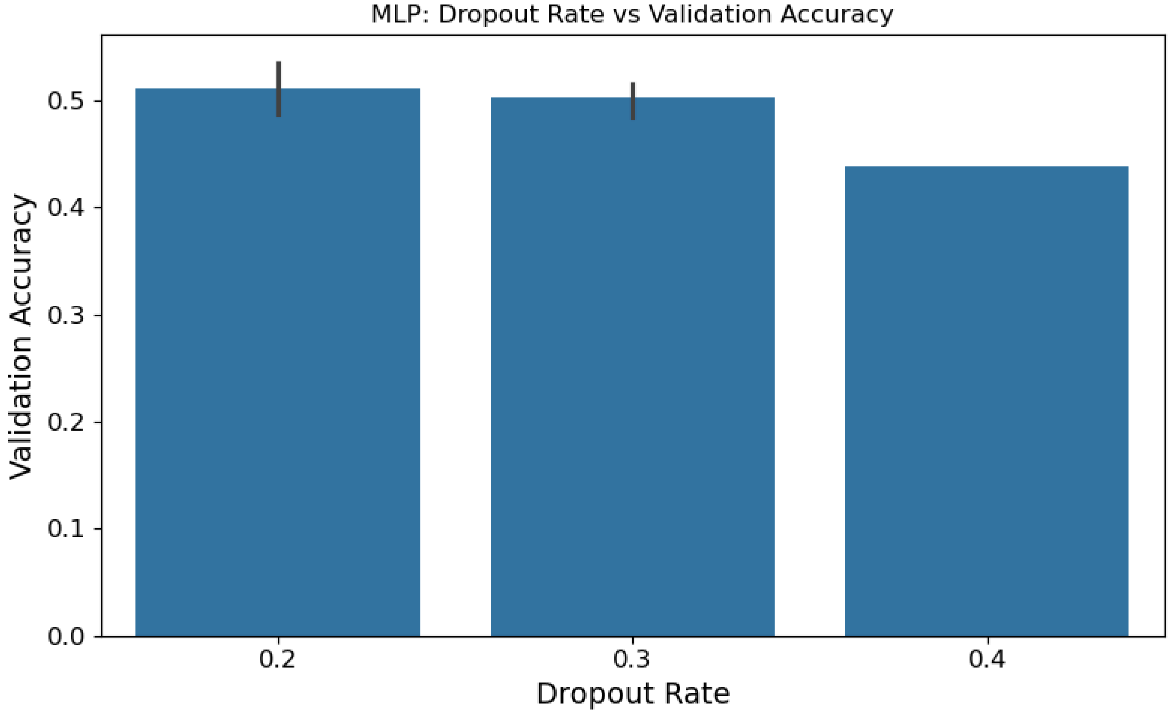
In [834…

```
mlp_df = pd.read_csv('mlp_tuner_results.csv')

# Create tag
mlp_df['param_combo'] = (
    'U1=' + mlp_df['units_1'].astype(str) +
    ', U2=' + mlp_df['units_2'].astype(str) +
    ', Dropout=' + mlp_df['dropout_rate'].astype(str) +
    ', LR=' + mlp_df['lr'].round(5).astype(str)
)

# Sort by accuracy - DESC
mlp_df_sorted = mlp_df.sort_values('score', ascending=False)

# barplot (top 10 hyperparameter combinations)
plt.figure(figsize=(12, 8))
sns.barplot(x='score', y='param_combo', data=mlp_df_sorted.head(10))
plt.xlabel('Validation Accuracy')
plt.ylabel('Hyperparameter Combination')
plt.title('Top 10 MLP Hyperparameter Combinations by Validation Accuracy')
plt.tight_layout()
plt.show()
```



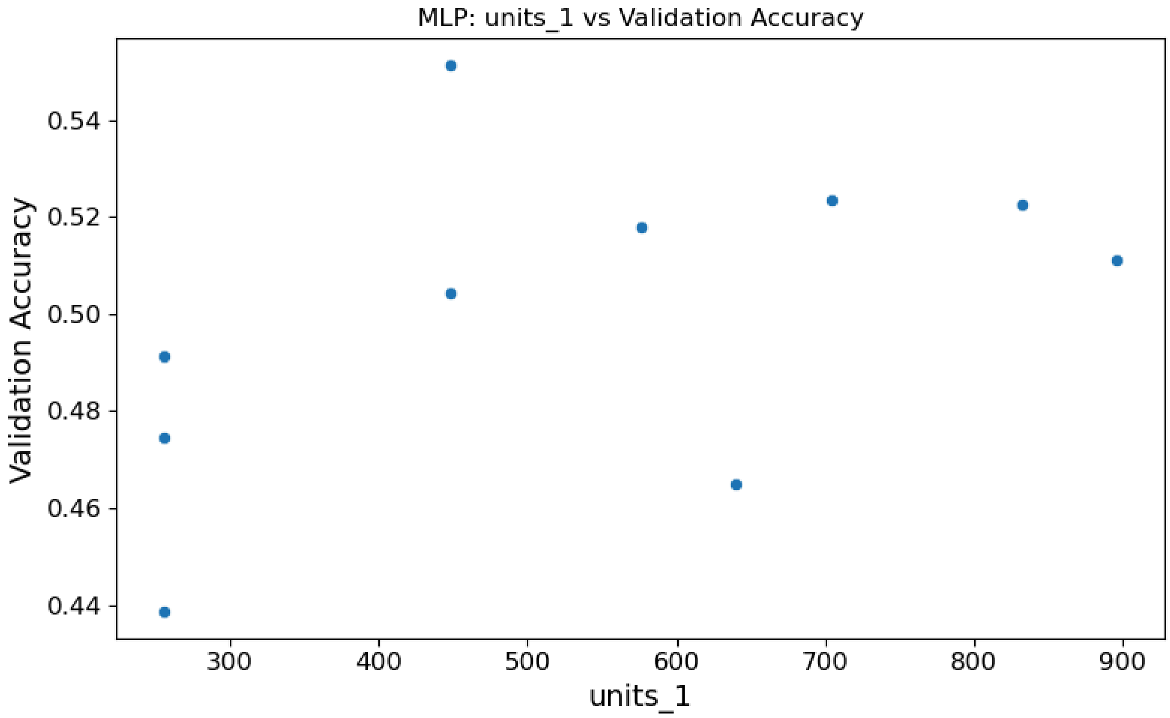
In [836…

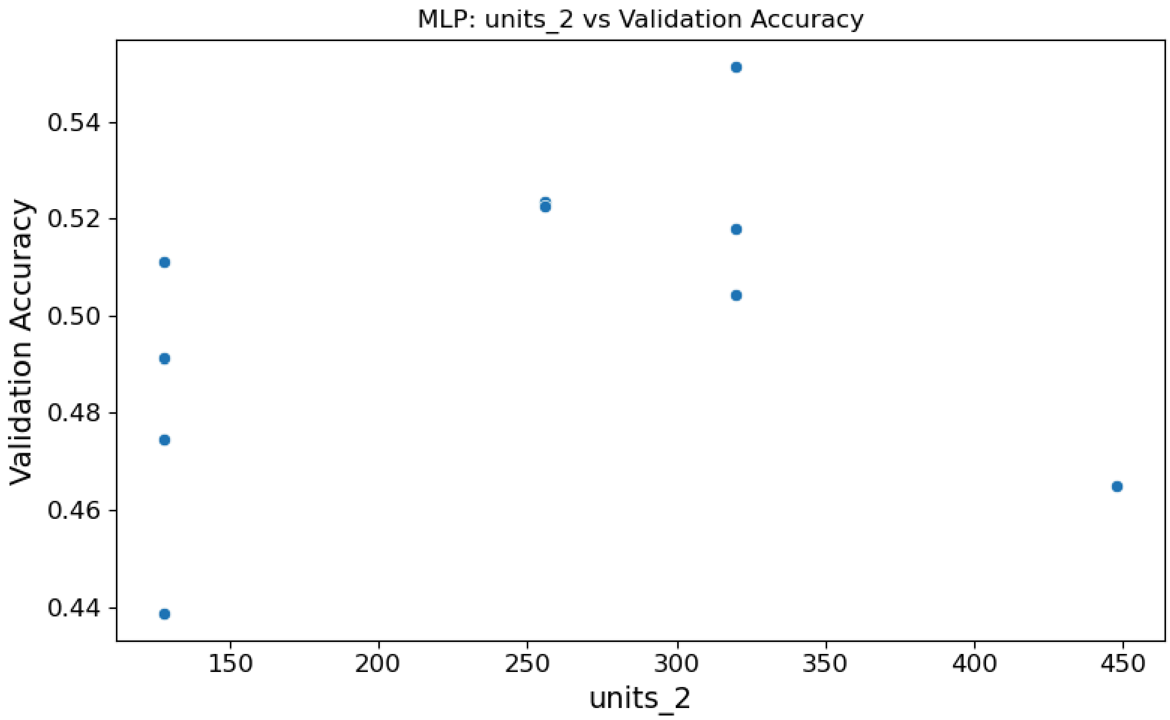
```
# Dropout Rate vs Validation Accuracy (bar)
plt.figure(figsize=(8, 5))
sns.barplot(x='dropout_rate', y='score', data=mlp_df)
plt.title('MLP: Dropout Rate vs Validation Accuracy')
plt.xlabel('Dropout Rate')
plt.ylabel('Validation Accuracy')
plt.tight_layout()
plt.show()
```



In [838…

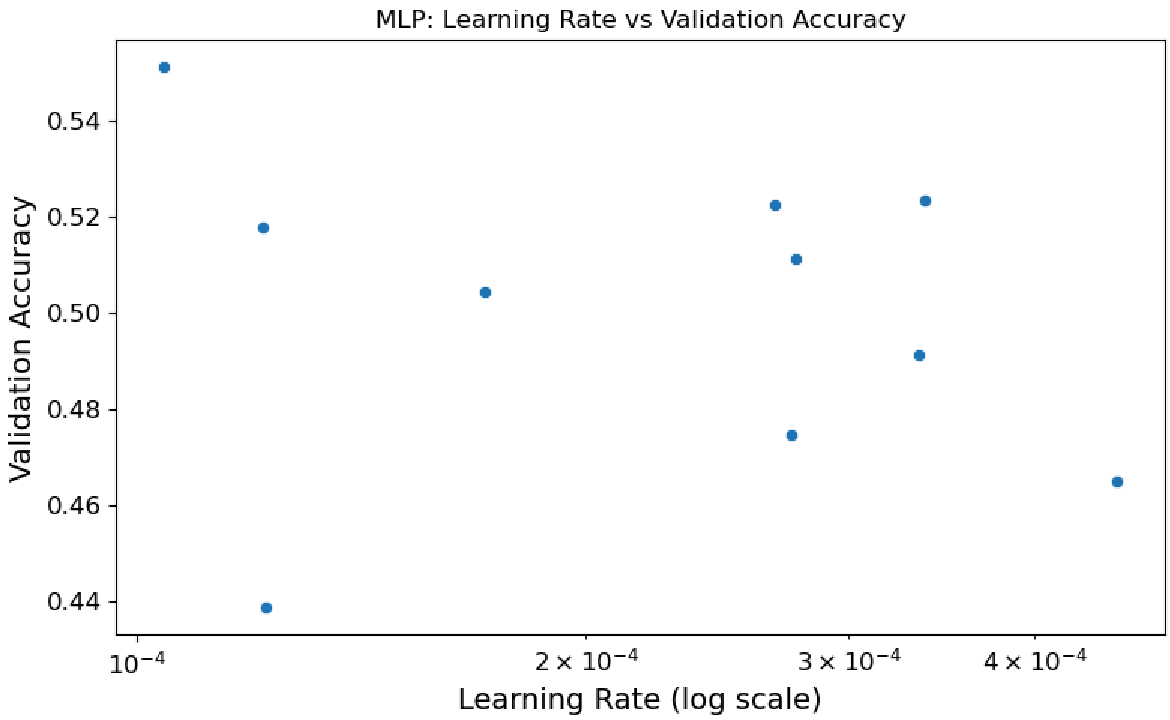
```
# Dense Layer Units vs Accuracy (scatter)
for units in ['units_1', 'units_2']:
    plt.figure(figsize=(8, 5))
    sns.scatterplot(x=units, y='score', data=mlp_df)
    plt.title(f'MLP: {units} vs Validation Accuracy')
    plt.xlabel(units)
    plt.ylabel('Validation Accuracy')
    plt.tight_layout()
    plt.show()
```





In [840…

```
# Learning Rate vs Accuracy (log scale)
plt.figure(figsize=(8, 5))
sns.scatterplot(x='lr', y='score', data=mlp_df)
plt.xscale('log')
plt.title('MLP: Learning Rate vs Validation Accuracy')
plt.xlabel('Learning Rate (log scale)')
plt.ylabel('Validation Accuracy')
plt.tight_layout()
plt.show()
```



Validation Model with Best Hyperparameters

To evaluate the training dynamics of the MLP model under the best-performing hyperparameter combination, we manually rebuild the model using:

- units_1 = 448
- units_2 = 320
- dropout_rate = 0.2
- learning_rate = 0.000104

We train the model for a fixed number of 28 epochs, and **plot the accuracy and loss curves** on both the training and validation sets. This helps us:

- Visualize the learning process
- Detect overfitting by comparing the gap between training and validation performance
- Decide whether to adjust the number of training epochs

This step ensures the chosen architecture and parameters generalize well

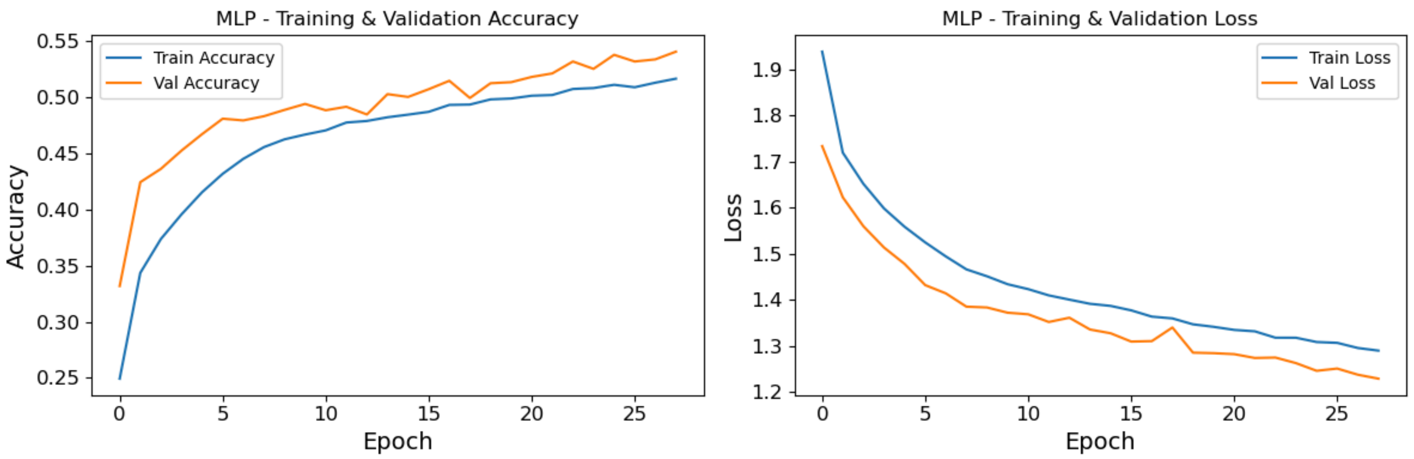
In [103…

```
def valid_mlp():
    model = keras.models.Sequential()
    model.add(keras.layers.Input(shape = (28, 28, 3)))
    model.add(keras.layers.Flatten())

    # Fixed parameters
    model.add(keras.layers.Dense(448, activation = 'relu'))
    model.add(keras.layers.Dropout(0.2))

    model.add(keras.layers.Dense(320, activation = 'relu'))
    model.add(keras.layers.Dropout(0.2))

    model.add(keras.layers.Dense(9, activation = 'softmax'))

    model.compile(
        optimizer = keras.optimizers.Adam(learning_rate = 0.000104),
        loss = 'sparse_categorical_crossentropy',
        metrics = ['accuracy']
    )

    return model
```

In [103…

```
# Fixed epoch = 28
valid = valid_mlp()
history_mlp = valid.fit(
    X_train_nn, y_train_nn,
    epochs = 28,
    validation_data = (X_valid, y_valid)
)

# Accuracy
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history_mlp.history['accuracy'], label='Train Accuracy')
plt.plot(history_mlp.history['val_accuracy'], label='Val Accuracy')
plt.title('MLP - Training & Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history_mlp.history['loss'], label='Train Loss')
plt.plot(history_mlp.history['val_loss'], label='Val Loss')
plt.title('MLP - Training & Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```

```
Epoch 1/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.2102 - loss: 2.0610 - val_accuracy: 0.3319 - val_loss: 1.7335
Epoch 2/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.3328 - loss: 1.7473 - val_accuracy: 0.4244 - val_loss: 1.6226
Epoch 3/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.3655 - loss: 1.6722 - val_accuracy: 0.4363 - val_loss: 1.5599
Epoch 4/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.3922 - loss: 1.6142 - val_accuracy: 0.4525 - val_loss: 1.5138
Epoch 5/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4119 - loss: 1.5735 - val_accuracy: 0.4672 - val_loss: 1.4783
Epoch 6/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4300 - loss: 1.5354 - val_accuracy: 0.4809 - val_loss: 1.4324
Epoch 7/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4442 - loss: 1.5056 - val_accuracy: 0.4794 - val_loss: 1.4145
Epoch 8/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4529 - loss: 1.4777 - val_accuracy: 0.4831 - val_loss: 1.3857
Epoch 9/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4617 - loss: 1.4631 - val_accuracy: 0.4888 - val_loss: 1.3839
Epoch 10/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4605 - loss: 1.4474 - val_accuracy: 0.4941 - val_loss: 1.3726
Epoch 11/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4662 - loss: 1.4349 - val_accuracy: 0.4884 - val_loss: 1.3691
Epoch 12/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4701 - loss: 1.4228 - val_accuracy: 0.4916 - val_loss: 1.3525
Epoch 13/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.4791 - loss: 1.4091 - val_accuracy: 0.4847 - val_loss: 1.3617
Epoch 14/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4770 - loss: 1.4035 - val_accuracy: 0.5028 - val_loss: 1.3362
Epoch 15/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4816 - loss: 1.3957 - val_accuracy: 0.5003 - val_loss: 1.3280
Epoch 16/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4855 - loss: 1.3877 - val_accuracy: 0.5072 - val_loss: 1.3100
Epoch 17/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4914 - loss: 1.3748 - val_accuracy: 0.5147 - val_loss: 1.3110
Epoch 18/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.4905 - loss: 1.3719 - val_accuracy: 0.4994 - val_loss: 1.3405
Epoch 19/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.4948 - loss: 1.3606 - val_accuracy: 0.5125 - val_loss: 1.2860
Epoch 20/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4968 - loss: 1.3550 - val_accuracy: 0.5134 - val_loss: 1.2849
Epoch 21/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.5023 - loss: 1.3446 - val_accuracy: 0.5181 - val_loss: 1.2828
Epoch 22/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5007 - loss: 1.3436 - val_accuracy: 0.5213 - val_loss: 1.2745
Epoch 23/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5032 - loss: 1.3289 - val_accuracy: 0.5319 - val_loss: 1.2754
Epoch 24/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5054 - loss: 1.3291 - val_accuracy: 0.5253 - val_loss: 1.2633
Epoch 25/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5082 - loss: 1.3197 - val_accuracy: 0.5378 - val_loss: 1.2467
Epoch 26/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5049 - loss: 1.3186 - val_accuracy: 0.5319 - val_loss: 1.2515
Epoch 27/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.5128 - loss: 1.3020 - val_accuracy: 0.5337 - val_loss: 1.2382
Epoch 28/28
900/900 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5162 - loss: 1.3009 - val_accuracy: 0.5406 - val_loss: 1.2297
```



Convolutional neural network

In [919…

```python
# Use Random Search
tuner_cnn = kt.RandomSearch(
    hypermodel = build_cnn,
    objective = 'val_accuracy',
    max_trials = 10,                # Search 10 different hyperparameter combinations
    executions_per_trial = 1,       # Run each combination once
```

```
    overwrite = True,                   # Overwrite previous results
    directory = 'keras_tuning_results',  # Results folder
    project_name = 'cnn'
)

# Early stopping has already defined in the previous(mlp) part
# Print a summary of the search
tuner_cnn.search_space_summary()

# Hyperparameter search
tuner_cnn.search(
    X_train_nn, y_train_nn,
    epochs = 30,
    validation_data = (X_valid, y_valid),
    callbacks = [early_stopping]
)

tuner_cnn.results_summary()
```

```
Trial 10 Complete [00h 01m 34s]
val_accuracy: 0.7799999713897705

Best val_accuracy So Far: 0.8853124976158142
Total elapsed time: 01h 13m 59s
Results summary
Results in keras_tuning_results/cnn
Showing 10 best trials
Objective(name="val_accuracy", direction="max")

Trial 04 summary
Hyperparameters:
filters: 128
dropout_rate: 0.30000000000000004
lr: 0.00013612460334701279
Score: 0.8853124976158142

Trial 05 summary
Hyperparameters:
filters: 64
dropout_rate: 0.30000000000000004
lr: 0.0002458321717641159
Score: 0.8678125143051147

Trial 02 summary
Hyperparameters:
filters: 128
dropout_rate: 0.30000000000000004
lr: 0.00011641658137192351
Score: 0.8668749928474426

Trial 01 summary
Hyperparameters:
filters: 128
dropout_rate: 0.30000000000000004
lr: 0.0006529927317508998
Score: 0.8615624904632568

Trial 07 summary
Hyperparameters:
filters: 64
dropout_rate: 0.2
lr: 0.00018974491572285046
Score: 0.8578125238418579

Trial 06 summary
Hyperparameters:
filters: 128
dropout_rate: 0.4
lr: 0.0007506269481542165
Score: 0.8518750071525574

Trial 09 summary
Hyperparameters:
filters: 32
dropout_rate: 0.30000000000000004
lr: 0.0013960407115272237
Score: 0.7799999713897705

Trial 00 summary
Hyperparameters:
filters: 32
dropout_rate: 0.4
lr: 0.0012158303534721207
Score: 0.7584375143051147

Trial 03 summary
Hyperparameters:
filters: 64
dropout_rate: 0.2
lr: 0.006172427728586157
Score: 0.4568749964237213

Trial 08 summary
Hyperparameters:
filters: 64
dropout_rate: 0.2
lr: 0.008779360094579483
Score: 0.14687499403953552
```

Visualization

In [921…

```
# Retrieve the top 10 best performing trials from the CNN tuner
cnn_trials = tuner_cnn.oracle.get_best_trials(num_trials=10)
```

```python
# Format the results
cnn_records = []
for trial in cnn_trials:
    record = trial.hyperparameters.values.copy()
    record['score'] = trial.score                         # this is the final val accuracy
    record['best_epoch'] = trial.metrics.get_best_step('val_accuracy') + 1 # epoch with best performance
    cnn_records.append(record)                            # +1 to make epoch indexing start from 1

# Convert the records into a DataFrame
cnn_df = pd.DataFrame(cnn_records)
print(cnn_df)

# Save the results
cnn_df.to_csv('cnn_tuner_results.csv', index=False)
```

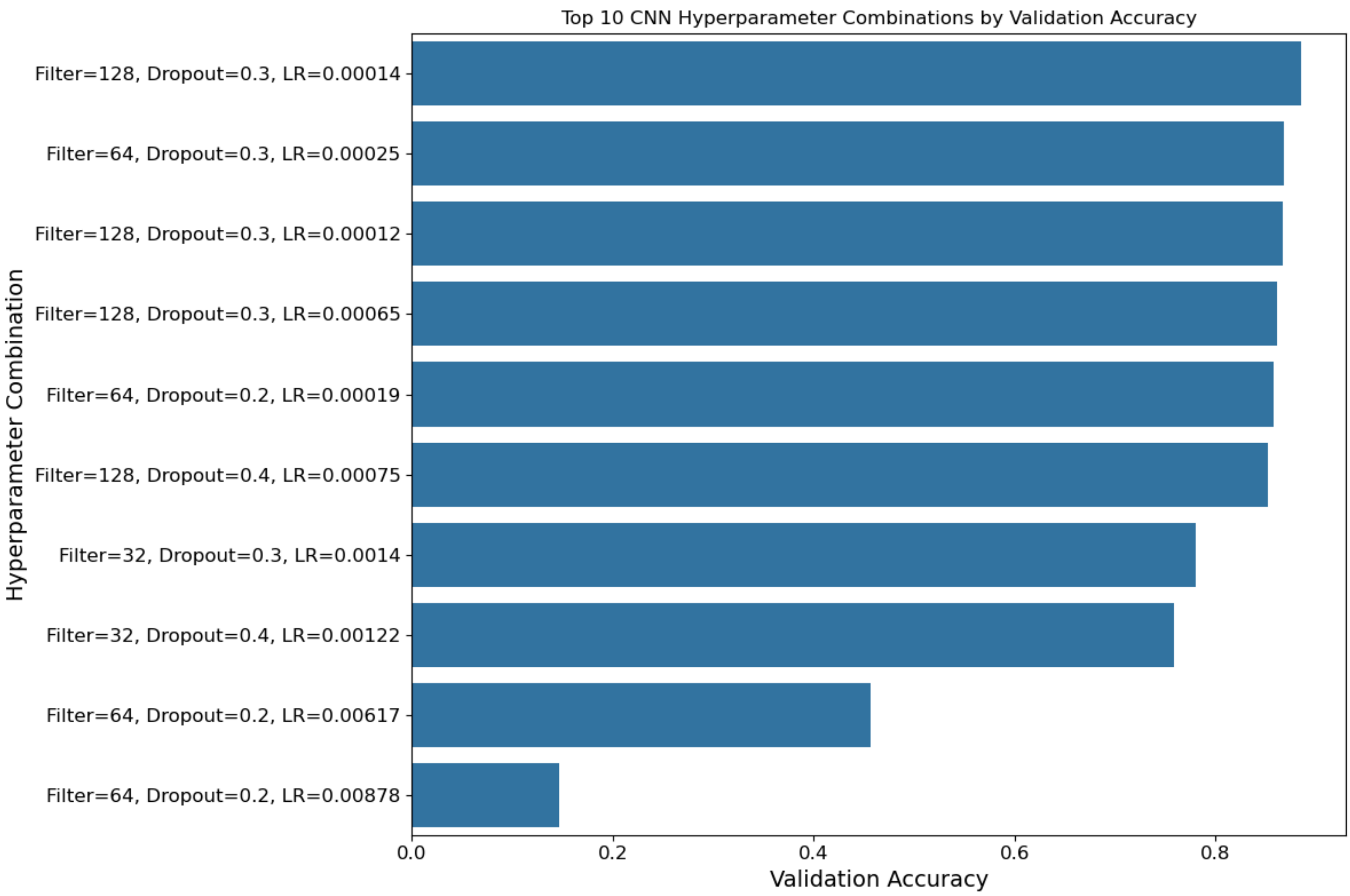
```
   filters  dropout_rate        lr     score  best_epoch
0      128           0.3  0.000136  0.885312          30
1       64           0.3  0.000246  0.867813          29
2      128           0.3  0.000116  0.866875          29
3      128           0.3  0.000653  0.861562          25
4       64           0.2  0.000190  0.857813          30
5      128           0.4  0.000751  0.851875          30
6       32           0.3  0.001396  0.780000          13
7       32           0.4  0.001216  0.758438          25
8       64           0.2  0.006172  0.456875          12
9       64           0.2  0.008779  0.146875           1
```

In [932…

```python
cnn_df = pd.read_csv('cnn_tuner_results.csv')

# Create tag
cnn_df['param_combo'] = (
    'Filter=' + cnn_df['filters'].astype(str) +
    ', Dropout=' + cnn_df['dropout_rate'].astype(str) +
    ', LR=' + cnn_df['lr'].round(5).astype(str)
)
```

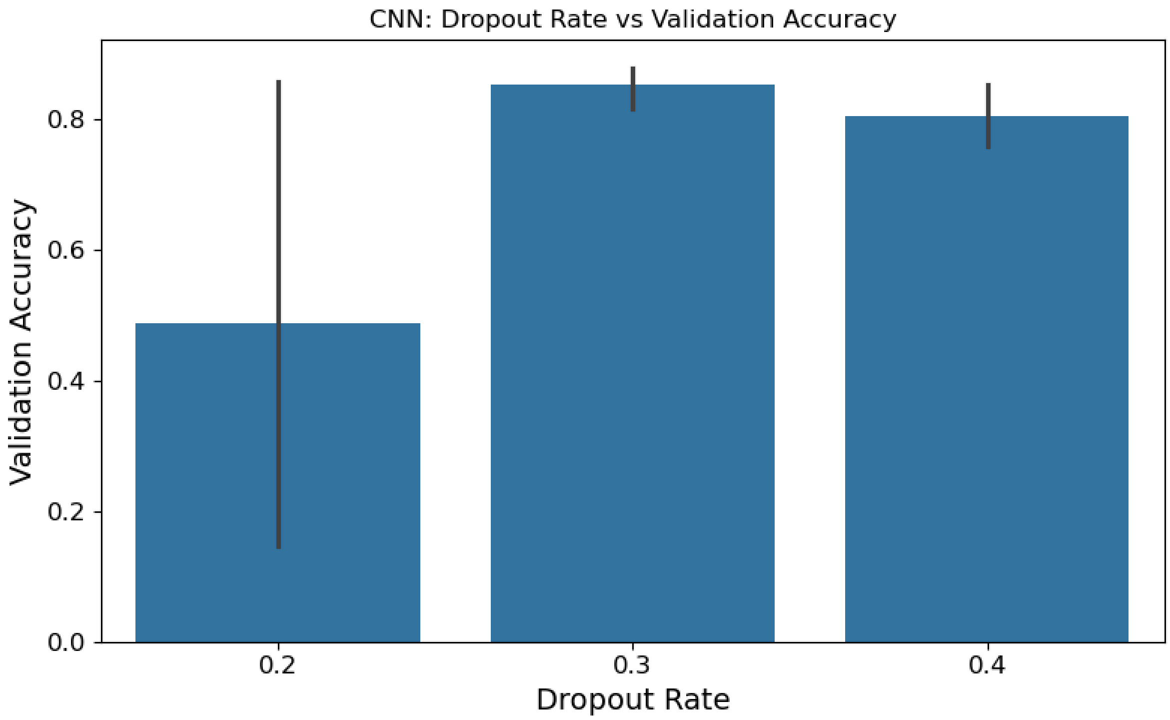
In [934…

```python
# Sort by accuracy - DESC
cnn_df_sorted = cnn_df.sort_values('score', ascending=False)

# barplot (top 10 hyperparameter combinations)
plt.figure(figsize=(12, 8))
sns.barplot(x='score', y='param_combo', data=cnn_df_sorted.head(10))
plt.xlabel('Validation Accuracy')
plt.ylabel('Hyperparameter Combination')
plt.title('Top 10 CNN Hyperparameter Combinations by Validation Accuracy')
plt.tight_layout()
plt.show()
```



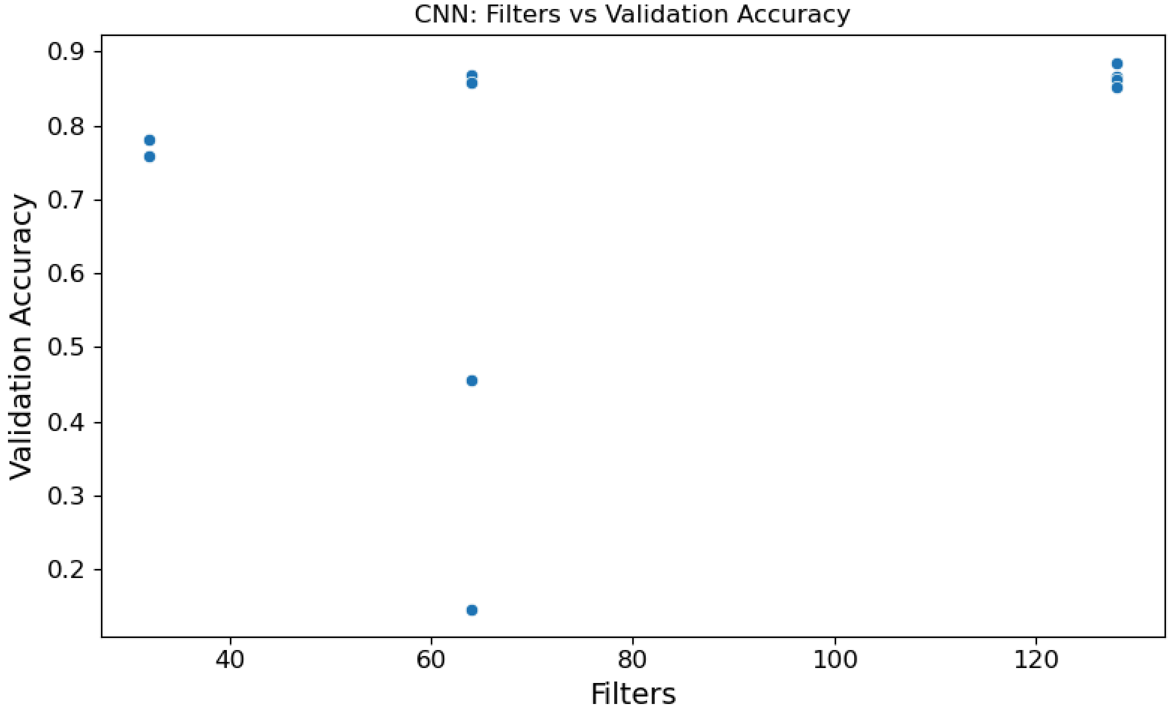
In [936…

```
# Dropout Rate vs Validation Accuracy (bar)
plt.figure(figsize=(8, 5))
sns.barplot(x='dropout_rate', y='score', data=cnn_df)
plt.title('CNN: Dropout Rate vs Validation Accuracy')
plt.xlabel('Dropout Rate')
plt.ylabel('Validation Accuracy')
plt.tight_layout()
plt.show()
```



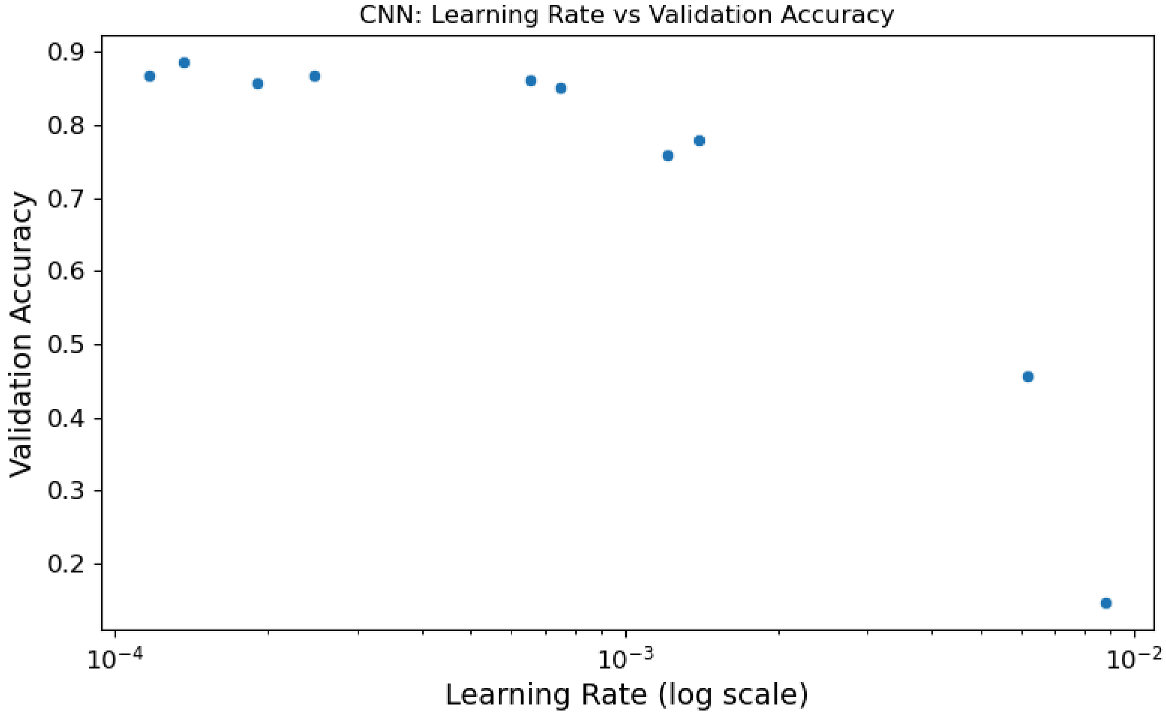
In [942…

```
# Dense Units vs Validation Accuracy (scatter)
plt.figure(figsize=(8, 5))
sns.scatterplot(x='filters', y='score', data=cnn_df)
plt.title('CNN: Filters vs Validation Accuracy')
plt.xlabel('Filters')
plt.ylabel('Validation Accuracy')
plt.tight_layout()
plt.show()
```



In [944…

```
# Learning Rate vs Validation Accuracy (log scale)
plt.figure(figsize=(8, 5))
sns.scatterplot(x='lr', y='score', data=cnn_df)
plt.xscale('log')
plt.title('CNN: Learning Rate vs Validation Accuracy')
plt.xlabel('Learning Rate (log scale)')
plt.ylabel('Validation Accuracy')
plt.tight_layout()
plt.show()
```



Validation Model with Best Hyperparameters

To evaluate the training dynamics of the CNN model using the best-performing hyperparameter configuration, we manually rebuild the model using:

- filters = 128
- dropout_rate = 0.3
- learning_rate = 0.000136

The model includes three convolutional layers with increasing depth, each followed by pooling and dropout layers (except the last conv layer). A fully connected layer is added before the final classification layer.

We train the model for a fixed number of epochs = 30, and plot the accuracy and loss curves on both training and validation sets.

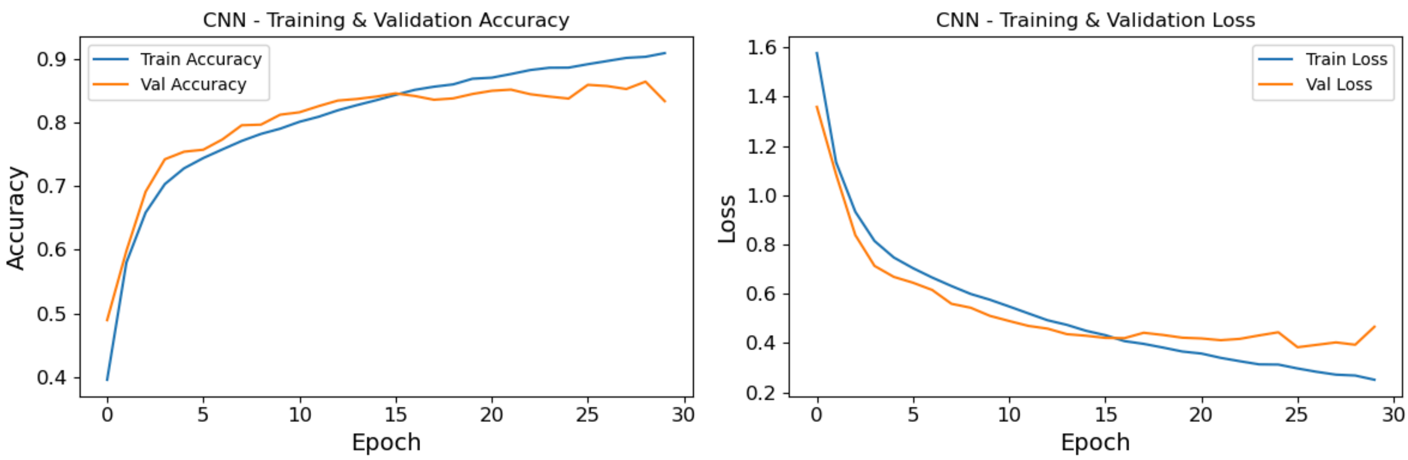
In [102…

```
def valid_cnn():
    model = keras.models.Sequential()
    model.add(keras.layers.Input(shape = (28, 28, 3)))

    # Fixed parameters
    # Block 1
    model.add(keras.layers.Conv2D(filters = 128, kernel_size = (3, 3), activation = 'relu'))
    model.add(keras.layers.MaxPooling2D(pool_size = (2, 2)))
    model.add(keras.layers.Dropout(0.3))

    # Block 2
    model.add(keras.layers.Conv2D(filters = 128 * 2, kernel_size = (3, 3), activation = 'relu'))
    model.add(keras.layers.MaxPooling2D(pool_size = (2, 2)))
    model.add(keras.layers.Dropout(0.3))

    # Block 3
    model.add(keras.layers.Conv2D(filters = 128 * 2, kernel_size = (3, 3), activation = 'relu'))

    model.add(keras.layers.Flatten())

    model.add(keras.layers.Dense(128 * 2, activation='relu'))
    model.add(keras.layers.Dropout(0.3))

    model.add(keras.layers.Dense(9, activation = 'softmax'))

    model.compile(
        optimizer = keras.optimizers.Adam(learning_rate = 0.000136),
        loss = 'sparse_categorical_crossentropy',
        metrics = ['accuracy']
    )

    return model
```

In [102…

```
# Fixed epoch =28
valid = valid_cnn()
history_cnn = valid.fit(
    X_train_nn, y_train_nn,
    epochs = 30,
    validation_data = (X_valid, y_valid)
)

plt.figure(figsize=(12, 4))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history_cnn.history['accuracy'], label='Train Accuracy')
plt.plot(history_cnn.history['val_accuracy'], label='Val Accuracy')
plt.title('CNN - Training & Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history_cnn.history['loss'], label='Train Loss')
plt.plot(history_cnn.history['val_loss'], label='Val Loss')
plt.title('CNN - Training & Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

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

```
Epoch 1/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 34ms/step - accuracy: 0.2970 - loss: 1.8241 - val_accuracy: 0.4897 - val_loss: 1.3582
Epoch 2/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 34ms/step - accuracy: 0.5505 - loss: 1.2006 - val_accuracy: 0.5981 - val_loss: 1.0841
Epoch 3/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 40s 44ms/step - accuracy: 0.6440 - loss: 0.9755 - val_accuracy: 0.6913 - val_loss: 0.8380
Epoch 4/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 35s 39ms/step - accuracy: 0.6916 - loss: 0.8411 - val_accuracy: 0.7422 - val_loss: 0.7129
Epoch 5/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 35ms/step - accuracy: 0.7188 - loss: 0.7702 - val_accuracy: 0.7541 - val_loss: 0.6684
Epoch 6/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 34s 38ms/step - accuracy: 0.7370 - loss: 0.7215 - val_accuracy: 0.7572 - val_loss: 0.6447
Epoch 7/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 34s 37ms/step - accuracy: 0.7526 - loss: 0.6804 - val_accuracy: 0.7734 - val_loss: 0.6152
Epoch 8/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 36ms/step - accuracy: 0.7650 - loss: 0.6432 - val_accuracy: 0.7956 - val_loss: 0.5592
Epoch 9/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 34ms/step - accuracy: 0.7758 - loss: 0.6139 - val_accuracy: 0.7966 - val_loss: 0.5432
Epoch 10/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 33s 36ms/step - accuracy: 0.7844 - loss: 0.5907 - val_accuracy: 0.8122 - val_loss: 0.5102
Epoch 11/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 34ms/step - accuracy: 0.7957 - loss: 0.5628 - val_accuracy: 0.8159 - val_loss: 0.4893
Epoch 12/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 34ms/step - accuracy: 0.8041 - loss: 0.5316 - val_accuracy: 0.8256 - val_loss: 0.4695
Epoch 13/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 35ms/step - accuracy: 0.8162 - loss: 0.5025 - val_accuracy: 0.8344 - val_loss: 0.4584
Epoch 14/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 34ms/step - accuracy: 0.8218 - loss: 0.4845 - val_accuracy: 0.8369 - val_loss: 0.4360
Epoch 15/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 33s 36ms/step - accuracy: 0.8286 - loss: 0.4597 - val_accuracy: 0.8406 - val_loss: 0.4296
Epoch 16/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 33s 37ms/step - accuracy: 0.8388 - loss: 0.4419 - val_accuracy: 0.8456 - val_loss: 0.4208
Epoch 17/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 34ms/step - accuracy: 0.8476 - loss: 0.4157 - val_accuracy: 0.8416 - val_loss: 0.4198
Epoch 18/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 35ms/step - accuracy: 0.8528 - loss: 0.4021 - val_accuracy: 0.8356 - val_loss: 0.4416
Epoch 19/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 30s 34ms/step - accuracy: 0.8584 - loss: 0.3856 - val_accuracy: 0.8378 - val_loss: 0.4327
Epoch 20/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 36ms/step - accuracy: 0.8683 - loss: 0.3692 - val_accuracy: 0.8447 - val_loss: 0.4216
Epoch 21/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 34s 38ms/step - accuracy: 0.8700 - loss: 0.3563 - val_accuracy: 0.8497 - val_loss: 0.4186
Epoch 22/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 35s 39ms/step - accuracy: 0.8754 - loss: 0.3450 - val_accuracy: 0.8516 - val_loss: 0.4115
Epoch 23/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 36ms/step - accuracy: 0.8819 - loss: 0.3261 - val_accuracy: 0.8444 - val_loss: 0.4168
Epoch 24/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 36ms/step - accuracy: 0.8837 - loss: 0.3205 - val_accuracy: 0.8406 - val_loss: 0.4308
Epoch 25/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 35ms/step - accuracy: 0.8855 - loss: 0.3102 - val_accuracy: 0.8375 - val_loss: 0.4437
Epoch 26/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 35ms/step - accuracy: 0.8901 - loss: 0.2973 - val_accuracy: 0.8591 - val_loss: 0.3830
Epoch 27/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 35ms/step - accuracy: 0.8974 - loss: 0.2837 - val_accuracy: 0.8572 - val_loss: 0.3927
Epoch 28/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 36ms/step - accuracy: 0.9010 - loss: 0.2729 - val_accuracy: 0.8525 - val_loss: 0.4025
Epoch 29/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 32s 36ms/step - accuracy: 0.9029 - loss: 0.2729 - val_accuracy: 0.8641 - val_loss: 0.3930
Epoch 30/30
900/900 ━━━━━━━━━━━━━━━━━━━━ 31s 35ms/step - accuracy: 0.9088 - loss: 0.2494 - val_accuracy: 0.8334 - val_loss: 0.4660
```



We did not choose the best epoch = 30 returned by the parameter search. Instead, we selected epoch = 18 for the final model training, for the following reasons:

- **Validation loss (val_loss) reached its lowest point around epoch 15**
  - val_loss reached a minimum at around epoch 18, then started to slightly increase, which may indicate early signs of overfitting.

- **Validation accuracy (val_accuracy) also became stable or slightly decreased after epoch 18**
  - As shown in the left plot, val_accuracy peaked around epoch 15, then fluctuated without further improvement;
  - Meanwhile, train_accuracy kept increasing, showing that the model was still fitting the training set and possibly starting to overfit.

Therefore, based on the plots above, we consider **epoch = 18** to be a good balance between generalization and training performance, and we use it as the final training setting.

4. Final models

In this section, we train each model with its **best hyperparmater combination independently of the hyperparameter tuning cells**, don't rely on the hyperparameter tuning cells having been run.

Algorithm of choice from first six weeks of course - Random Forest

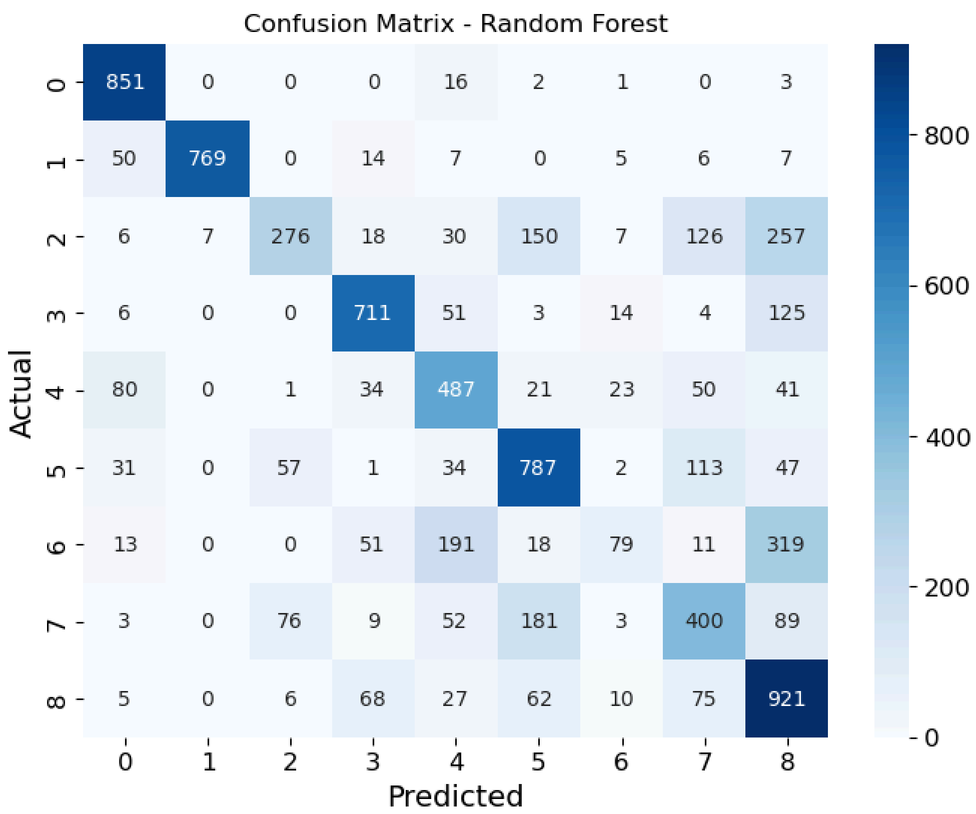
In [226…
```
# Rebuild a new RF based on the optimal parameters
final_rf = RandomForestClassifier(
    n_estimators = 200,
    max_depth = 30,
    min_samples_split = 5,
    max_features = 'sqrt',
    random_state=42
)

# Retrain on the training set
final_rf.fit(X_train_rf, y_train)
```

Out[226…
```
RandomForestClassifier

RandomForestClassifier(max_depth=30, min_samples_split=5, n_estimators=200,
                       random_state=42)
```

In [149…
```
# Evaluate on the test set
y_pred_test_rf = final_rf.predict(X_test_rf)
report_rf = classification_report(y_test, y_pred_test_rf, output_dict=True)

acc_rf = report_rf['accuracy']
macro_rf = report_rf['macro avg']['f1-score']

print("Final RF - Test Set Classification Report:")
print(classification_report(y_test, y_pred_test_rf))
```

```
Final RF - Test Set Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.97      0.89       873
           1       0.99      0.90      0.94       858
           2       0.66      0.31      0.43       877
           3       0.78      0.78      0.78       914
           4       0.54      0.66      0.60       737
           5       0.64      0.73      0.69      1072
           6       0.55      0.12      0.19       682
           7       0.51      0.49      0.50       813
           8       0.51      0.78      0.62      1174

    accuracy                           0.66      8000
   macro avg       0.67      0.64      0.63      8000
weighted avg       0.67      0.66      0.64      8000
```

In [150…
```
# Print the confusion matrix
cm = confusion_matrix(y_test, y_pred_test_rf)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix - Random Forest")
plt.show()
```



Fully connected neural network

In [171…

```python
# Rebuild a new MLP based on the optimal parameters
def build_final_mlp():
    model = keras.models.Sequential()
    model.add(keras.layers.Input(shape = (28, 28, 3)))
    model.add(keras.layers.Flatten())

    # Fixed parameter
    model.add(keras.layers.Dense(448, activation = 'relu'))
    model.add(keras.layers.Dropout(0.2))

    model.add(keras.layers.Dense(320, activation = 'relu'))
    model.add(keras.layers.Dropout(0.2))

    model.add(keras.layers.Dense(9, activation = 'softmax'))

    model.compile(
        optimizer = keras.optimizers.Adam(learning_rate = 0.000104),
        loss = 'sparse_categorical_crossentropy',
        metrics = ['accuracy']
    )

    return model
```

Previously, we used train_test_split() to allocate **90% of the training data for hyperparameter tuning and 10% of the training data for validation**.

- Now that the optimal hyperparameters have been selected, we will train the final model using the **full training set**, without using X_valid, since it has already been involved in the tuning process.

In [174…

```python
final_mlp = build_final_mlp()

# Retrain on the overall training set
history_mlp = final_mlp.fit(X_train_scale,
              y_train,
              epochs = 28
)
```

```
Epoch 1/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.2210 - loss: 2.0389
Epoch 2/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.3268 - loss: 1.7498
Epoch 3/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.3718 - loss: 1.6659
Epoch 4/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.3947 - loss: 1.6083
Epoch 5/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4162 - loss: 1.5564
Epoch 6/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4364 - loss: 1.5225
Epoch 7/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4452 - loss: 1.4877
Epoch 8/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4645 - loss: 1.4568
Epoch 9/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4626 - loss: 1.4424
Epoch 10/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4732 - loss: 1.4234
Epoch 11/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4728 - loss: 1.4115
Epoch 12/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4827 - loss: 1.4009
Epoch 13/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4860 - loss: 1.3812
Epoch 14/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4890 - loss: 1.3751
Epoch 15/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4972 - loss: 1.3603
Epoch 16/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.4970 - loss: 1.3534
Epoch 17/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5011 - loss: 1.3430
Epoch 18/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5002 - loss: 1.3346
Epoch 19/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5042 - loss: 1.3276
Epoch 20/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.5052 - loss: 1.3166
Epoch 21/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.5059 - loss: 1.3153
Epoch 22/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5138 - loss: 1.2986
Epoch 23/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5163 - loss: 1.2926
Epoch 24/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5223 - loss: 1.2889
Epoch 25/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5224 - loss: 1.2785
Epoch 26/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5201 - loss: 1.2750
Epoch 27/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.5247 - loss: 1.2614
Epoch 28/28
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.5268 - loss: 1.2578
```

In [175…
```
final_mlp.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
flatten_3 (Flatten)	(None, 2352)	0
dense_8 (Dense)	(None, 448)	1,054,144
dropout_2 (Dropout)	(None, 448)	0
dense_9 (Dense)	(None, 320)	143,680
dropout_3 (Dropout)	(None, 320)	0
dense_10 (Dense)	(None, 9)	2,889

Total params: 3,602,141 (13.74 MB)
Trainable params: 1,200,713 (4.58 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2,401,428 (9.16 MB)

final_mlp.evaluate(X_test_scale, y_test)

- It calculates the **overall accuracy** of the model.

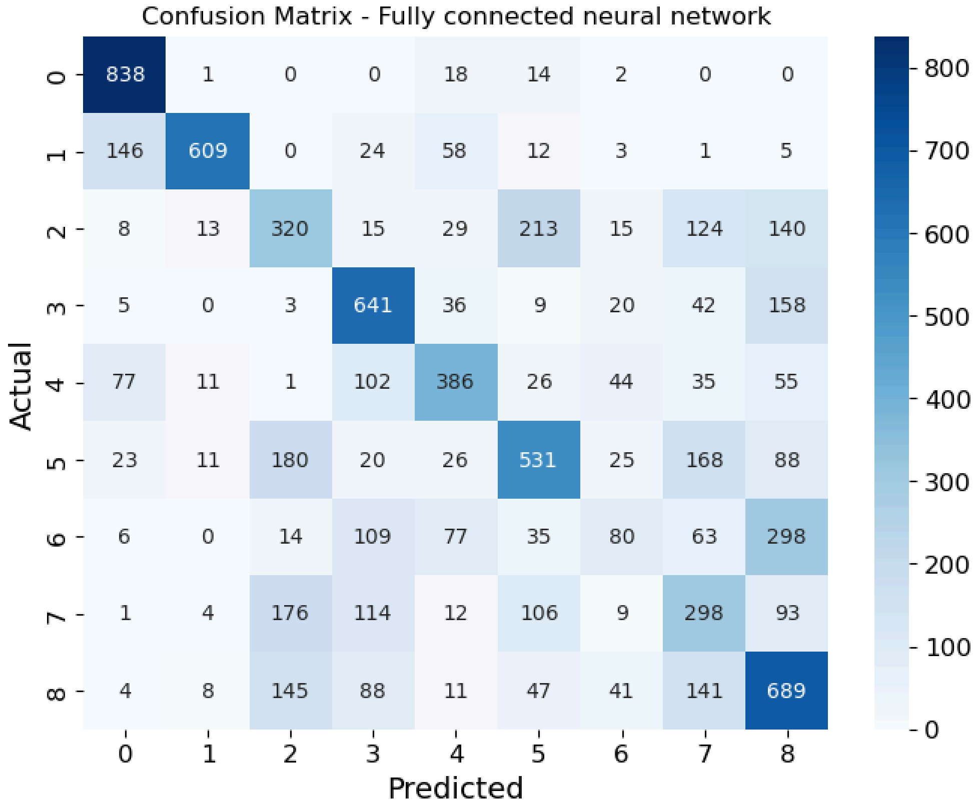
In [177…
```
# Evaluate on the test set
loss_mlp, acc_mlp = final_mlp.evaluate(X_test_scale, y_test)
print(f"Accuracy on test data: {acc_mlp:.4f}")
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.5415 - loss: 1.1903
Accuracy on test data: 0.5490
```

In [178…
```
y_pred_mlp = np.argmax(final_mlp.predict(X_test_scale), axis=1)
report_mlp = classification_report(y_test, y_pred_mlp, output_dict=True)
macro_mlp = report_mlp['macro avg']['f1-score']

print(classification_report(y_test, y_pred_mlp))
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 889us/step
              precision    recall  f1-score   support

           0       0.76      0.96      0.85       873
           1       0.93      0.71      0.80       858
           2       0.38      0.36      0.37       877
           3       0.58      0.70      0.63       914
           4       0.59      0.52      0.56       737
           5       0.53      0.50      0.51      1072
           6       0.33      0.12      0.17       682
           7       0.34      0.37      0.35       813
           8       0.45      0.59      0.51      1174

    accuracy                           0.55      8000
   macro avg       0.54      0.54      0.53      8000
weighted avg       0.55      0.55      0.54      8000
```

In [179…
```
# Print the confusion matrix
cm = confusion_matrix(y_test, y_pred_mlp)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix - Fully connected neural network")
plt.show()
```



Convolutional neural network

In [186…
```
# Rebuild a new CNN based on the optimal parameters
def build_final_cnn():
    model = keras.models.Sequential()
    model.add(keras.layers.Input(shape = (28, 28, 3)))

    # Block 1
    model.add(keras.layers.Conv2D(filters = 128, kernel_size = (3, 3), activation = 'relu'))
    model.add(keras.layers.MaxPooling2D(pool_size = (2, 2)))
    model.add(keras.layers.Dropout(0.3))
```

```python
    # Block 2
    model.add(keras.layers.Conv2D(filters = 128 * 2, kernel_size = (3, 3), activation = 'relu'))
    model.add(keras.layers.MaxPooling2D(pool_size = (2, 2)))
    model.add(keras.layers.Dropout(0.3))

    model.add(keras.layers.Conv2D(filters = 128 * 2, kernel_size = (3, 3), activation = 'relu'))

    model.add(keras.layers.Flatten())


    model.add(keras.layers.Dense(128 * 2, activation='relu'))
    model.add(keras.layers.Dropout(0.3))

    model.add(keras.layers.Dense(9, activation = 'softmax'))

    model.compile(
        optimizer = keras.optimizers.Adam(learning_rate = 0.000136),
        loss = 'sparse_categorical_crossentropy',
        metrics = ['accuracy']
    )

    return model
```

In [188…

```python
# epoch = 18 (not 30 -> reduce computing time and the performance is not much different)
final_cnn = build_final_cnn()

# Retrain on the overall training set
history_cnn = final_cnn.fit(
    X_train_scale, y_train,
    epochs = 18
)
```

```
Epoch 1/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 30s 29ms/step - accuracy: 0.2993 - loss: 1.8284
Epoch 2/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 32s 32ms/step - accuracy: 0.5642 - loss: 1.1567
Epoch 3/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 32s 32ms/step - accuracy: 0.6474 - loss: 0.9617
Epoch 4/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 33s 33ms/step - accuracy: 0.6934 - loss: 0.8410
Epoch 5/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 35s 35ms/step - accuracy: 0.7240 - loss: 0.7568
Epoch 6/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 34s 34ms/step - accuracy: 0.7448 - loss: 0.6991
Epoch 7/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 33s 33ms/step - accuracy: 0.7631 - loss: 0.6540
Epoch 8/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 34s 34ms/step - accuracy: 0.7736 - loss: 0.6283
Epoch 9/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 35s 35ms/step - accuracy: 0.7846 - loss: 0.5981
Epoch 10/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 34s 34ms/step - accuracy: 0.7966 - loss: 0.5674
Epoch 11/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 33s 33ms/step - accuracy: 0.8024 - loss: 0.5500
Epoch 12/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 31s 31ms/step - accuracy: 0.8151 - loss: 0.5107
Epoch 13/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 29s 29ms/step - accuracy: 0.8208 - loss: 0.4980
Epoch 14/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 29s 29ms/step - accuracy: 0.8312 - loss: 0.4668
Epoch 15/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 29s 29ms/step - accuracy: 0.8325 - loss: 0.4536
Epoch 16/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 29s 29ms/step - accuracy: 0.8445 - loss: 0.4279
Epoch 17/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 30s 30ms/step - accuracy: 0.8484 - loss: 0.4121
Epoch 18/18
1000/1000 ━━━━━━━━━━━━━━━━━━━━ 29s 29ms/step - accuracy: 0.8545 - loss: 0.4039
```

In [189…

```python
final_cnn.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 26, 26, 128)	3,584
max_pooling2d_2 (MaxPooling2D)	(None, 13, 13, 128)	0
dropout_4 (Dropout)	(None, 13, 13, 128)	0
conv2d_3 (Conv2D)	(None, 11, 11, 256)	295,168
max_pooling2d_3 (MaxPooling2D)	(None, 5, 5, 256)	0
dropout_5 (Dropout)	(None, 5, 5, 256)	0
conv2d_4 (Conv2D)	(None, 3, 3, 256)	590,080
flatten_4 (Flatten)	(None, 2304)	0
dense_11 (Dense)	(None, 256)	590,080
dropout_6 (Dropout)	(None, 256)	0
dense_12 (Dense)	(None, 9)	2,313

Total params: 4,443,677 (16.95 MB)
Trainable params: 1,481,225 (5.65 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2,962,452 (11.30 MB)

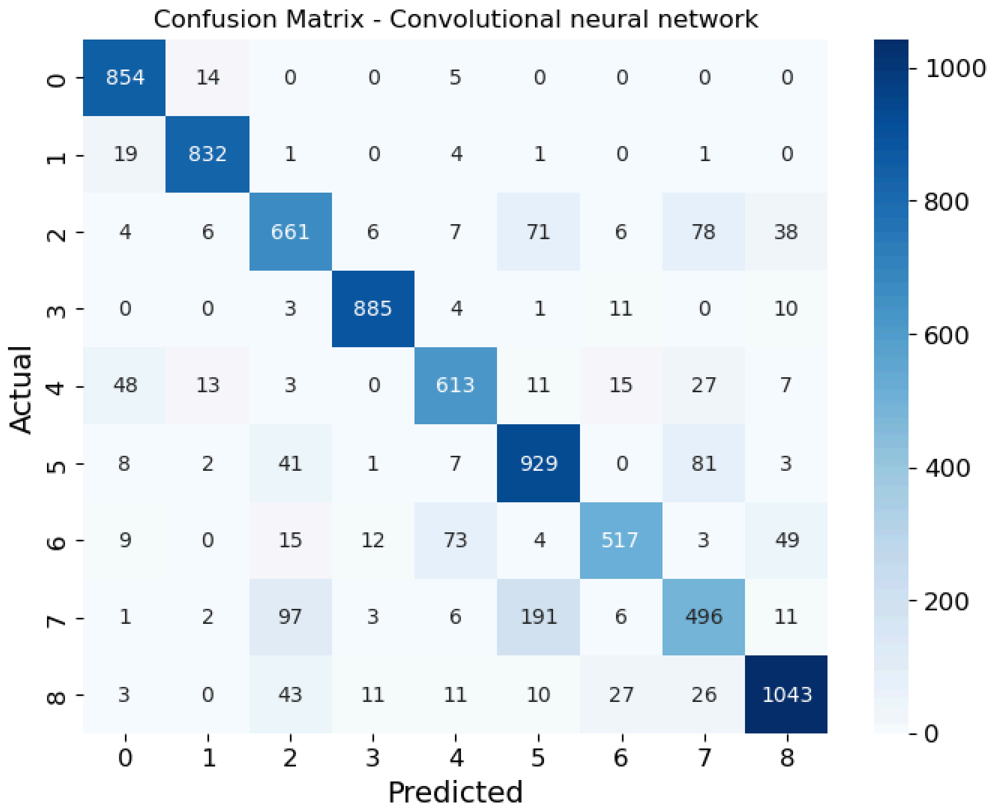
In [190…
```
# Evaluate on the test set
loss_cnn, acc_cnn = final_cnn.evaluate(X_test_scale, y_test)
print(f"Accuracy on test data: {acc_cnn:.4f}")
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.8557 - loss: 0.3834
Accuracy on test data: 0.8537
```

In [197…
```
y_pred_cnn = np.argmax(final_cnn.predict(X_test_scale), axis=1)
report_cnn = classification_report(y_test, y_pred_cnn, output_dict=True)
macro_cnn = report_cnn['macro avg']['f1-score']

print(classification_report(y_test, y_pred_cnn))
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step
              precision    recall  f1-score   support

           0       0.90      0.98      0.94       873
           1       0.96      0.97      0.96       858
           2       0.77      0.75      0.76       877
           3       0.96      0.97      0.97       914
           4       0.84      0.83      0.84       737
           5       0.76      0.87      0.81      1072
           6       0.89      0.76      0.82       682
           7       0.70      0.61      0.65       813
           8       0.90      0.89      0.89      1174

    accuracy                           0.85      8000
   macro avg       0.85      0.85      0.85      8000
weighted avg       0.85      0.85      0.85      8000
```

In [199…
```
# confusion matrix
cm = confusion_matrix(y_test, y_pred_cnn)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix - Convolutional neural network")
plt.show()
```

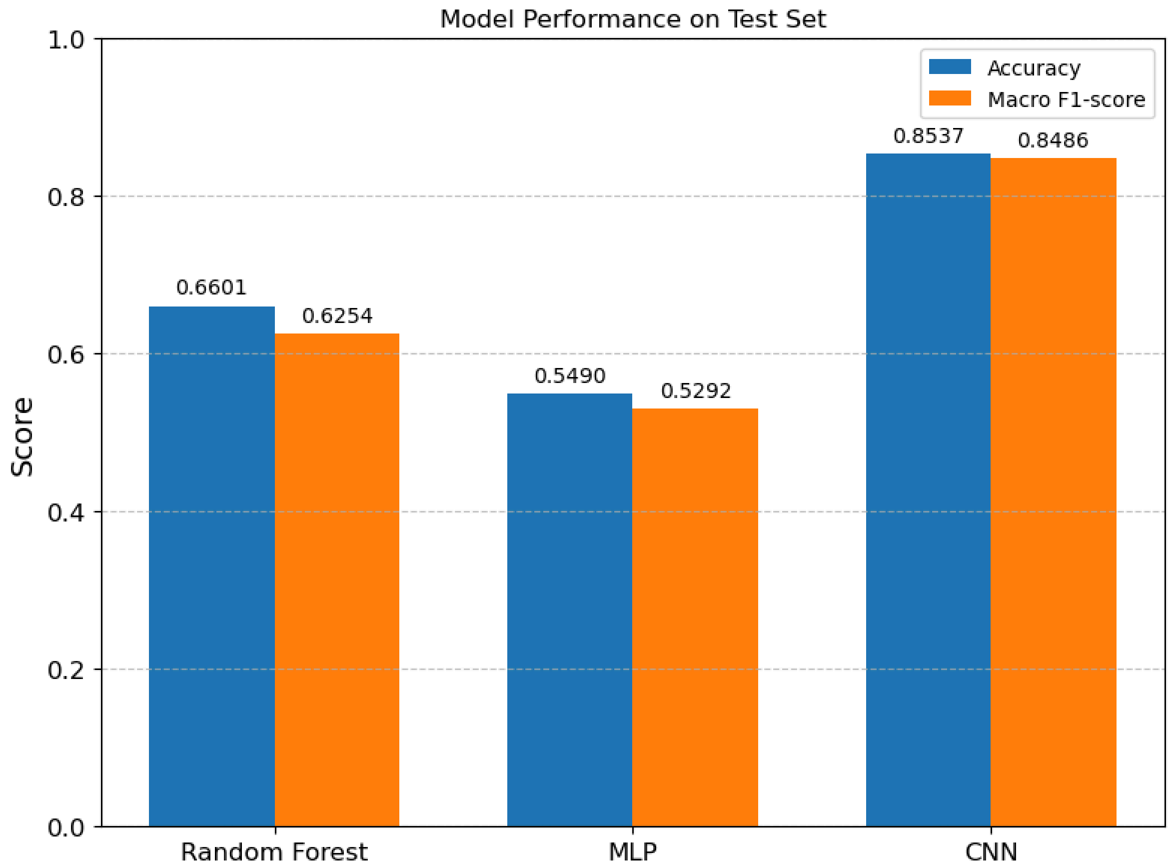


Model comparison

- **Accuracy** is sensitive to class imbalance and may mask poor performance on minority classes.
- **Macro F1** averages the F1 scores across all classes without considering class weights. It is less affected by class distribution and better reflects overall fairness.

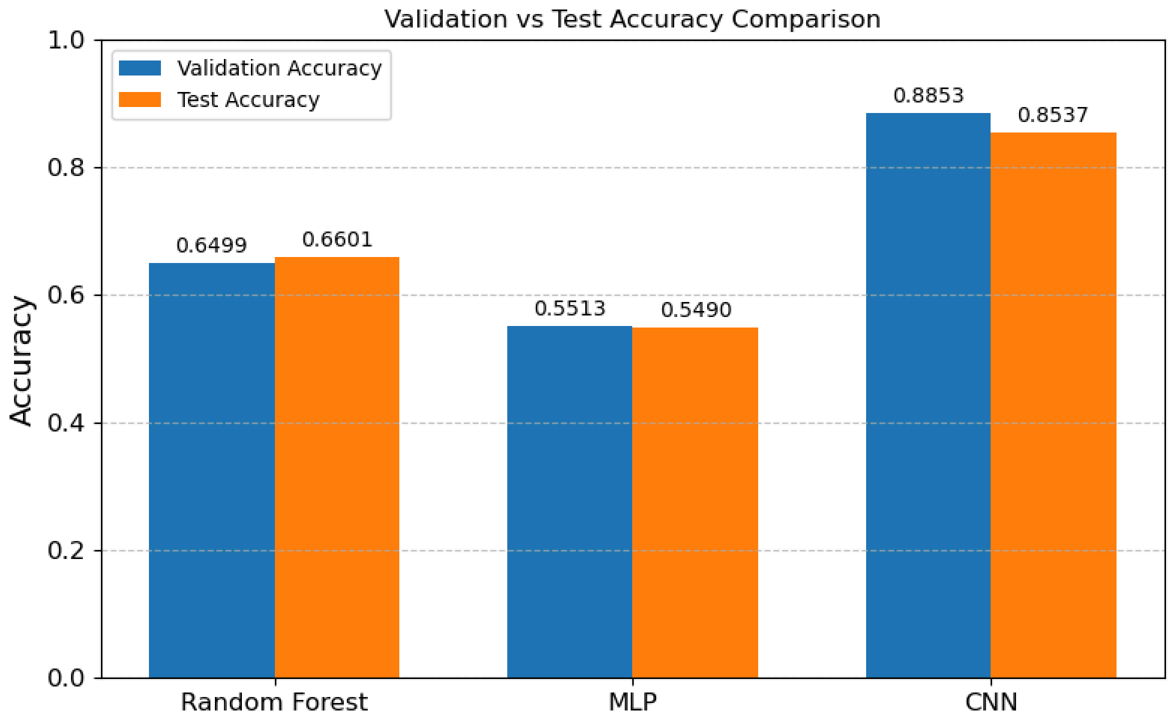
In [234…

```
models = ['Random Forest', 'MLP', 'CNN']
accuracies = [acc_rf, acc_mlp, acc_cnn]
f1_scores = [macro_rf, macro_mlp, macro_cnn]

x = np.arange(len(models))
width = 0.35

# Model Performance on Test Set
plt.figure(figsize=(8, 6))
bars1 = plt.bar(x - width/2, accuracies, width, label='Accuracy')
bars2 = plt.bar(x + width/2, f1_scores, width, label='Macro F1-score')

plt.xticks(x, models)
plt.ylim(0, 1)
plt.ylabel('Score')
plt.title('Model Performance on Test Set')
plt.legend()
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Display the value on each bar
for bar in bars1 + bars2:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2,
             height + 0.01,
             f'{height:.4f}',
             ha='center', va='bottom')

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



Model performance on the validation set: Since we do not repeat hyperparameter tuning, the final testing phase uses the full training and test sets. Therefore, the validation scores shown here refer to the best validation performance recorded during the tuning process under the optimal hyperparameter combination.

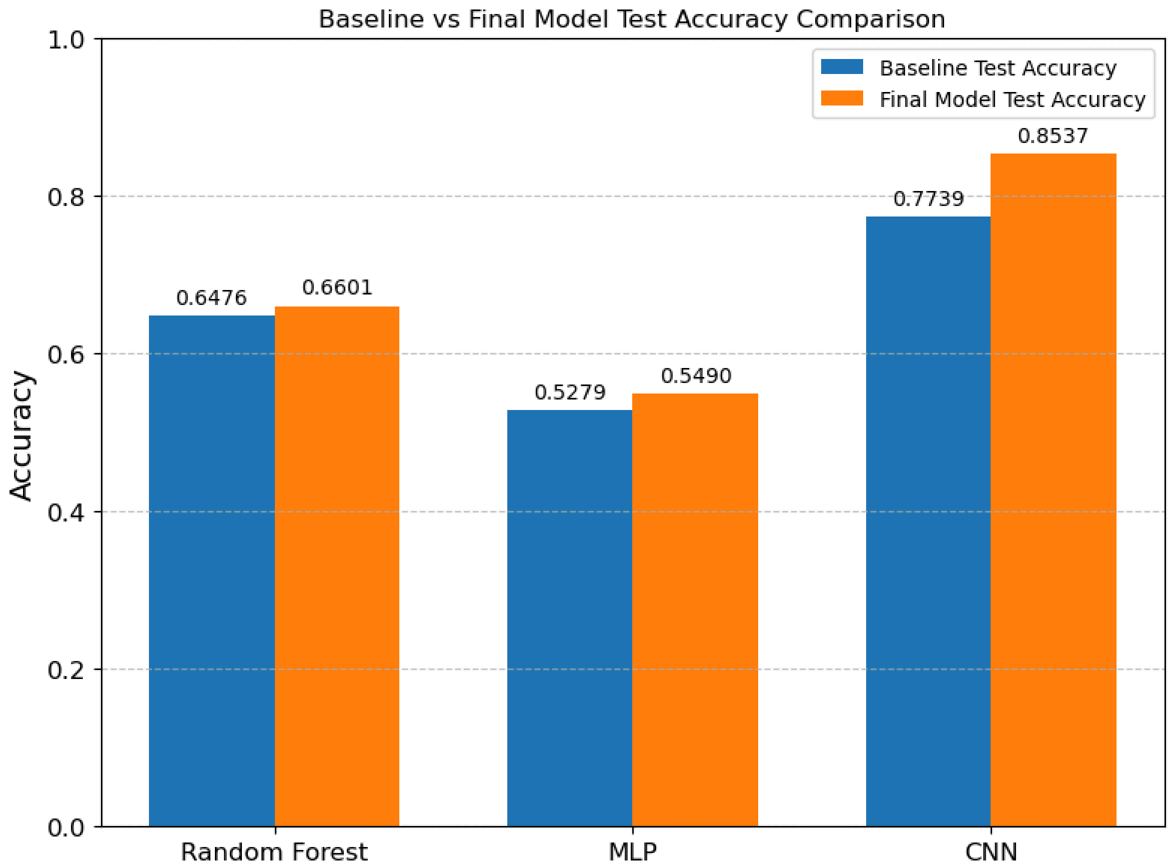
In [221…
```
# Validation vs Test Accuracy Comparison
val_scores = [0.649875, 0.551250, 0.885312]

plt.figure(figsize=(8, 5))
bars3 = plt.bar(x - width/2, val_scores, width, label='Validation Accuracy')
bars4 = plt.bar(x + width/2, accuracies, width, label='Test Accuracy')

plt.xticks(x, models)
plt.ylim(0, 1)
plt.ylabel('Accuracy')
plt.title('Validation vs Test Accuracy Comparison')
plt.legend()
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Display the value on each bar
for bar in bars3 + bars4:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2,
             height + 0.01,
             f'{height:.4f}',
             ha='center', va='bottom')

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



Baseline model vs Final model: The figure compares the accuracy performance of the three models on the test set after baseline and hyperparameter tuning.

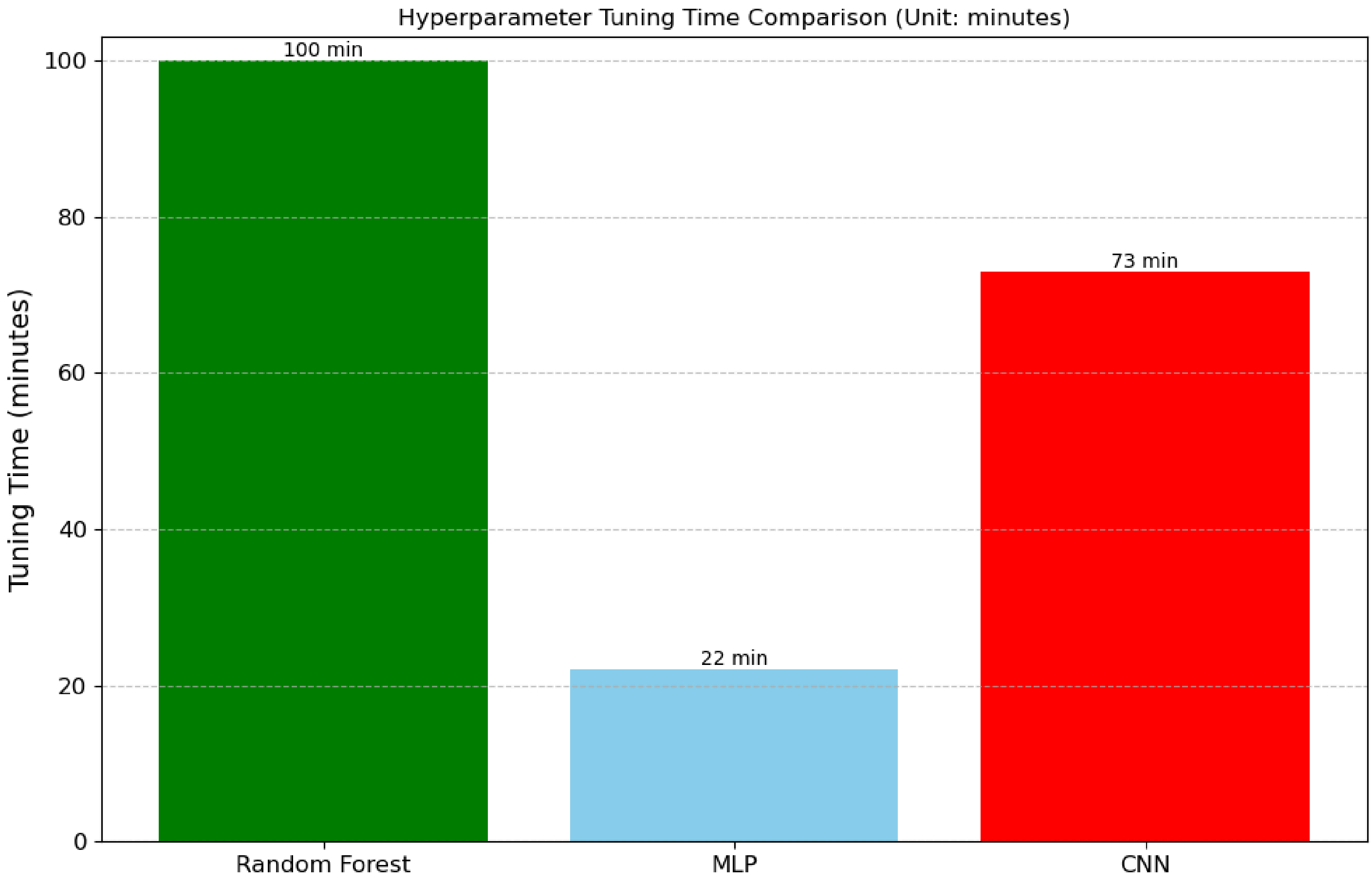
In [224…

```
# Baseline vs Final Model Test Accuracy Comparison
base_scores = [acc_base_rf, acc_base_mlp, acc_base_cnn]

plt.figure(figsize=(8, 6))
bars5 = plt.bar(x - width/2, base_scores, width, label='Baseline Test Accuracy')
bars6 = plt.bar(x + width/2, accuracies, width, label='Final Model Test Accuracy')

plt.xticks(x, models)
plt.ylim(0, 1)
plt.ylabel('Accuracy')
plt.title('Baseline vs Final Model Test Accuracy Comparison')
plt.legend()
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Display the value on each bar
for bar in bars5 + bars6:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2,
             height + 0.01,
             f'{height:.4f}',
             ha='center', va='bottom')

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



In [266…

```
# Hyperparameter tuning time (Unit: minutes)
tuning_times = [100, 22, 73]

plt.figure(figsize=(10, 6.5))

bars = plt.bar(models, tuning_times, color=['green', 'skyblue', 'red'])

for bar in bars:
    height = bar.get_height()
    plt.text(
        bar.get_x() + bar.get_width()/2,
        height + 0.01,
        f'{height} min',
        ha='center',va='bottom')

plt.title('Hyperparameter Tuning Time Comparison (Unit: minutes)')
plt.ylabel('Tuning Time (minutes)')
plt.ylim(0, max(tuning_times) + 3)
plt.grid(axis='y', linestyle='--', alpha=0.7)

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


Hyperparameter Tuning Time Comparison (Unit: minutes)
Tuning Time (minutes)
100
80
60
40
20
0
100 min
22 min
73 min
Random Forest
MLP
CNN

In [ ]: