Fashion MNIST classification using SVM and CNN

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Importing libraries required for the project

```
import torch #open-source deep learning library- used for building and training neural networks
import torch.nn as nn #define custom neural network architectures
import torch.optim as optim #provides optimization algorithms used to update weights of neural network to minimize the loss
import torchvision #PyTorch library for computer vision tasks - provides datasets, transforms, and models specific to vision tasks
from torchvision import datasets, transforms #handling datasets and data transformations, respectively
from torch.utils.data import DataLoader, random_split #efficiently load and iterate over datasets during training; splitting a dat
import matplotlib.pyplot as plt #plotting library in Python - used for visualizing data and results
import numpy as np #package for scientific computing
import pandas as pd #data manipulation and analysis library
import seaborn as sns #statistical data visualization library based on Matplotlib
import tensorflow as tf #open-source machine learning framework- it's used for specific functionalities not covered by PyTorch
from tensorflow.keras.datasets import fashion_mnist #importing the dataset required for our project from TensorFlow's Keras datase
from sklearn.decomposition import PCA #importing PCA- the tool for Dimensionality reduction- visualizing high-dimensional data in
from pandas.plotting import scatter_matrix #creating scatterplot matrices
from tensorflow.keras.models import Sequential#linear stack of layers
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,Dropout, Conv3D, MaxPooling3D #layers used in Convolution
from tensorflow.keras.utils import plot_model #creating a plot of a neural network model
from sklearn.metrics import classification_report #importing classification_report for evaluation
from sklearn.metrics import confusion_matrix #importing confusion_matrix for evaluation
from mpl_toolkits.mplot3d import Axes3D #for 3D plotting

from sklearn import svm
import time
from tensorflow.keras import layers
from sklearn.svm import SVC

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold

from sklearn.model_selection import train_test_split
```

```
pip install umap-learn #install umap-learn
```

```
Requirement already satisfied: umap-learn in /usr/local/lib/python3.10/dist-packages (0.5.5)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from umap-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.1 in /usr/local/lib/python3.10/dist-packages (from umap-learn) (1.11.3)
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.10/dist-packages (from umap-learn) (1.2.2)
Requirement already satisfied: numba>=0.51.2 in /usr/local/lib/python3.10/dist-packages (from umap-learn) (0.58.1)
Requirement already satisfied: pynndescent>=0.5 in /usr/local/lib/python3.10/dist-packages (from umap-learn) (0.5.11)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from umap-learn) (4.66.1)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in /usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->uma
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-packages (from pynndescent>=0.5->umap-learn) (
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22->uma
```

```
import umap #Import UMAP for dimensionality reduction and data visualization
```

```
#Loading the dataset
fashion__mnist = tf.keras.datasets.fashion_mnist.load_data()
```

Data Preparation

```
# # Data Splitting
(train_images, train_labels), (test_images, test_labels) = fashion__mnist
```

```
# Split the data into training, validation, and testing sets
# Using train_test_split to achieve the 70:10:20 ratio
train_images, val_images, train_labels, val_labels = train_test_split(train_images, train_labels, test_size=0.125, random_state=
```

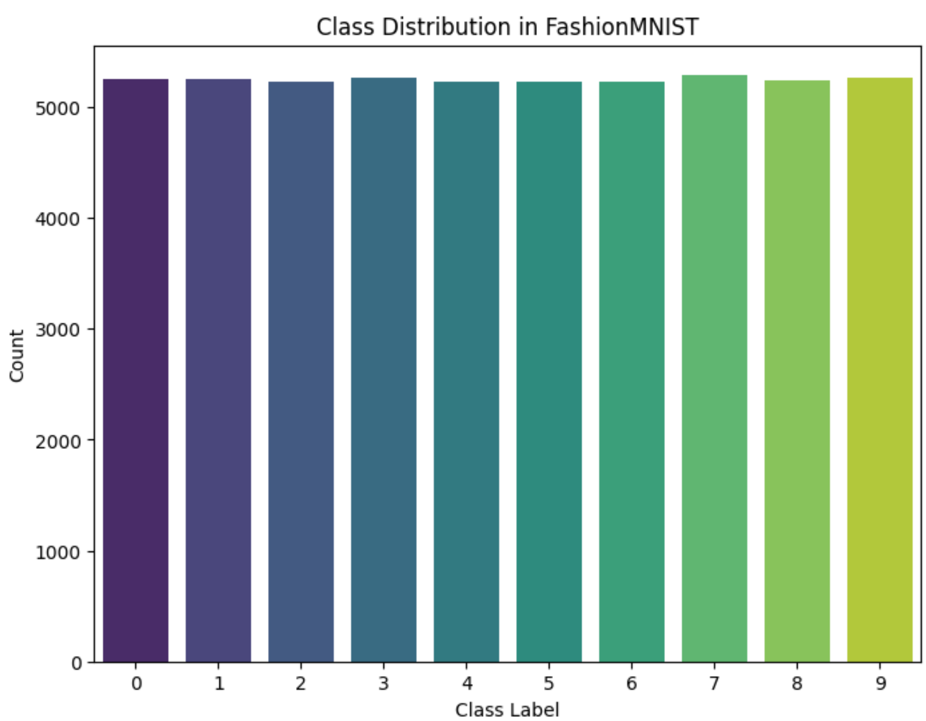
```
# Data transformation

# Normalizing the pixel values to the [0, 1] range
train_images = train_images / 255.0
val_images = val_images / 255.0
test_images = test_images / 255.0
```

EDA

```
#Data Statistics -I (1)
# Print the shapes of the resulting sets
print("Training set shape:", train_images.shape)
print("Validation set shape:", val_images.shape)
print("Testing set shape:", test_images.shape)
print("\n Number of classes:", len(set(train_labels)))
```

```
Training set shape: (52500, 28, 28)
Validation set shape: (7500, 28, 28)
Testing set shape: (10000, 28, 28)

 Number of classes: 10
```

```
# Data Statistics - II(1)
# Class distribution
plt.figure(figsize=(8, 6))
sns.countplot(x=train_labels, palette="viridis")
plt.title('Class Distribution in FashionMNIST')
plt.xlabel('Class Label')
plt.ylabel('Count')
plt.show()
```

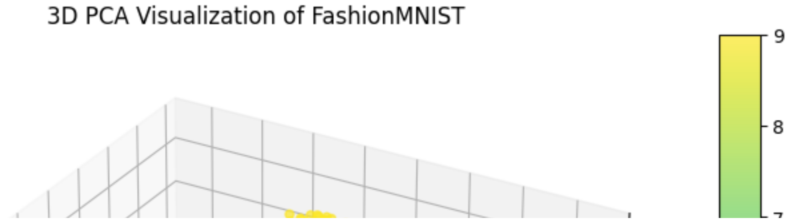



```
# Data Visualization - I

# Plotting examples from classes

# Define class names
class_names = [
```

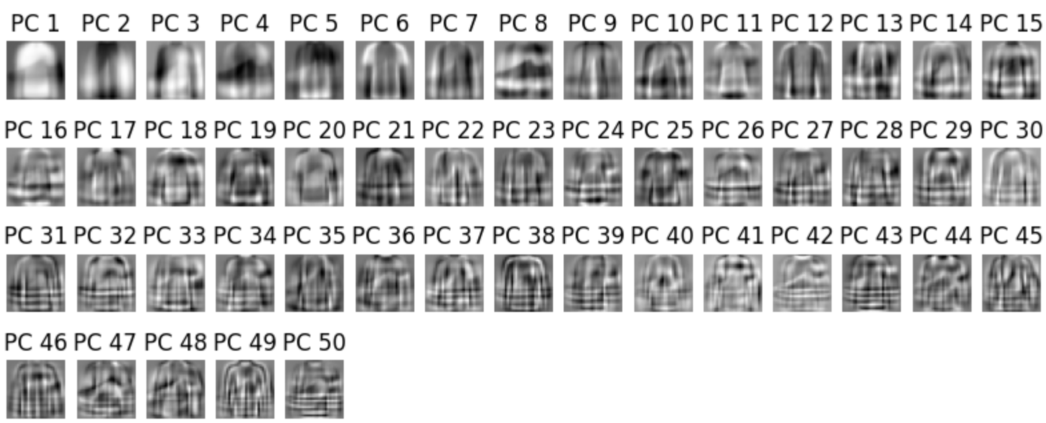
```
    "T-shirt/top",
    "Trouser",
    "Pullover",
    "Dress",
    "Coat",
    "Sandal",
    "Shirt",
    "Sneaker",
    "Bag",
    "Ankle boot",
]

# Function to display a grid of images
def display_images(images, labels, class_names, num_images=25):
    plt.figure(figsize=(10, 10))
    for i in range(num_images):
        plt.subplot(5, 5, i + 1)
        plt.xticks([])
        plt.yticks([])
        plt.grid(False)
        plt.imshow(images[i], cmap=plt.cm.binary)
        plt.xlabel(class_names[labels[i]])
    plt.show()

# Display a grid of 25 sample images from the training dataset
display_images(train_images, train_labels, class_names)
```


```
# Data Visualization - II

# Data Visualization - II(1)

# Data Visualization - II(1)(i)
```

```
#Performing PCA (Principal Component Analysis
#Dimensionality reduction and 3D visualization

# Flatten the 28x28 images to a 1D array of length 784
train_images_flat = train_images.reshape(-1, 784)
val_images_flat = val_images.reshape(-1, 784)
test_images_flat = test_images.reshape(-1, 784)

# Initialize PCA with count of components as 50
n_components = 50
pca = PCA(n_components=n_components)

# Fit PCA on the training data
pca.fit(train_images_flat)

# Apply PCA transformation to the training and testing data
train_images_pca = pca.transform(train_images_flat)
val_images_pca = pca.transform(val_images_flat)
test_images_pca = pca.transform(test_images_flat)

# Now, train_images_pca and test_images_pca contain the reduced dimensionality representations of the data

# Visualize 3D PCA representation
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')

# Scatter plot
scatter = ax.scatter(
    train_images_pca[:, 0],  # First principal component
    train_images_pca[:, 1],  # Second principal component
    train_images_pca[:, 2],  # Third principal component
    c=train_labels,           # Use labels for color
    cmap=plt.get_cmap('viridis'),
    marker='o',
    alpha=0.7
)

# Set labels and title
ax.set_xlabel('Principal Component 1')
ax.set_ylabel('Principal Component 2')
ax.set_zlabel('Principal Component 3')
ax.set_title('3D PCA Visualization of FashionMNIST')

# Add colorbar
cbar = fig.colorbar(scatter)
cbar.set_label('Class Label')

plt.show()
```

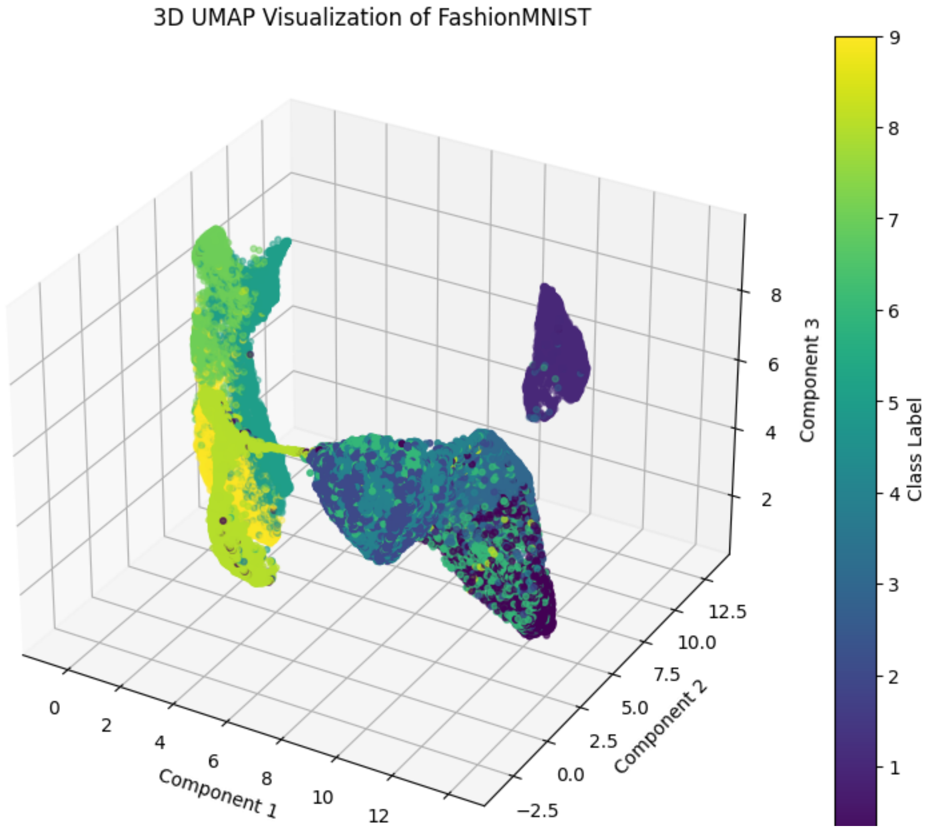



```
# Data Visualization - II(1)(ii)

# Displaying the components of PCA

# Access the principal components
principal_components = pca.components_

# Number of principal components
n_components = principal_components.shape[0]

# Create subplots to display the components
plt.figure(figsize=(10, 5))
for i in range(n_components):
    plt.subplot(5, 15, i + 1)
    component = principal_components[i].reshape(28, 28)
    plt.imshow(component, cmap='gray')
    plt.title(f'PC {i+1}')
    plt.axis('off')

plt.show()
```




```
# Data Visualization - II(2)

# Perform UMAP for dimensionality reduction

umap_model = umap.UMAP(n_components=3, random_state=42)
train_images_umap = umap_model.fit_transform(train_images_flat)
# Visualize the 3D UMAP projection
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')
scatter = ax.scatter(
    train_images_umap[:, 0],
    train_images_umap[:, 1],
    train_images_umap[:, 2],
    c=train_labels,
    cmap='viridis',
    marker='o',
    s=10
)
ax.set_title('3D UMAP Visualization of FashionMNIST')
ax.set_xlabel('Component 1')
ax.set_ylabel('Component 2')
ax.set_zlabel('Component 3')
fig.colorbar(scatter, ax=ax, label='Class Label')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/umap/umap_.py:1943: UserWarning: n_jobs value -1 overridden to 1 by setting random_s
  warn(f"n_jobs value {self.n_jobs} overridden to 1 by setting random_state. Use no seed for parallelism.")
```



Model selection

1. Support Vector Machine (SVM) classifier:

(i) Explain the algorithm selection: SVMs are capable of capturing non-linear relationships in the data, allowing businesses to identify subtle distinctions between fashion categories.

(ii) Model building: Building the SVM model

(iii) Evaluation metrics: To check for these metrics, we implemented the **classification report** consisting of accuracy, precision, recall, F1-score; qualitative analysis- **confusion matrix** for classification on test set.

(iv) Model intepretability : We implemented a **feature importance graph** for displaying the model interpretability.

```
#Support Vector Machine Classifier-  fitting the model

#1(ii)

# Train an SVM Classifier
svm = SVC(kernel='linear')
svm.fit(train_images_pca, train_labels)

# Make predictions on the validation set
val_predictions = svm.predict(val_images_pca)

# Evaluate the model on the validation set
accuracy = accuracy_score(val_labels, val_predictions)
print("Validation Accuracy:", accuracy)

# Make predictions on the test set
test_predictions = svm.predict(test_images_pca)

# Evaluate the model on the test set
test_accuracy = accuracy_score(test_labels, test_predictions)
print("Test Accuracy:", test_accuracy)
```

```
Validation Accuracy: 0.8496
Test Accuracy: 0.8346
```

```
# The below code is the hyperparameter tuning of the above SVM Model.


# from sklearn.model_selection import GridSearchCV
# from sklearn.svm import SVC
# from sklearn.metrics import accuracy_score

# # Define the parameter grid
# param_grid = {'C': [0.1, 1, 10, 100],
#               'kernel': ['linear', 'rbf', 'poly']}

# # Create an SVM classifier
# svm = SVC()

# # Use GridSearchCV to find the best hyperparameters
# grid_search = GridSearchCV(svm, param_grid, cv=5, scoring='accuracy')
# grid_search.fit(train_images_pca, train_labels)

# # Print the best hyperparameters
# print("Best Hyperparameters:", grid_search.best_params_)

# # Make predictions on the validation set using the best model
# val_predictions = grid_search.predict(val_images_pca)

# # Evaluate the model on the validation set
# accuracy = accuracy_score(val_labels, val_predictions)
# print("Validation Accuracy:", accuracy)

# # Make predictions on the test set using the best model
# test_predictions = grid_search.predict(test_images_pca)

# # Evaluate the model on the test set
# test_accuracy = accuracy_score(test_labels, test_predictions)
# print("Test Accuracy:", test_accuracy)


# About the trained model
print("Support Vectors:", svm.support_vectors_)
print("\n Number of Support Vectors for each class:", svm.n_support_)
print("\n Coefficients of the support vector machine:", svm.coef_)
print("\n Intercept:", svm.intercept_)
```

```
Support Vectors: [[-4.97814649 -3.77356513 -2.09364714 ...  0.09230476  0.12736404
   0.1477406 ]
 [-3.30124587 -3.11313135 -0.83853322 ...  0.08675093  0.52827944
  -0.06783927]
 [-1.79087591 -3.05330968 -1.00567215 ... -0.27749579  0.06445637
   0.45275521]
 ...
 [-5.12679347 -0.30437448 -0.86582919 ...  0.35852533  0.12450761
   0.28371529]
 [-5.56727085 -0.63183974  0.03990639 ...  0.21857486 -0.24072983
  -0.56830001]
 [-3.84252019  4.74142673  1.68135014 ...  0.04363543 -0.3210394
  -0.0943023 ]]

 Number of Support Vectors for each class: [2255  397 2996 1582 2832  905 4107 1127  679  739]

 Coefficients of the support vector machine: [[ 0.01459123  0.51644335  0.4608851  ...  0.35816929 -0.96178465
   0.25710463]
 [-0.03425394 -0.37143503  0.58987167 ... -0.22816112 -0.08590674
  -0.17691064]
 [ 0.24437948  0.19740376  0.07538572 ... -0.57998288 -0.82225589
   0.35432817]
 ...
 [-1.25088471  0.31556561  0.76395404 ... -1.01192774  0.19414565
  -0.28007651]
 [ 0.36893004 -1.01091087 -0.25135704 ... -1.64239457  1.09265071
  -0.8997556 ]
 [ 0.89165014 -0.24526897 -1.06426559 ... -0.63904259 -0.10213659
  -0.18999416]]

 Intercept: [ 1.44066851 -0.67913977 -0.4702948  -0.37747284  4.01285667 -0.71389235
  4.41595925 -0.53851008  2.31789355 -3.30192494 -1.97179063 -3.93993086
  1.89322168 -2.67645358  1.86624809 -1.46157448  0.72308458  0.94730077
  0.97863341  3.41194854 -0.31052709  3.05902914  0.42552956  1.71824513
 -0.37716892  2.66272408 -1.02423514  2.52376331 -0.21490722  1.61436402
  3.90152878 -0.90157223  3.27260081  0.04403919  1.56671249 -5.00461789
```

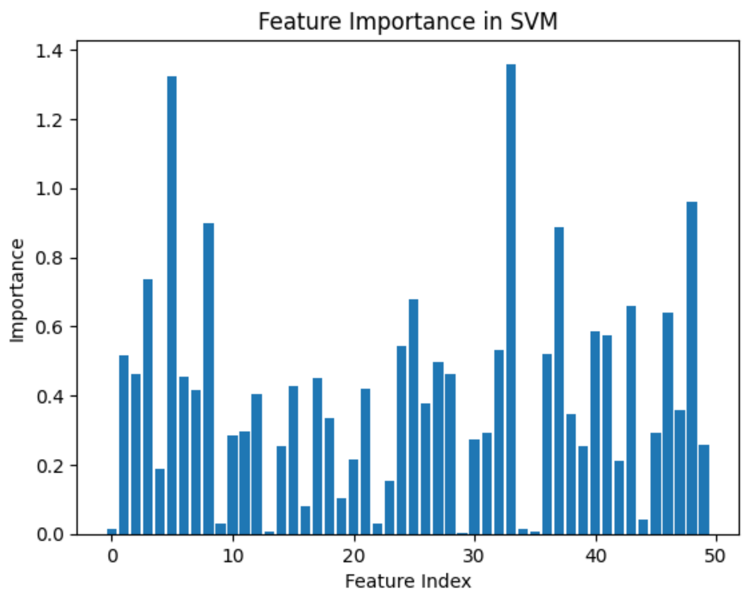
```
  1.23244058 -5.93015841  2.8837582   4.0871648   0.28589797  2.66928112
 -5.58423937  3.28725808  3.6970214 ]
```

```
# 1(iii)

# Model evaluation

# Evaluation metrics
accuracy = accuracy_score(test_labels, test_predictions)
report = classification_report(test_labels, test_predictions)

print(f"Accuracy: {accuracy}")
print(f"Classification Report: {report}")
```

```
Accuracy: 0.8346
Classification Report:               precision    recall  f1-score   support

           0       0.77      0.81      0.79      1000
           1       0.97      0.95      0.96      1000
           2       0.73      0.71      0.72      1000
           3       0.83      0.86      0.85      1000
           4       0.73      0.74      0.73      1000
           5       0.94      0.92      0.93      1000
           6       0.59      0.54      0.56      1000
           7       0.90      0.93      0.92      1000
           8       0.94      0.94      0.94      1000
           9       0.94      0.94      0.94      1000

    accuracy                           0.83     10000
   macro avg       0.83      0.83      0.83     10000
weighted avg       0.83      0.83      0.83     10000
```

```
# Qualitative Analysis

# Visualize the confusion matrix
conf_matrix = confusion_matrix(test_labels, test_predictions)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", cbar=False,
            xticklabels=np.unique(test_labels),
            yticklabels=np.unique(test_labels))
plt.title("\n Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()
```

```
# 1(iv)

# Model Interpretability

# Extract feature importance from coefficients
feature_importance = np.abs(svm.coef_)

# # Print or visualize feature importance
# print("Feature Importance:")
# for i, importance in enumerate(feature_importance[0]):
#     print(f"Feature {i+1}: {importance}")

# Plot feature importance
plt.bar(range(len(feature_importance[0])), feature_importance[0])
plt.xlabel('Feature Index')
plt.ylabel('Importance')
plt.title('Feature Importance in SVM')
plt.show()
```



2. Connvolution Neural Network (CNN) classifier:

(i) Explain algorithm selection : The hierarchical feature learning of CNNs allows for the extraction of complex patterns, textures, and shapes within the images.

(ii) Model building: Building the SVM model

(iii) Evaluation metrics: To check for these metrics, we implemented the **classification report** consisting of accuracy, precision, recall, F1-score; qualitative analysis- **confusion matrix** for classification on test set.

```
#2(ii)


# CNN without hyperparameter tuning

# Reshape the images to add a channel dimension
train_images = train_images.reshape((train_images.shape[0], 28, 28, 1))
val_images = val_images.reshape((val_images.shape[0], 28, 28, 1))
test_images = test_images.reshape((test_images.shape[0], 28, 28, 1))

# Define the CNN model
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(10, activation='softmax'))
```

```
# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
history = model.fit(train_images, train_labels, epochs=1, validation_data=(val_images, val_labels))
```

```
1641/1641 [==============================] - 88s 52ms/step - loss: 0.5096 - accuracy: 0.8132 - val_loss: 0.3618 - val_accura
```

```
#classification report for CNN without hyperparameter tuning

from sklearn.metrics import classification_report

# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')

# Use the trained model to predict the test set
predictions = model.predict(test_images)

# Convert the one-hot encoded predictions to class labels
predicted_labels = tf.argmax(predictions, axis=1)

# Print the classification report
print(classification_report(test_labels, predicted_labels))
```

```
313/313 [==============================] - 3s 9ms/step - loss: 0.3777 - accuracy: 0.8587
Test accuracy: 0.8586999773979187
313/313 [==============================] - 5s 14ms/step
              precision    recall  f1-score   support

           0       0.83      0.78      0.80      1000
           1       0.99      0.97      0.98      1000
           2       0.78      0.80      0.79      1000
           3       0.89      0.88      0.88      1000
           4       0.75      0.78      0.77      1000
           5       0.99      0.91      0.95      1000
           6       0.60      0.64      0.62      1000
           7       0.91      0.93      0.92      1000
           8       0.97      0.94      0.96      1000
           9       0.91      0.97      0.94      1000

    accuracy                           0.86     10000
   macro avg       0.86      0.86      0.86     10000
weighted avg       0.86      0.86      0.86     10000
```

```
# import tensorflow as tf
# from tensorflow.keras.models import Sequential
# from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
# from tensorflow.keras import layers
# from kerastuner.tuners import RandomSearch

# # Assuming train_images, train_labels, val_images, val_labels are defined

# # Function to define the model for hyperparameter tuning
# def build_model(hp):
#     model = Sequential()
#     model.add(Conv2D(hp.Int('conv1_filters', min_value=32, max_value=128, step=32),
#                      (3, 3), activation='relu', input_shape=(28, 28, 1)))
#     model.add(MaxPooling2D((2, 2)))
#     model.add(Conv2D(hp.Int('conv2_filters', min_value=32, max_value=128, step=32),
#                      (3, 3), activation='relu'))
#     model.add(MaxPooling2D((2, 2)))
#     model.add(Conv2D(hp.Int('conv3_filters', min_value=32, max_value=128, step=32),
#                      (3, 3), activation='relu'))
#     model.add(Flatten())
#     model.add(Dense(hp.Int('dense_units', min_value=32, max_value=256, step=32),
#                     activation='relu'))
#     model.add(Dense(10, activation='softmax'))

#     model.compile(optimizer='adam',
#                   loss='sparse_categorical_crossentropy',
#                   metrics=['accuracy'])
```

```
#     return model

# # Initialize the tuner
# tuner = RandomSearch(
#     build_model,
#     objective='val_accuracy',
#     max_trials=5,  # You can adjust this number based on computational resources
#     executions_per_trial=1,
#     directory='my_dir',
#     project_name='cnn_tuning')

# # Perform the search
# tuner.search(train_images, train_labels, epochs=10, validation_data=(val_images, val_labels))

# # Get the best model
# best_model = tuner.get_best_models(num_models=1)[0]

# # Summary of the best model
# best_model.summary()
```

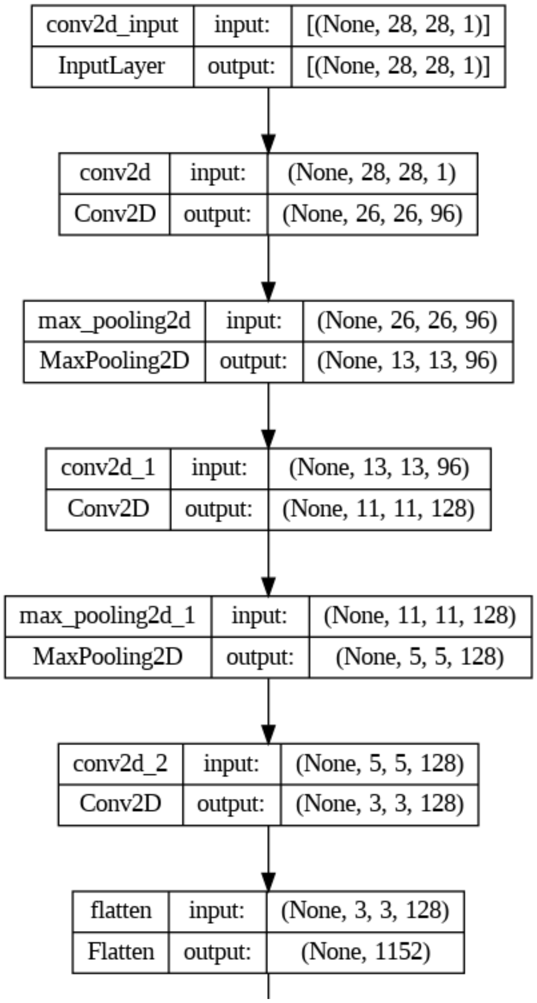
```
<ipython-input-22-efac4200dadc>:5: DeprecationWarning: `import kerastuner` is deprecated, please use `import keras_tuner`.
  from kerastuner.tuners import RandomSearch
Reloading Tuner from my_dir/cnn_tuning/tuner0.json
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 96)        960

 max_pooling2d (MaxPooling2  (None, 13, 13, 96)        0
 D)

 conv2d_1 (Conv2D)           (None, 11, 11, 128)       110720

 max_pooling2d_1 (MaxPoolin  (None, 5, 5, 128)         0
 g2D)

 conv2d_2 (Conv2D)           (None, 3, 3, 128)         147584

 flatten (Flatten)           (None, 1152)              0

 dense (Dense)               (None, 224)               258272

 dense_1 (Dense)             (None, 10)                2250

=================================================================
Total params: 519786 (1.98 MB)
Trainable params: 519786 (1.98 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
# # Fit the best model and capture the history
# history = best_model.fit(train_images, train_labels, epochs=5, validation_data=(val_images, val_labels))
```

```
# For simplicity, we show the case for an epoch
best_model.fit(train_images, train_labels, epochs=1, validation_data=(val_images, val_labels))
```

```
1641/1641 [==============================] - 231s 141ms/step - loss: 0.1822 - accuracy: 0.9308 - val_loss: 0.2495 - val_accu
<keras.src.callbacks.History at 0x7bd28de53d30>
```

```
 # Visualize the model architecture
plot_model(best_model, show_shapes=True, to_file='cnn_model.png')
```



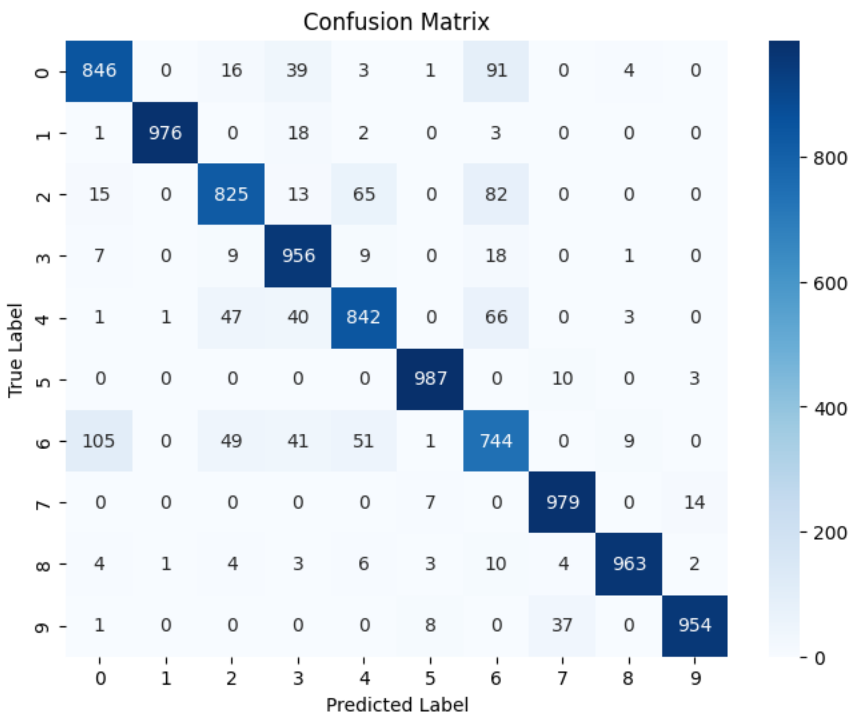

```
# # Plot the accuracy after performing hyperparameter tuning on 5 epochs
# plt.plot(history.history['accuracy'], label='accuracy')
# plt.plot(history.history['val_accuracy'], label='val_accuracy')
# plt.xlabel('Epoch')
# plt.ylabel('Accuracy')
# plt.legend(loc='lower right')
# plt.show()

# # Plot the loss
# plt.plot(history.history['loss'], label='loss')
# plt.plot(history.history['val_loss'], label='val_loss')
# plt.xlabel('Epoch')
# plt.ylabel('Loss')
# plt.legend(loc='upper right')
# plt.show()


#3(ii)
#classification report

from sklearn.metrics import classification_report

# Evaluate the model on the test set
test_loss, test_acc = best_model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')

# Use the trained model to predict the test set
predictions = best_model.predict(test_images)

# Convert the one-hot encoded predictions to class labels
predicted_labels = tf.argmax(predictions, axis=1)

# Print the classification report
print(classification_report(test_labels, predicted_labels))
```

```
313/313 [==============================] - 13s 42ms/step - loss: 0.2637 - accuracy: 0.9072
Test accuracy: 0.9071999788284302
```

```
313/313 [==============================] - 9s 27ms/step
              precision    recall  f1-score   support

           0       0.86      0.85      0.85      1000
           1       1.00      0.98      0.99      1000
           2       0.87      0.82      0.85      1000
           3       0.86      0.96      0.91      1000
           4       0.86      0.84      0.85      1000
           5       0.98      0.99      0.98      1000
           6       0.73      0.74      0.74      1000
           7       0.95      0.98      0.96      1000
           8       0.98      0.96      0.97      1000
           9       0.98      0.95      0.97      1000

    accuracy                           0.91     10000
   macro avg       0.91      0.91      0.91     10000
weighted avg       0.91      0.91      0.91     10000
```

```
#2(ii)

# Visualize the confusion matrix
predictions = np.argmax(best_model.predict(test_images), axis=1)
cm = confusion_matrix(test_labels, predictions)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(test_labels), yticklabels=np.unique(test_labels))
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
313/313 [==============================] - 9s 30ms/step
```




```
test_images_reshaped = test_images.reshape((test_images.shape[0], 28, 28, 1))


# Use the best model to make predictions on the validation set
predictions = best_model.predict(val_images)
predicted_labels = np.argmax(predictions, axis=1)


# Display some images with their true and predicted labels
num_images_to_display = 5
plt.figure(figsize=(15, 3))

# Find indices where predictions are correct, incorrect respectively.
correct_indices = np.where(predicted_labels == val_labels)[0]
```

```
incorrect_indices = np.where(predicted_labels != val_labels)[0]
```