In [ ]:
```
# 1.    Load the basic libraries and packages

import numpy as np
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import classification_report
import matplotlib.pyplot as plt
```

In [ ]:
```
# 2.    Load the dataset

from tensorflow.keras.datasets import fashion_mnist

# Load Fashion MNIST dataset
(train_X, train_Y), (test_X, test_Y) = fashion_mnist.load_data()

# Split data into training and validation sets
valid_X, valid_Y = train_X[:5000], train_Y[:5000]
train_X, train_Y = train_X[5000:], train_Y[5000:]
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
s/train-labels-idx1-ubyte.gz
29515/29515 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
s/train-images-idx3-ubyte.gz
26421880/26421880 ━━━━━━━━━━━━━━━━━━━━ 2s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
s/t10k-labels-idx1-ubyte.gz
5148/5148 ━━━━━━━━━━━━━━━━━━━━ 0s 1us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
s/t10k-images-idx3-ubyte.gz
4422102/4422102 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
```

In [ ]:
```
# 3.    Analyse the dataset

print(f"Training data shape: {train_X.shape}, Labels shape: {train_Y.shape}")
print(f"Validation data shape: {valid_X.shape}, Labels shape: {valid_Y.shape}")
print(f"Test data shape: {test_X.shape}, Labels shape: {test_Y.shape}")
print("Unique classes:", np.unique(train_Y))
```

```
Training data shape: (55000, 28, 28), Labels shape: (55000,)
Validation data shape: (5000, 28, 28), Labels shape: (5000,)
Test data shape: (10000, 28, 28), Labels shape: (10000,)
Unique classes: [0 1 2 3 4 5 6 7 8 9]
```

In [ ]:
```
# 4.    Normalize the data

# Normalize pixel values to range 0-1
train_X = train_X.astype('float32') / 255.0
valid_X = valid_X.astype('float32') / 255.0
test_X = test_X.astype('float32') / 255.0
```

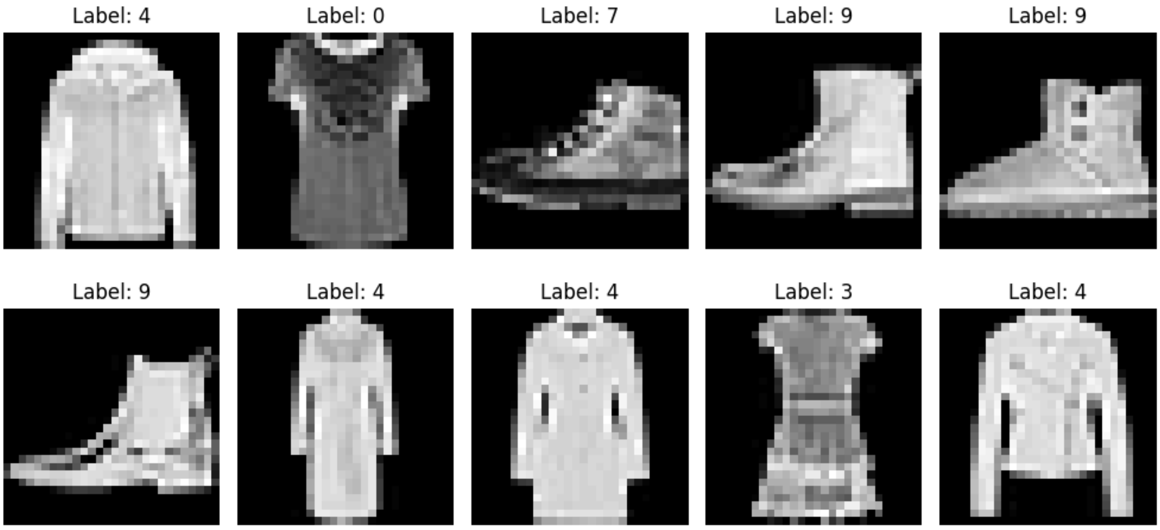
In [ ]:
```
# 5.    Pre-process the data

# Reshape to include channel dimension
train_X = train_X.reshape(-1, 28, 28, 1)
valid_X = valid_X.reshape(-1, 28, 28, 1)
test_X = test_X.reshape(-1, 28, 28, 1)
```

```
# Convert labels to one-hot encoding
num_classes = 10
train_label = to_categorical(train_Y, num_classes)
valid_label = to_categorical(valid_Y, num_classes)
test_Y_one_hot = to_categorical(test_Y, num_classes)
```

In [ ]:
```
# 6.    Visualize the Data

plt.figure(figsize=(10, 5))
for i in range(10):
    plt.subplot(2, 5, i + 1)
    plt.imshow(train_X[i].reshape(28, 28), cmap='gray')
    plt.title(f"Label: {train_Y[i]}")
    plt.axis('off')
plt.tight_layout()
plt.show()
```




In [ ]:
```
# 7.    Write the CNN model function

def create_cnn_model():
    model = tf.keras.Sequential()
    model.add(tf.keras.layers.Conv2D(32, (3, 3), activation='linear', padding='s
    model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
    model.add(tf.keras.layers.MaxPooling2D((2, 2), padding='same'))
    model.add(tf.keras.layers.Dropout(0.25))
    model.add(tf.keras.layers.Conv2D(64, (3, 3), activation='linear', padding='s
    model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
    model.add(tf.keras.layers.MaxPooling2D((2, 2), padding='same'))
    model.add(tf.keras.layers.Dropout(0.25))
    model.add(tf.keras.layers.Conv2D(128, (3, 3), activation='linear', padding='
    model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
    model.add(tf.keras.layers.MaxPooling2D((2, 2), padding='same'))
    model.add(tf.keras.layers.Dropout(0.4))
    model.add(tf.keras.layers.Flatten())
    model.add(tf.keras.layers.Dense(128, activation='linear'))
    model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
    model.add(tf.keras.layers.Dropout(0.3))
    model.add(tf.keras.layers.Dense(num_classes, activation='softmax'))
    return model
```

In [ ]:
```
# 8.    Write the Cost Function
```

```python
# Categorical Crossentropy as the loss function
cost_function = tf.keras.losses.CategoricalCrossentropy()
```

In [ ]:
```python
# 9.    Write the Gradient Descent optimization algorithm

# Adam optimizer with default parameters
optimizer = tf.keras.optimizers.Adam()
```

In [ ]:
```python
# 10.   Apply the training over the dataset to minimize the loss

fashion_model = create_cnn_model()
fashion_model.compile(loss=cost_function, optimizer=optimizer, metrics=['accurac

# Train the model
fashion_train = fashion_model.fit(
    train_X, train_label,
    batch_size=64, epochs=20,
    verbose=1, validation_data=(valid_X, valid_label)
)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.
py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a laye
r. When using Sequential models, prefer using an `Input(shape)` object as the fir
st layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/local/lib/python3.10/dist-packages/keras/src/layers/activations/leaky_relu.p
y:41: UserWarning: Argument `alpha` is deprecated. Use `negative_slope` instead.
  warnings.warn(
```

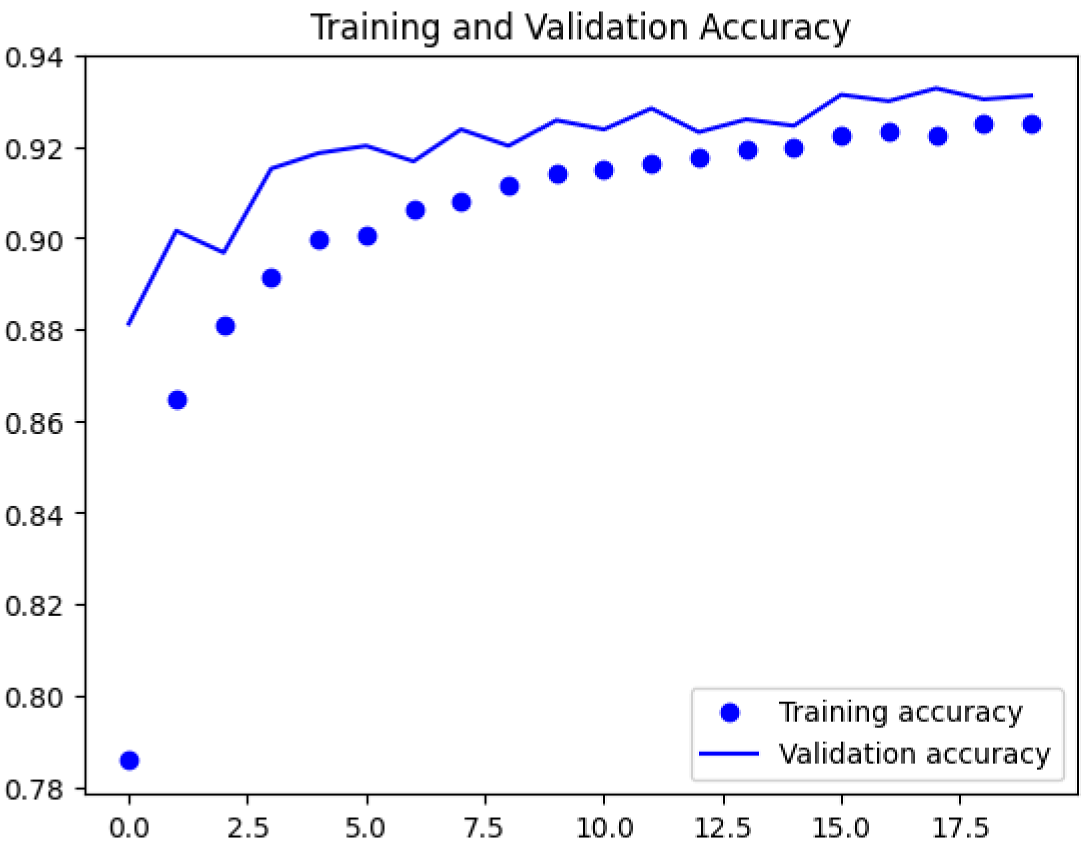
```
Epoch 1/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 118s 132ms/step - accuracy: 0.6928 - loss: 0.8301 - val_accuracy: 0.8812 - val_loss: 0.3291
Epoch 2/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 142s 133ms/step - accuracy: 0.8584 - loss: 0.3817 - val_accuracy: 0.9016 - val_loss: 0.2733
Epoch 3/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 141s 132ms/step - accuracy: 0.8792 - loss: 0.3272 - val_accuracy: 0.8968 - val_loss: 0.2619
Epoch 4/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 144s 135ms/step - accuracy: 0.8881 - loss: 0.3022 - val_accuracy: 0.9152 - val_loss: 0.2320
Epoch 5/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 114s 133ms/step - accuracy: 0.8979 - loss: 0.2751 - val_accuracy: 0.9186 - val_loss: 0.2210
Epoch 6/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 111s 129ms/step - accuracy: 0.9000 - loss: 0.2611 - val_accuracy: 0.9202 - val_loss: 0.2164
Epoch 7/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 141s 127ms/step - accuracy: 0.9068 - loss: 0.2490 - val_accuracy: 0.9168 - val_loss: 0.2238
Epoch 8/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 111s 129ms/step - accuracy: 0.9103 - loss: 0.2398 - val_accuracy: 0.9238 - val_loss: 0.2036
Epoch 9/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 143s 130ms/step - accuracy: 0.9096 - loss: 0.2374 - val_accuracy: 0.9202 - val_loss: 0.2103
Epoch 10/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 114s 133ms/step - accuracy: 0.9129 - loss: 0.2298 - val_accuracy: 0.9258 - val_loss: 0.1988
Epoch 11/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 115s 133ms/step - accuracy: 0.9162 - loss: 0.2227 - val_accuracy: 0.9238 - val_loss: 0.2044
Epoch 12/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 142s 134ms/step - accuracy: 0.9155 - loss: 0.2247 - val_accuracy: 0.9284 - val_loss: 0.1954
Epoch 13/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 114s 132ms/step - accuracy: 0.9178 - loss: 0.2180 - val_accuracy: 0.9232 - val_loss: 0.2054
Epoch 14/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 141s 131ms/step - accuracy: 0.9196 - loss: 0.2125 - val_accuracy: 0.9260 - val_loss: 0.1952
Epoch 15/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 117s 136ms/step - accuracy: 0.9184 - loss: 0.2105 - val_accuracy: 0.9246 - val_loss: 0.2030
Epoch 16/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 114s 132ms/step - accuracy: 0.9215 - loss: 0.2067 - val_accuracy: 0.9314 - val_loss: 0.1901
Epoch 17/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 117s 136ms/step - accuracy: 0.9245 - loss: 0.2027 - val_accuracy: 0.9300 - val_loss: 0.1901
Epoch 18/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 116s 135ms/step - accuracy: 0.9248 - loss: 0.1973 - val_accuracy: 0.9328 - val_loss: 0.1891
Epoch 19/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 147s 140ms/step - accuracy: 0.9277 - loss: 0.1933 - val_accuracy: 0.9304 - val_loss: 0.1850
Epoch 20/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 139s 136ms/step - accuracy: 0.9268 - loss: 0.1937 - val_accuracy: 0.9312 - val_loss: 0.1869
```

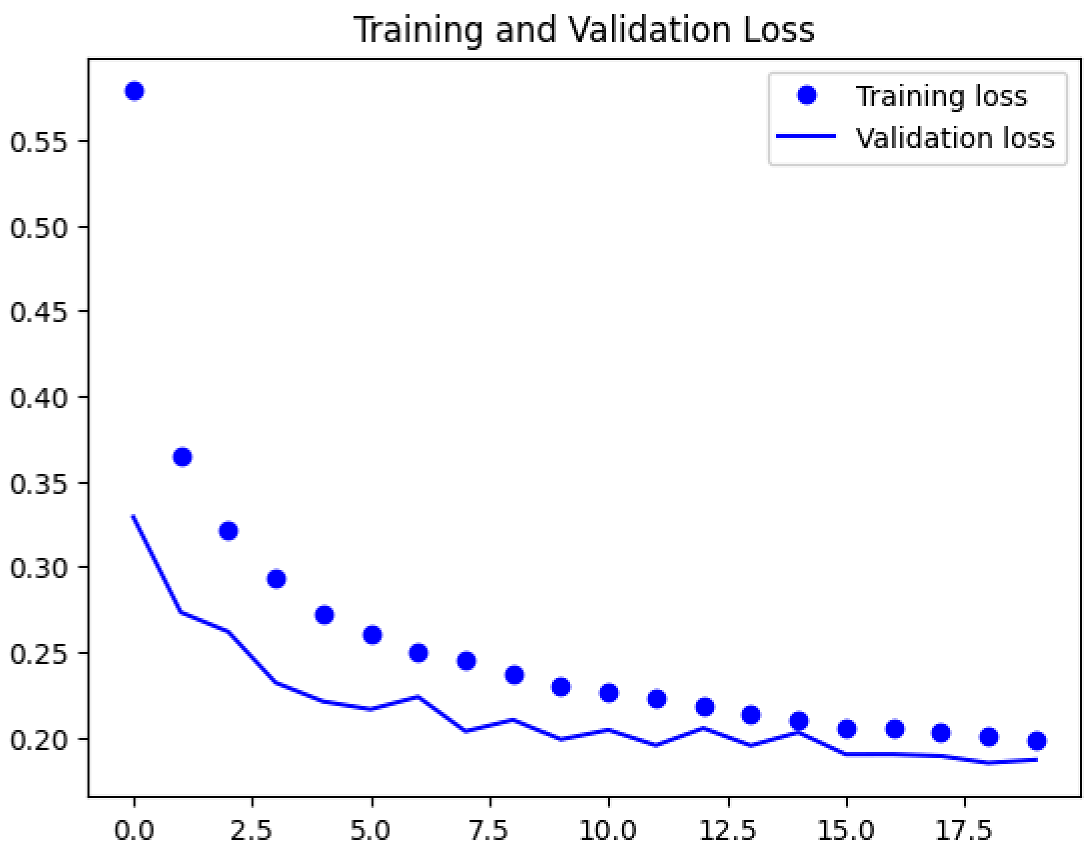
```
In [ ]: # 11.   Observe the cost function vs iterations learning curve

accuracy = fashion_train.history['accuracy']
val_accuracy = fashion_train.history['val_accuracy']
loss = fashion_train.history['loss']
val_loss = fashion_train.history['val_loss']
epochs = range(len(accuracy))

# Accuracy Curve
plt.plot(epochs, accuracy, 'bo', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()
plt.figure()

# Loss Curve
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()
```






Result

In [ ]:
```
# a.    Training dataset

print("Training data shape:", train_X.shape)
print("Validation data shape:", valid_X.shape)
print("Test data shape:", test_X.shape)
print("Number of classes:", num_classes)
print("Unique classes:", np.unique(train_Y))
```

```
Training data shape: (55000, 28, 28, 1)
Validation data shape: (5000, 28, 28, 1)
Test data shape: (10000, 28, 28, 1)
Number of classes: 10
Unique classes: [0 1 2 3 4 5 6 7 8 9]
```

In [ ]:
```
# b.    Model summary

# Before Regularization
model = tf.keras.Sequential()
model.add(tf.keras.layers.Conv2D(32, (3, 3), activation='linear', padding='same'
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
model.add(tf.keras.layers.MaxPooling2D((2, 2), padding='same'))
model.add(tf.keras.layers.Conv2D(64, (3, 3), activation='linear', padding='same'
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
model.add(tf.keras.layers.MaxPooling2D((2, 2), padding='same'))
model.add(tf.keras.layers.Conv2D(128, (3, 3), activation='linear', padding='same
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
model.add(tf.keras.layers.MaxPooling2D((2, 2), padding='same'))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(128, activation='linear'))
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
```

```
model.add(tf.keras.layers.Dense(num_classes, activation='softmax'))
model.summary()
```

**Model: "sequential_1"**

| Layer (type) | Output Shape | |
|---|---|---|
| conv2d_3 (Conv2D) | (None, 28, 28, 32) | |
| leaky_re_lu_4 (LeakyReLU) | (None, 28, 28, 32) | |
| max_pooling2d_3 (MaxPooling2D) | (None, 14, 14, 32) | |
| conv2d_4 (Conv2D) | (None, 14, 14, 64) | |
| leaky_re_lu_5 (LeakyReLU) | (None, 14, 14, 64) | |
| max_pooling2d_4 (MaxPooling2D) | (None, 7, 7, 64) | |
| conv2d_5 (Conv2D) | (None, 7, 7, 128) | |
| leaky_re_lu_6 (LeakyReLU) | (None, 7, 7, 128) | |
| max_pooling2d_5 (MaxPooling2D) | (None, 4, 4, 128) | |
| flatten_1 (Flatten) | (None, 2048) | |
| dense_2 (Dense) | (None, 128) | |
| leaky_re_lu_7 (LeakyReLU) | (None, 128) | |
| dense_3 (Dense) | (None, 10) | |

**Total params:** 356,234 (1.36 MB)

**Trainable params:** 356,234 (1.36 MB)

**Non-trainable params:** 0 (0.00 B)

In [ ]:

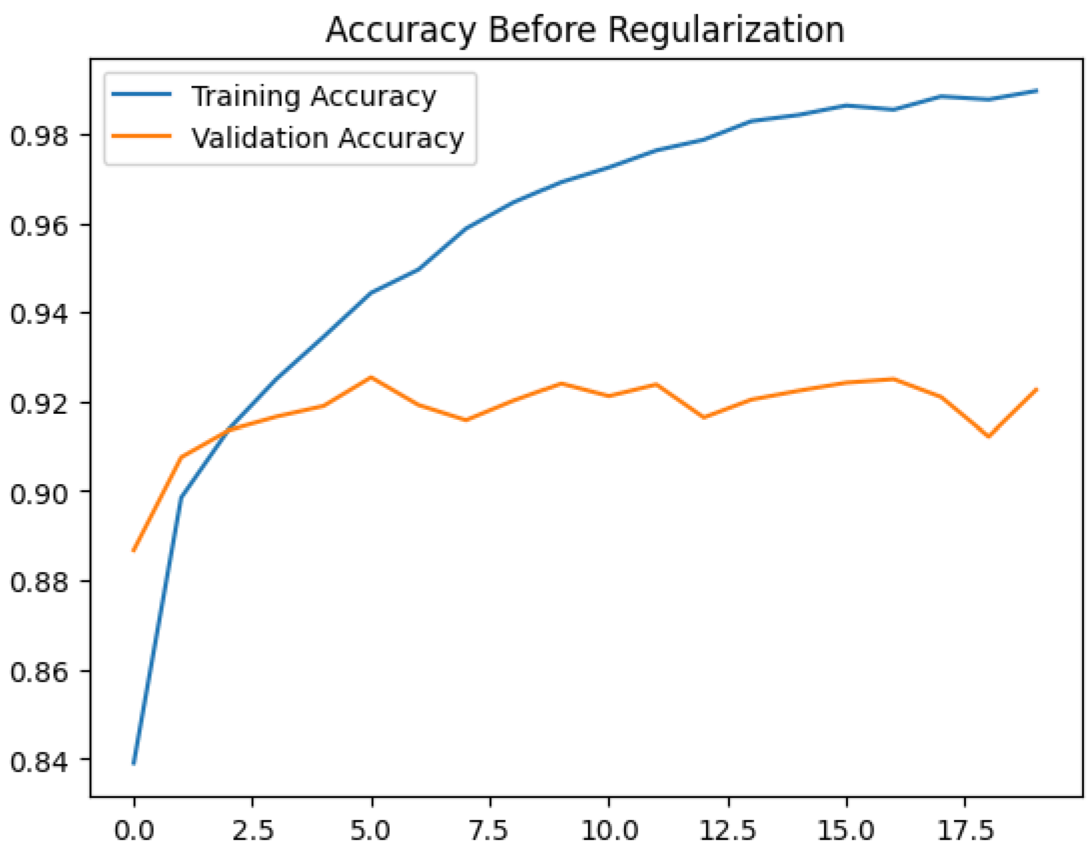
```
# c.    Training and validation accuracy w.r.t epochs before regularization

model.compile(loss=tf.keras.losses.CategoricalCrossentropy(), optimizer=tf.keras

# Train model without regularization
train_no_reg = model.fit(train_X, train_label, batch_size=64, epochs=20, validat

plt.plot(train_no_reg.history['accuracy'], label='Training Accuracy')
plt.plot(train_no_reg.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy Before Regularization')
plt.legend()
plt.show()
```

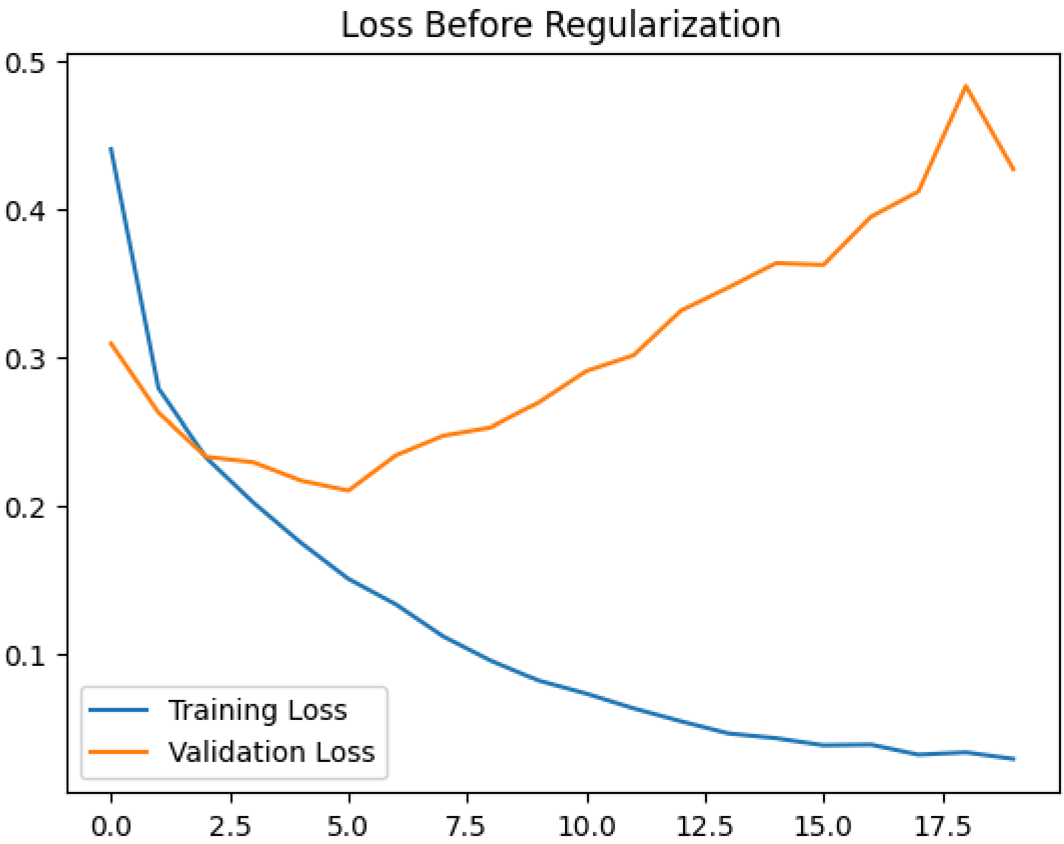
```
Epoch 1/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 111s 126ms/step - accuracy: 0.7685 - loss: 0.6339 -
val_accuracy: 0.8868 - val_loss: 0.3094
Epoch 2/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 142s 126ms/step - accuracy: 0.8993 - loss: 0.2801 -
val_accuracy: 0.9076 - val_loss: 0.2627
Epoch 3/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 144s 128ms/step - accuracy: 0.9132 - loss: 0.2340 -
val_accuracy: 0.9136 - val_loss: 0.2332
Epoch 4/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 142s 128ms/step - accuracy: 0.9227 - loss: 0.2067 -
val_accuracy: 0.9166 - val_loss: 0.2294
Epoch 5/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 140s 125ms/step - accuracy: 0.9337 - loss: 0.1766 -
val_accuracy: 0.9190 - val_loss: 0.2171
Epoch 6/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 138s 121ms/step - accuracy: 0.9457 - loss: 0.1498 -
val_accuracy: 0.9254 - val_loss: 0.2103
Epoch 7/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 145s 125ms/step - accuracy: 0.9513 - loss: 0.1305 -
val_accuracy: 0.9192 - val_loss: 0.2341
Epoch 8/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 139s 122ms/step - accuracy: 0.9612 - loss: 0.1060 -
val_accuracy: 0.9158 - val_loss: 0.2474
Epoch 9/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 145s 125ms/step - accuracy: 0.9672 - loss: 0.0900 -
val_accuracy: 0.9202 - val_loss: 0.2529
Epoch 10/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 142s 125ms/step - accuracy: 0.9704 - loss: 0.0779 -
val_accuracy: 0.9240 - val_loss: 0.2696
Epoch 11/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 143s 126ms/step - accuracy: 0.9752 - loss: 0.0656 -
val_accuracy: 0.9212 - val_loss: 0.2907
Epoch 12/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 138s 121ms/step - accuracy: 0.9791 - loss: 0.0564 -
val_accuracy: 0.9238 - val_loss: 0.3015
Epoch 13/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 107s 124ms/step - accuracy: 0.9806 - loss: 0.0491 -
val_accuracy: 0.9164 - val_loss: 0.3317
Epoch 14/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 143s 125ms/step - accuracy: 0.9845 - loss: 0.0406 -
val_accuracy: 0.9204 - val_loss: 0.3473
Epoch 15/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 109s 127ms/step - accuracy: 0.9864 - loss: 0.0367 -
val_accuracy: 0.9224 - val_loss: 0.3637
Epoch 16/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 142s 128ms/step - accuracy: 0.9874 - loss: 0.0353 -
val_accuracy: 0.9242 - val_loss: 0.3626
Epoch 17/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 115s 134ms/step - accuracy: 0.9858 - loss: 0.0376 -
val_accuracy: 0.9250 - val_loss: 0.3952
Epoch 18/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 136s 127ms/step - accuracy: 0.9886 - loss: 0.0301 -
val_accuracy: 0.9210 - val_loss: 0.4122
Epoch 19/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 144s 130ms/step - accuracy: 0.9897 - loss: 0.0283 -
val_accuracy: 0.9122 - val_loss: 0.4835
Epoch 20/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 135s 122ms/step - accuracy: 0.9913 - loss: 0.0251 -
val_accuracy: 0.9226 - val_loss: 0.4272
```




In [ ]:

```
# d.    Training and validation loss w.r.t epochs before regularization

plt.plot(train_no_reg.history['loss'], label='Training Loss')
plt.plot(train_no_reg.history['val_loss'], label='Validation Loss')
plt.title('Loss Before Regularization')
plt.legend()
plt.show()
```




In [ ]:

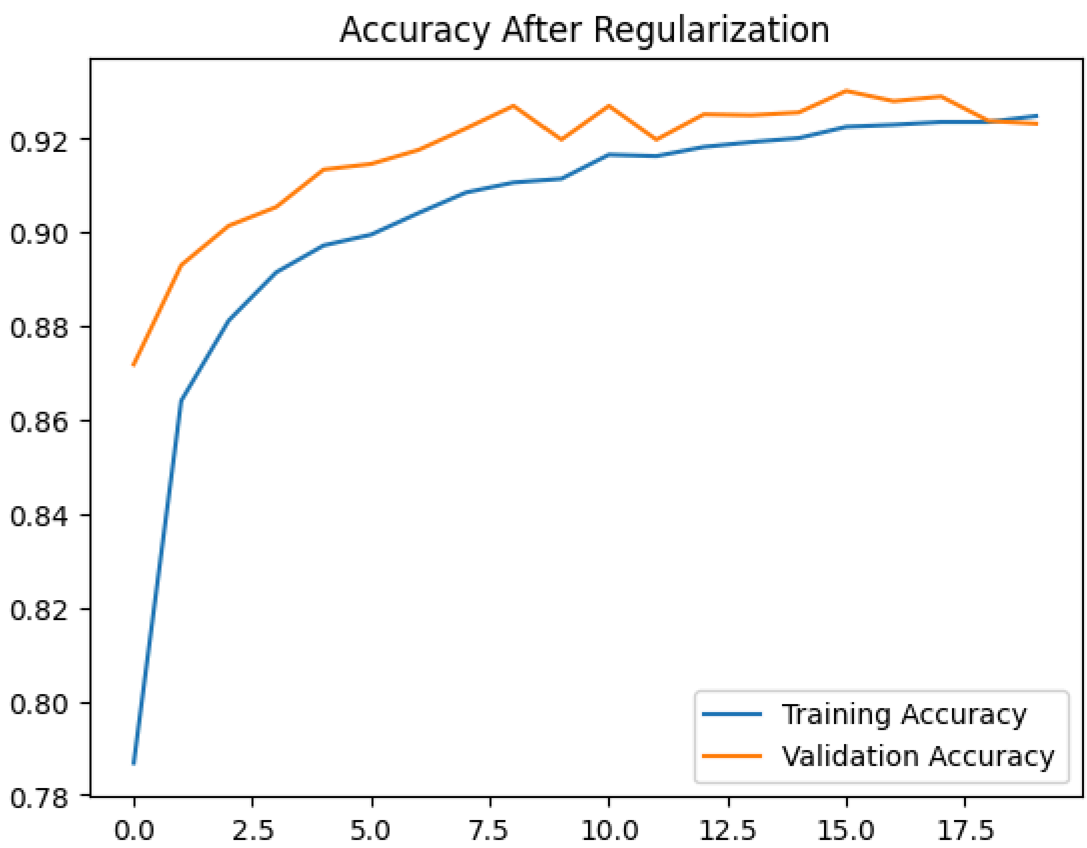
```
# e.    Training and validation accuracy w.r.t epochs after regularization

# Model with Dropout Regularization
reg_model = create_cnn_model()
reg_model.compile(loss=tf.keras.losses.CategoricalCrossentropy(), optimizer=tf.k

train_with_reg = reg_model.fit(train_X, train_label, batch_size=64, epochs=20, v

plt.plot(train_with_reg.history['accuracy'], label='Training Accuracy')
plt.plot(train_with_reg.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy After Regularization')
plt.legend()
plt.show()
```

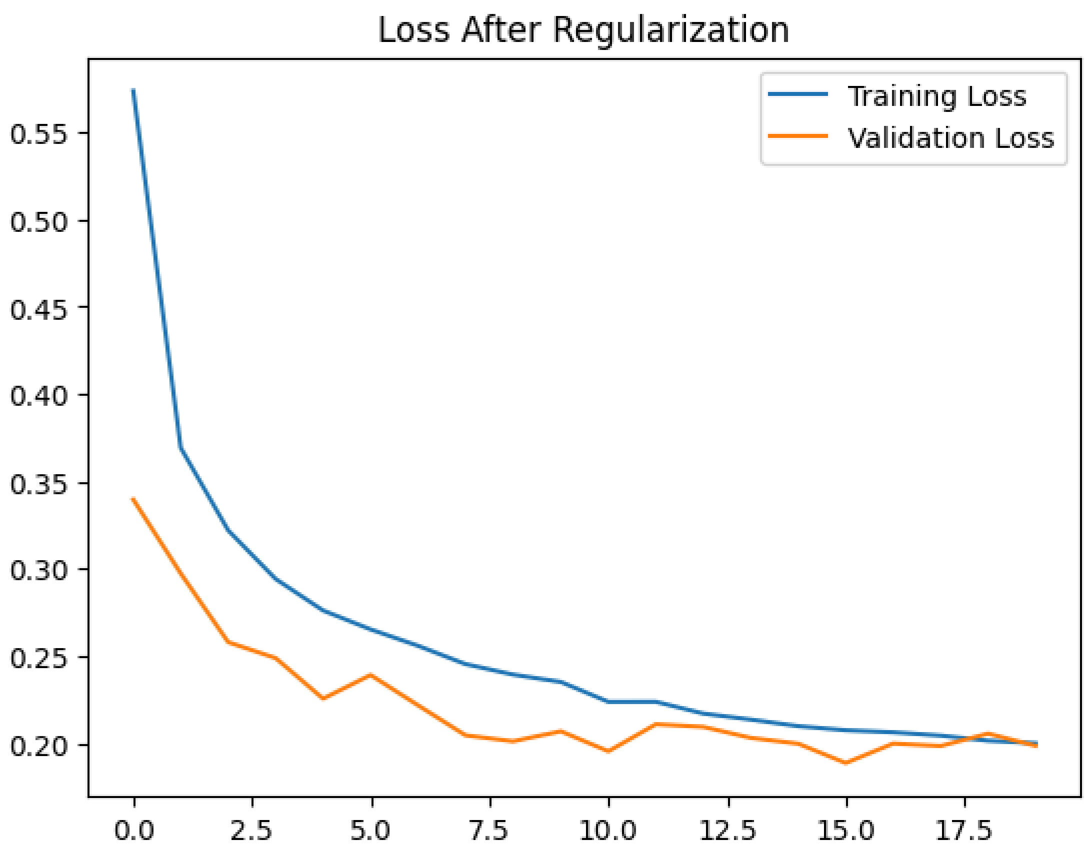
```
Epoch 1/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 121s 138ms/step - accuracy: 0.6963 - loss: 0.8150 - val_accuracy: 0.8718 - val_loss: 0.3397
Epoch 2/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 142s 138ms/step - accuracy: 0.8599 - loss: 0.3797 - val_accuracy: 0.8930 - val_loss: 0.2973
Epoch 3/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 143s 139ms/step - accuracy: 0.8768 - loss: 0.3310 - val_accuracy: 0.9014 - val_loss: 0.2579
Epoch 4/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 117s 136ms/step - accuracy: 0.8881 - loss: 0.2994 - val_accuracy: 0.9054 - val_loss: 0.2487
Epoch 5/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 144s 138ms/step - accuracy: 0.8967 - loss: 0.2809 - val_accuracy: 0.9134 - val_loss: 0.2255
Epoch 6/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 139s 135ms/step - accuracy: 0.9000 - loss: 0.2628 - val_accuracy: 0.9146 - val_loss: 0.2390
Epoch 7/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 145s 138ms/step - accuracy: 0.9048 - loss: 0.2553 - val_accuracy: 0.9176 - val_loss: 0.2216
Epoch 8/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 117s 136ms/step - accuracy: 0.9091 - loss: 0.2447 - val_accuracy: 0.9222 - val_loss: 0.2044
Epoch 9/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 118s 137ms/step - accuracy: 0.9117 - loss: 0.2387 - val_accuracy: 0.9270 - val_loss: 0.2010
Epoch 10/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 141s 136ms/step - accuracy: 0.9124 - loss: 0.2332 - val_accuracy: 0.9198 - val_loss: 0.2068
Epoch 11/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 145s 139ms/step - accuracy: 0.9174 - loss: 0.2211 - val_accuracy: 0.9270 - val_loss: 0.1953
Epoch 12/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 137s 134ms/step - accuracy: 0.9174 - loss: 0.2222 - val_accuracy: 0.9198 - val_loss: 0.2108
Epoch 13/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 119s 139ms/step - accuracy: 0.9183 - loss: 0.2162 - val_accuracy: 0.9252 - val_loss: 0.2093
Epoch 14/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 116s 135ms/step - accuracy: 0.9204 - loss: 0.2102 - val_accuracy: 0.9250 - val_loss: 0.2030
Epoch 15/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 148s 142ms/step - accuracy: 0.9189 - loss: 0.2103 - val_accuracy: 0.9256 - val_loss: 0.1996
Epoch 16/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 117s 136ms/step - accuracy: 0.9243 - loss: 0.2052 - val_accuracy: 0.9302 - val_loss: 0.1886
Epoch 17/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 143s 138ms/step - accuracy: 0.9244 - loss: 0.2006 - val_accuracy: 0.9280 - val_loss: 0.1997
Epoch 18/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 123s 143ms/step - accuracy: 0.9258 - loss: 0.1988 - val_accuracy: 0.9290 - val_loss: 0.1983
Epoch 19/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 136s 136ms/step - accuracy: 0.9241 - loss: 0.1985 - val_accuracy: 0.9238 - val_loss: 0.2054
Epoch 20/20
860/860 ━━━━━━━━━━━━━━━━━━━━ 121s 141ms/step - accuracy: 0.9245 - loss: 0.1991 - val_accuracy: 0.9232 - val_loss: 0.1984
```




In [ ]:

```
# f.    Training and validation loss w.r.t epochs after regularization

plt.plot(train_with_reg.history['loss'], label='Training Loss')
plt.plot(train_with_reg.history['val_loss'], label='Validation Loss')
plt.title('Loss After Regularization')
plt.legend()
plt.show()
```

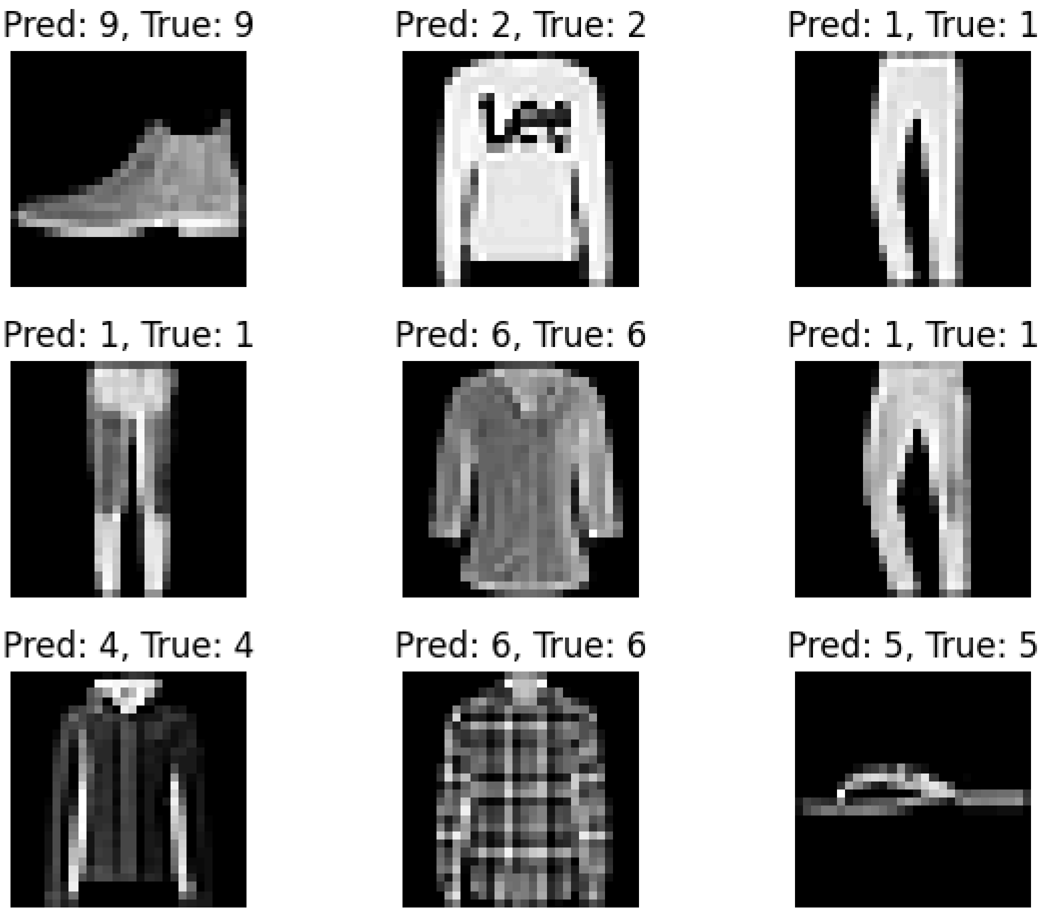



In [ ]:
```python
# g.    Original v/s predicted labels for correct predicted observations

predicted_classes = np.argmax(reg_model.predict(test_X), axis=1)
correct_indices = np.where(predicted_classes == test_Y)[0]

print(f"Number of Correct Predictions: {len(correct_indices)}")
for i, correct in enumerate(correct_indices[:9]):
    plt.subplot(3, 3, i + 1)
    plt.imshow(test_X[correct].reshape(28, 28), cmap='gray')
    plt.title(f"Pred: {predicted_classes[correct]}, True: {test_Y[correct]}")
    plt.axis('off')
plt.tight_layout()
plt.show()
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 6s 19ms/step
Number of Correct Predictions: 9187
```



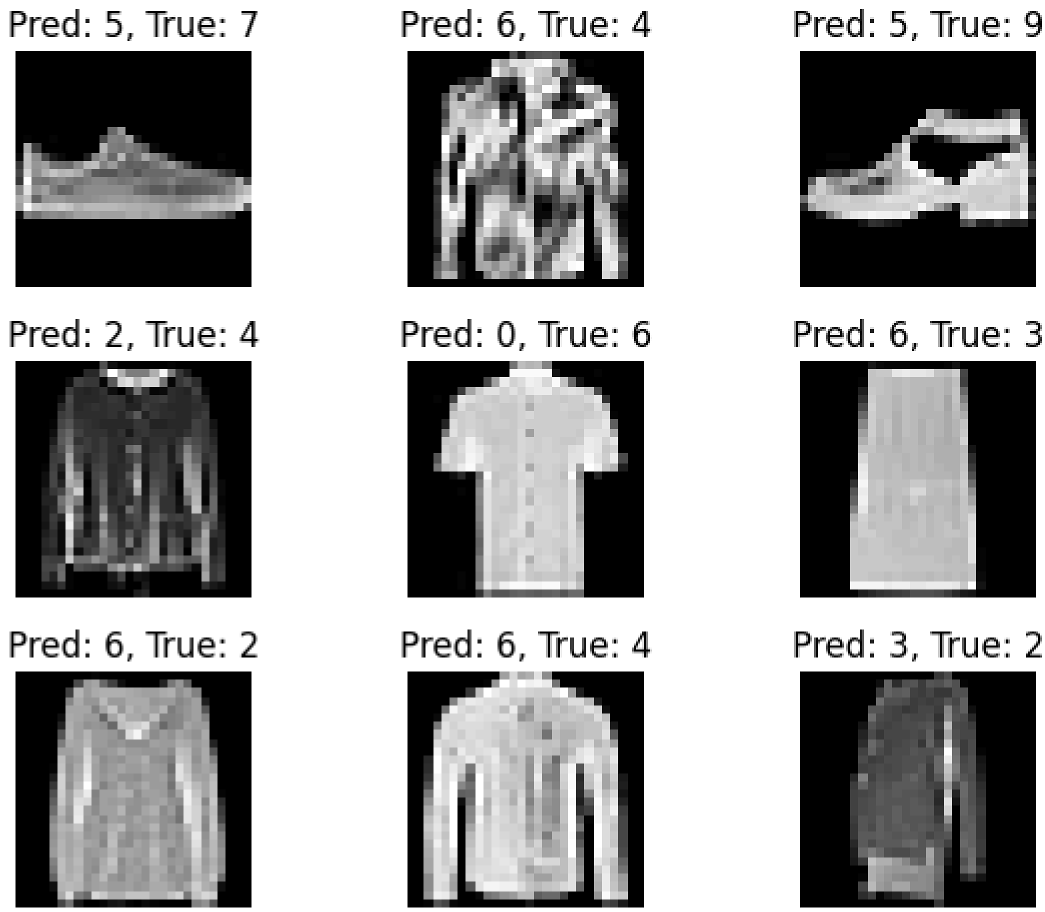

In [ ]:

```
# h.    Original v/s predicted labels for incorrect predicted observations

incorrect_indices = np.where(predicted_classes != test_Y)[0]

print(f"Number of Incorrect Predictions: {len(incorrect_indices)}")
for i, incorrect in enumerate(incorrect_indices[:9]):
    plt.subplot(3, 3, i + 1)
    plt.imshow(test_X[incorrect].reshape(28, 28), cmap='gray')
    plt.title(f"Pred: {predicted_classes[incorrect]}, True: {test_Y[incorrect]}"
    plt.axis('off')
plt.tight_layout()
plt.show()
```

```
Number of Incorrect Predictions: 813
```


Pred: 5, True: 7
Pred: 6, True: 4
Pred: 5, True: 9
Pred: 2, True: 4
Pred: 0, True: 6
Pred: 6, True: 3
Pred: 6, True: 2
Pred: 6, True: 4
Pred: 3, True: 2

**Aim:** To understand the process of convolution over the image and apply over the classification problem

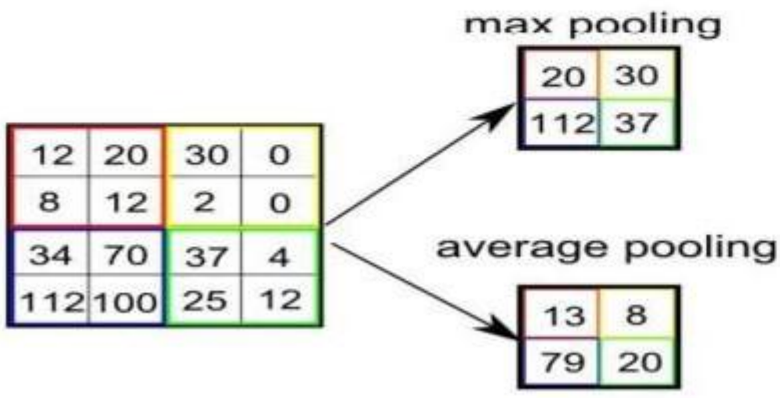
**IDE:** Google Colab

## Theory:

Convolutional Neural Networks (CNN) are complex feed forward neural networks. CNNs are used for image classification and recognition because of its high accuracy There are three types of layers in a convolutional neural network: i. Convolutional layer ii. Pooling layer iii. Fully connected layer Each of these layers has different parameters that can be optimized and performs a different task on the input data.

**What is Pooling Layer?**

Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. There are two types of Pooling i. Average Pooling. ii. Max Pooling Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel. Max Pooling also performs as a Noise Suppressant. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction. On the other hand, Average Pooling simply performs dimensionality reduction as a noise suppressing mechanism. Hence, we can say that Max Pooling performs a lot better than Average Pooling.




**What is Convolutional Layer?**

Convolutional layers are the major building blocks used in convolutional neural networks. A convolution is the simple application of a filter to an input that results in an activation. Repeated application of the same filter to an input results in a map of activations called a feature map, indicating the locations and strength of a detected feature in an input, such as an image. A convolutional layer contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons.

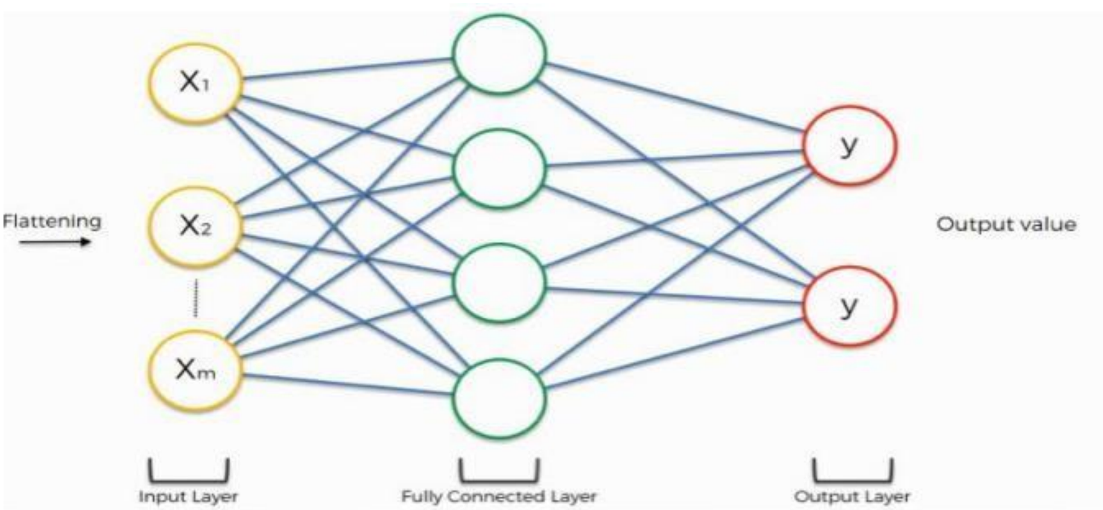
**What is Fully Connected Layer?**

A fully connected layer that takes the output of convolution/pooling and predicts the best label to describe the image We have three layers in the full connection step i. Input layer ii. Fully-connected layer iii. Output layer

**Input Layer**: It takes the output of the previous layers, "flattens" them and turns them into a single vector that can be an input for the next stage.

**Fully Connected Layer**: It takes the inputs from the feature analysis and applies weights to predict the correct label.

**Output Layer**: It gives the final probabilities for each label.




**ReLU Layer**: ReLU is an activation function. Rectified Linear Unit (ReLU) transform function only activates a node if the input is above a certain quantity, while the input is below zero, the output is zero, but when the input rises above a certain threshold, it has a linear relationship with the dependent variable. The main aim is to remove all the negative values from the convolution. All the positive values remain the same but all the negative values get changed to zero.

## Methodology:

1. Load the basic libraries and packages
2. Load the dataset
3. Analyse the dataset
4. Normalize the data
5. Pre-process the data
6. Visualize the Data

7. Write the CNN model function
8. Write the Cost Function
9. Write the Gradient Descent optimization algorithm
10. Apply the training over the dataset to minimize the loss
11. Observe the cost function vs iterations learning curve

## Program (Code):

To be attached with

## Results:

To be attached with

a. Training dataset
b. Model summary
c. Training and validation accuracy w.r.t epochs before regularization
d. Training and validation loss w.r.t epochs before regularization
e. Training and validation accuracy w.r.t epochs after regularization
f. Training and validation loss w.r.t epochs after regularization
g. Original v/s predicted labels for correct predicted observations
h. Original v/s predicted labels for incorrect predicted observations

## Pre Lab Exercise:

a. What is Convolution process? Explain giving example.

____________________________________________________________

____________________________________________________________

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b. What are different layers in CNN model?

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c. What is the requirement of the pooling layer in the CNN model?

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____________________________________________________________

d. What is the requirement of the use of ReLU activation function after convolution step?

## Observation and Result Analysis:

e. Nature of the dataset

f. Training Process without regularization

g. After regularization in the training Process

h. Observation over the Learning Curves

## Post Lab Exercise:

a. Why CNN is preferred over ANN for images

b. Can CNN be applied over Text data? If yes, then how. If no, then why?

c. What is the role of dropout layer?

d. What will happen if maxpooling is replaced with minpooling?