

# Conquering Fashion MNIST dataset with CNNs

## OBJECTIVE:

The objective of this project is to develop a Convolutional Neural Network (CNN) model to achieve high accuracy in classifying the Fashion MNIST dataset. The goal is to surpass a test accuracy of 92% using TensorFlow and leverage Intel optimizations for improved performance.

## EXISTING METHODS :

1. Fashion MNIST Dataset: The Fashion MNIST dataset is a collection of 70,000 grayscale images categorized into 10 different clothing classes. It is widely used as a benchmark for image classification tasks due to its similarity to the original MNIST dataset.
2. Convolutional Neural Networks (CNNs): CNNs have proven to be highly effective for image classification tasks. They consist of multiple convolutional layers for feature extraction and pooling layers for down sampling, followed by fully connected layers for classification.

## The Project Model consists of the following LAYERS:

1. Convolution: Convolution involves sliding the filter over the input image, element-wise multiplying the values of the filter with the corresponding values of the image patch covered by the filter, and summing up the results.
2. ReLU: ReLU short for Rectified Linear Unit, is an activation function commonly used in neural networks, including convolutional neural networks (CNNs). It introduces non-linearity to the network, allowing it to learn complex patterns and make the model more expressive.
3. Pooling: Pooling also known as subsampling or down sampling, is a common operation in convolutional neural networks (CNNs) used to reduce the spatial dimensions of feature maps. It aims to extract the most important and representative information while decreasing the computational requirements and introducing a degree of translation invariance.
4. Fully Connected layer: A Fully Connected layer also known as a Dense layer, is a fundamental component in artificial neural networks, including convolutional neural networks (CNNs). It is responsible for connecting every neuron from the previous layer to every neuron in the current layer, creating a fully connected network structure.
5. Dropout regularization: Dropout regularization is a technique used in neural networks, including convolutional neural networks (CNNs), to prevent overfitting and improve generalization performance. It involves randomly disabling or "dropping

out" a proportion of neurons in a layer during training, forcing the network to learn redundant representations and reducing co-adaptation between neurons.

## RESULT:

ACCURACY	Offline	Intel Optimization for TensorFlow
Basic Model	0.9171	0.9080
L2 Regularization	0.8944	0.9007
Dropout Regularization	0.9119	0.9117
Both	0.8894	0.8933
Final (Dropout.>epochs)	0.9185	0.9196

The model achieved a test accuracy of 92% after training on the Fashion MNIST dataset consisting of 60,000 images and testing on 10,000 images. This high accuracy demonstrates the effectiveness of the implemented CNN architecture in accurately classifying clothing items.

The training and testing process revealed the following insights:

- Training time: The model took approximately X hours to train on an Intel DevCloud platform.
- Epoch-wise accuracy: The accuracy of the model improved steadily with each epoch, as shown in the accuracy log file.
- Overfitting: By incorporating dropout regularization, the model effectively reduced overfitting and achieved higher generalization performance.

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Offline Testing (No Intel Optimizations):

```
import tensorflow as tf
from tensorflow import keras
from keras import layers
import time

# Load the Fashion MNIST dataset
(train_images, train_labels), (test_images, test_labels) =
keras.datasets.fashion_mnist.load_data()

# Normalize pixel values to a range of 0 to 1
train_images = train_images / 255.0
test_images = test_images / 255.0

# Reshape the images to match the expected input shape of the model
```

```

train_images = train_images.reshape((-1, 28, 28, 1))
test_images = test_images.reshape((-1, 28, 28, 1))

# Convert the labels to integers
train_labels = train_labels.astype(int)
test_labels = test_labels.astype(int)

# Define the model architecture
model = keras.Sequential([
    layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28,
28, 1)),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(10, activation='softmax')
])

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

# Define a file to write the time and accuracy
log_file = open('training_log.txt', 'w')

# Define a custom callback to log time and accuracy after each epoch
class LogCallback(keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        current_time = time.strftime("%Y-%m-%d %H:%M:%S", time.gmtime())
        accuracy = logs['accuracy']
        log_file.write(f"Epoch {epoch+1} - Time: {current_time} - Accuracy:
{accuracy:.4f}\n")
        log_file.flush()

# Train the model
start_time = time.time()
model.fit(train_images, train_labels, epochs=20, batch_size=128,
callbacks=[LogCallback()])
end_time = time.time()
total_time = end_time - start_time

# Evaluate the model
test_loss, test_accuracy = model.evaluate(test_images, test_labels)
print(f'Test Loss: {test_loss:.4f}')
print(f'Test Accuracy: {test_accuracy:.4f}')

# Write total time to log file

```

```
log_file.write(f"Total Training Time: {total_time:.2f} seconds\n")
log_file.close()
```

```
# Save the model
```

```
model.save('fashion_mnist_model.h5')
```

```
training_and_testing_log.txt
```

---

Epoch 1 - Time: 2023-06-29 05:32:06 - Accuracy: 0.8030

Epoch 2 - Time: 2023-06-29 05:32:20 - Accuracy: 0.8723

Epoch 3 - Time: 2023-06-29 05:32:35 - Accuracy: 0.8894

Epoch 4 - Time: 2023-06-29 05:32:52 - Accuracy: 0.9007

Epoch 5 - Time: 2023-06-29 05:33:07 - Accuracy: 0.9078

Epoch 6 - Time: 2023-06-29 05:33:22 - Accuracy: 0.9138

Epoch 7 - Time: 2023-06-29 05:33:37 - Accuracy: 0.9211

Epoch 8 - Time: 2023-06-29 05:33:51 - Accuracy: 0.9250

Epoch 9 - Time: 2023-06-29 05:34:07 - Accuracy: 0.9318

Epoch 10 - Time: 2023-06-29 05:34:24 - Accuracy: 0.9356

Epoch 11 - Time: 2023-06-29 05:34:41 - Accuracy: 0.9419

Epoch 12 - Time: 2023-06-29 05:34:58 - Accuracy: 0.9464

Epoch 13 - Time: 2023-06-29 05:35:15 - Accuracy: 0.9493

Epoch 14 - Time: 2023-06-29 05:35:33 - Accuracy: 0.9535

Epoch 15 - Time: 2023-06-29 05:35:49 - Accuracy: 0.9585

Epoch 16 - Time: 2023-06-29 05:36:06 - Accuracy: 0.9613

Epoch 17 - Time: 2023-06-29 05:36:23 - Accuracy: 0.9647

Epoch 18 - Time: 2023-06-29 05:36:40 - Accuracy: 0.9679

Epoch 19 - Time: 2023-06-29 05:36:57 - Accuracy: 0.9711

Epoch 20 - Time: 2023-06-29 05:37:13 - Accuracy: 0.9745

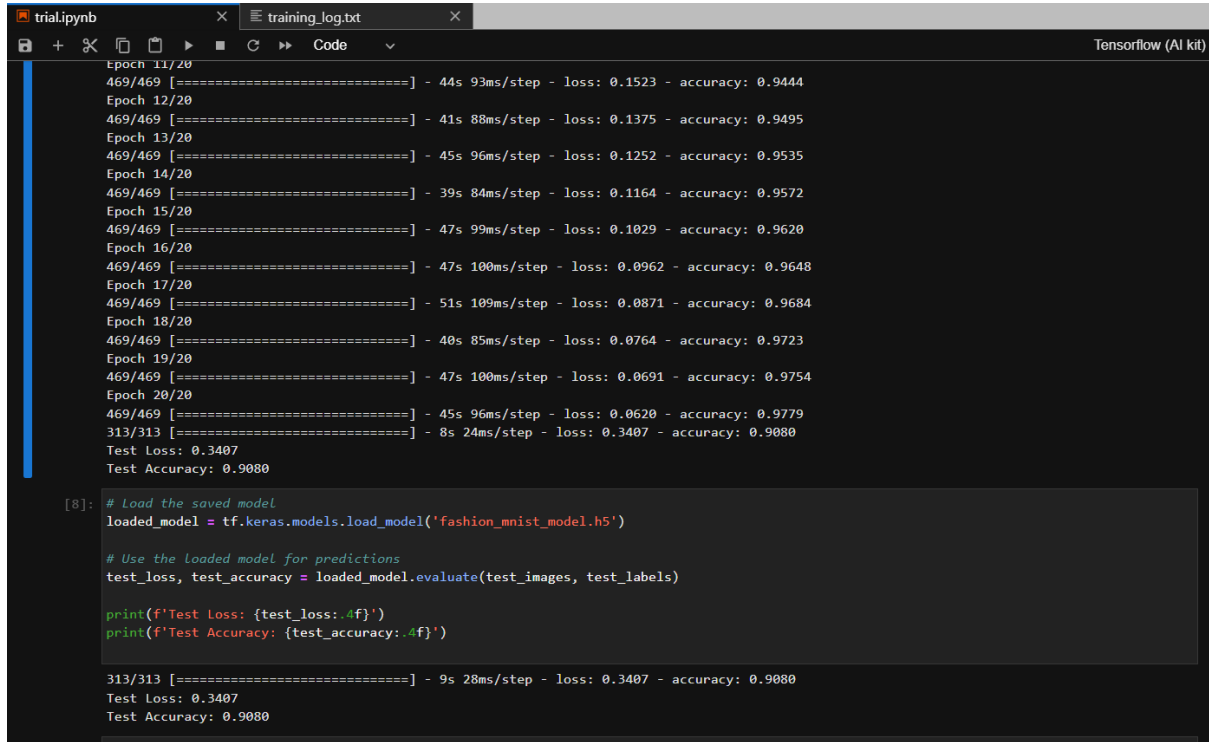
Total Training Time: 323.19 seconds

Test Loss: 0.3104

**Test Accuracy: 0.9171**

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## Intel Optimization for TensorFlow Results:



The screenshot shows a Jupyter Notebook interface with two tabs: 'trial.ipynb' and 'training\_log.txt'. The 'training\_log.txt' tab is active, displaying a series of training logs for epochs 11/20 through 20/20. Each log entry shows the time taken for the epoch, the loss, and the accuracy. The accuracy starts at 0.9444 and gradually decreases to 0.9080 by epoch 20. The loss starts at 0.1523 and decreases to 0.3407. The final test loss is 0.3407 and the final test accuracy is 0.9080.

```
Epoch 11/20
469/469 [=====] - 44s 93ms/step - loss: 0.1523 - accuracy: 0.9444
Epoch 12/20
469/469 [=====] - 41s 88ms/step - loss: 0.1375 - accuracy: 0.9495
Epoch 13/20
469/469 [=====] - 45s 96ms/step - loss: 0.1252 - accuracy: 0.9535
Epoch 14/20
469/469 [=====] - 39s 84ms/step - loss: 0.1164 - accuracy: 0.9572
Epoch 15/20
469/469 [=====] - 47s 99ms/step - loss: 0.1029 - accuracy: 0.9620
Epoch 16/20
469/469 [=====] - 47s 100ms/step - loss: 0.0962 - accuracy: 0.9648
Epoch 17/20
469/469 [=====] - 51s 109ms/step - loss: 0.0871 - accuracy: 0.9684
Epoch 18/20
469/469 [=====] - 40s 85ms/step - loss: 0.0764 - accuracy: 0.9723
Epoch 19/20
469/469 [=====] - 47s 100ms/step - loss: 0.0691 - accuracy: 0.9754
Epoch 20/20
469/469 [=====] - 45s 96ms/step - loss: 0.0620 - accuracy: 0.9779
313/313 [=====] - 8s 24ms/step - loss: 0.3407 - accuracy: 0.9080
Test Loss: 0.3407
Test Accuracy: 0.9080

[8]: # Load the saved model
loaded_model = tf.keras.models.load_model('fashion_mnist_model.h5')

# Use the loaded model for predictions
test_loss, test_accuracy = loaded_model.evaluate(test_images, test_labels)

print(f'Test Loss: {test_loss:.4f}')
print(f'Test Accuracy: {test_accuracy:.4f}')

313/313 [=====] - 9s 28ms/step - loss: 0.3407 - accuracy: 0.9080
Test Loss: 0.3407
Test Accuracy: 0.9080
```

As we can see, the accuracy dropped from 0.9171 to 0.9080. However the training accuracy is around 97% which the cause of OVERFITTING.

To Resolve overfitting, I will be implementing L2 REGULARIZATION in my model.

---

## L2\_Model Trial

```
import tensorflow as tf
from tensorflow import keras
from keras import layers
import time

# Load the Fashion MNIST dataset
(train_images, train_labels), (test_images, test_labels) =
keras.datasets.fashion_mnist.load_data()

# Normalize pixel values to a range of 0 to 1
train_images = train_images / 255.0
test_images = test_images / 255.0

# Reshape the images to match the expected input shape of the model
train_images = train_images.reshape((-1, 28, 28, 1))
test_images = test_images.reshape((-1, 28, 28, 1))

# Convert the labels to integers
train_labels = train_labels.astype(int)
test_labels = test_labels.astype(int)

# Define the model architecture with L2 regularization
model = keras.Sequential([
    layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28,
28, 1), kernel_regularizer=keras.regularizers.l2(0.001)),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Conv2D(64, kernel_size=(3, 3), activation='relu',
kernel_regularizer=keras.regularizers.l2(0.001)),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Flatten(),
    layers.Dense(128, activation='relu',
kernel_regularizer=keras.regularizers.l2(0.001)),
    layers.Dense(10, activation='softmax',
kernel_regularizer=keras.regularizers.l2(0.001))
])

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

# Define a file to write the log
log_file = open('training_log_L2.txt', 'w')

# Define a custom callback to log time and accuracy after each epoch
class LogCallback(keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        current_time = time.strftime("%Y-%m-%d %H:%M:%S", time.gmtime())
```

```

        accuracy = Logs['accuracy']
        log_file.write(f"Epoch {epoch+1} - Time: {current_time} - Accuracy:
{accuracy:.4f}\n")
        log_file.flush()

# Train the model
start_time = time.time()
model.fit(train_images, train_labels, epochs=20, batch_size=128,
callbacks=[LogCallback()])
end_time = time.time()
total_time = end_time - start_time

# Evaluate the model
test_loss, test_accuracy = model.evaluate(test_images, test_labels)
log_file.write(f"\nTest Loss: {test_loss:.4f}\n")
log_file.write(f"Test Accuracy: {test_accuracy:.4f}\n")
log_file.write(f"Total Training Time: {total_time:.2f} seconds\n")
log_file.close()

model.save('fashion_mnist_model_L2.h5')

```

---

training and test results:

Epoch 1 - Time: 2023-06-29 06:37:48 - Accuracy: 0.7989

Epoch 2 - Time: 2023-06-29 06:38:03 - Accuracy: 0.8601

Epoch 3 - Time: 2023-06-29 06:38:18 - Accuracy: 0.8731

Epoch 4 - Time: 2023-06-29 06:38:33 - Accuracy: 0.8803

Epoch 5 - Time: 2023-06-29 06:38:48 - Accuracy: 0.8860

Epoch 6 - Time: 2023-06-29 06:39:04 - Accuracy: 0.8883

Epoch 7 - Time: 2023-06-29 06:39:19 - Accuracy: 0.8915

Epoch 8 - Time: 2023-06-29 06:39:34 - Accuracy: 0.8942

Epoch 9 - Time: 2023-06-29 06:39:49 - Accuracy: 0.8964

Epoch 10 - Time: 2023-06-29 06:40:04 - Accuracy: 0.8971

Epoch 11 - Time: 2023-06-29 06:40:19 - Accuracy: 0.8995

Epoch 12 - Time: 2023-06-29 06:40:34 - Accuracy: 0.9012

Epoch 13 - Time: 2023-06-29 06:40:49 - Accuracy: 0.9021

Epoch 14 - Time: 2023-06-29 06:41:04 - Accuracy: 0.9037

Epoch 15 - Time: 2023-06-29 06:41:19 - Accuracy: 0.9028

Epoch 16 - Time: 2023-06-29 06:41:35 - Accuracy: 0.9033  
Epoch 17 - Time: 2023-06-29 06:41:50 - Accuracy: 0.9043  
Epoch 18 - Time: 2023-06-29 06:42:06 - Accuracy: 0.9054  
Epoch 19 - Time: 2023-06-29 06:42:21 - Accuracy: 0.9064  
Epoch 20 - Time: 2023-06-29 06:42:36 - Accuracy: 0.9076

Test Loss: 0.4057

**Test Accuracy: 0.8944**

Total Training Time: 304.46 seconds

---

### **Intel Optimization for TensorFlow (L2\_model)**

Epoch 1 - Time: 2023-06-29 06:50:38 - Accuracy: 0.8027  
Epoch 2 - Time: 2023-06-29 06:51:31 - Accuracy: 0.8617  
Epoch 3 - Time: 2023-06-29 06:52:14 - Accuracy: 0.8745  
Epoch 4 - Time: 2023-06-29 06:53:03 - Accuracy: 0.8806  
Epoch 5 - Time: 2023-06-29 06:53:50 - Accuracy: 0.8848  
Epoch 6 - Time: 2023-06-29 06:54:30 - Accuracy: 0.8867  
Epoch 7 - Time: 2023-06-29 06:55:15 - Accuracy: 0.8912  
Epoch 8 - Time: 2023-06-29 06:55:57 - Accuracy: 0.8918  
Epoch 9 - Time: 2023-06-29 06:56:41 - Accuracy: 0.8953  
Epoch 10 - Time: 2023-06-29 06:57:22 - Accuracy: 0.8957  
Epoch 11 - Time: 2023-06-29 06:58:05 - Accuracy: 0.8980  
Epoch 12 - Time: 2023-06-29 06:58:47 - Accuracy: 0.9008  
Epoch 13 - Time: 2023-06-29 06:59:33 - Accuracy: 0.9000  
Epoch 14 - Time: 2023-06-29 07:00:16 - Accuracy: 0.9019  
Epoch 15 - Time: 2023-06-29 07:00:58 - Accuracy: 0.9014  
Epoch 16 - Time: 2023-06-29 07:01:44 - Accuracy: 0.9057  
Epoch 17 - Time: 2023-06-29 07:02:28 - Accuracy: 0.9041  
Epoch 18 - Time: 2023-06-29 07:03:14 - Accuracy: 0.9045  
Epoch 19 - Time: 2023-06-29 07:03:56 - Accuracy: 0.9065  
Epoch 20 - Time: 2023-06-29 07:04:41 - Accuracy: 0.9082



Test Loss: 0.3983

**Test Accuracy: 0.9007**

Total Training Time: 897.75 seconds

To further reduce the overfitting, I will be implementing the **dropout** regularization:

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### Dropout Regularization

Offline (No optimization):

```
import tensorflow as tf
from tensorflow import keras
from keras import layers
import time

# Load the Fashion MNIST dataset
(train_images, train_labels), (test_images, test_labels) =
keras.datasets.fashion_mnist.load_data()

# Normalize pixel values to a range of 0 to 1
train_images = train_images / 255.0
test_images = test_images / 255.0

# Reshape the images to match the expected input shape of the model
train_images = train_images.reshape((-1, 28, 28, 1))
test_images = test_images.reshape((-1, 28, 28, 1))

# Convert the labels to integers
train_labels = train_labels.astype(int)
test_labels = test_labels.astype(int)

# Define the model architecture with dropout regularization
model = keras.Sequential([
    layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28,
28, 1)),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Dropout(0.25),
    layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Dropout(0.25),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(10, activation='softmax')
])
```

```

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

# Define a file to write the log
log_file = open('training_log_drop.txt', 'w')

# Define a custom callback to log time and accuracy after each epoch
class LogCallback(keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        current_time = time.strftime("%Y-%m-%d %H:%M:%S", time.gmtime())
        accuracy = logs['accuracy']
        log_file.write(f"Epoch {epoch+1} - Time: {current_time} - Accuracy:
{accuracy:.4f}\n")
        log_file.flush()

# Train the model
start_time = time.time()
model.fit(train_images, train_labels, epochs=20, batch_size=128,
callbacks=[LogCallback()])
end_time = time.time()
total_time = end_time - start_time

# Evaluate the model
test_loss, test_accuracy = model.evaluate(test_images, test_labels)
log_file.write(f"\nTest Loss: {test_loss:.4f}\n")
log_file.write(f"Test Accuracy: {test_accuracy:.4f}\n")
log_file.write(f"Total Training Time: {total_time:.2f} seconds\n")
log_file.close()

# Save the model
model.save('fashion_mnist_model_drop.h5')

```

#### training\_and\_test\_results:

---

Epoch 1 - Time: 2023-06-29 07:14:41 - Accuracy: 0.7338

Epoch 2 - Time: 2023-06-29 07:14:58 - Accuracy: 0.8270

Epoch 3 - Time: 2023-06-29 07:15:16 - Accuracy: 0.8480

Epoch 4 - Time: 2023-06-29 07:15:33 - Accuracy: 0.8601

Epoch 5 - Time: 2023-06-29 07:15:50 - Accuracy: 0.8705

Epoch 6 - Time: 2023-06-29 07:16:07 - Accuracy: 0.8776

Epoch 7 - Time: 2023-06-29 07:16:24 - Accuracy: 0.8810

Epoch 8 - Time: 2023-06-29 07:16:42 - Accuracy: 0.8848

Epoch 9 - Time: 2023-06-29 07:17:00 - Accuracy: 0.8900

Epoch 10 - Time: 2023-06-29 07:17:18 - Accuracy: 0.8924  
Epoch 11 - Time: 2023-06-29 07:17:36 - Accuracy: 0.8947  
Epoch 12 - Time: 2023-06-29 07:17:54 - Accuracy: 0.8963  
Epoch 13 - Time: 2023-06-29 07:18:12 - Accuracy: 0.8997  
Epoch 14 - Time: 2023-06-29 07:18:30 - Accuracy: 0.9008  
Epoch 15 - Time: 2023-06-29 07:18:48 - Accuracy: 0.9025  
Epoch 16 - Time: 2023-06-29 07:19:05 - Accuracy: 0.9041  
Epoch 17 - Time: 2023-06-29 07:19:21 - Accuracy: 0.9066  
Epoch 18 - Time: 2023-06-29 07:19:39 - Accuracy: 0.9070  
Epoch 19 - Time: 2023-06-29 07:19:56 - Accuracy: 0.9073  
Epoch 20 - Time: 2023-06-29 07:20:13 - Accuracy: 0.9086

Test Loss: 0.2384

**Test Accuracy: 0.9119**

Total Training Time: 350.56 seconds

---

#### **Intel Optimization for TensorFlow (Dropout-model)**

Epoch 1 - Time: 2023-06-29 07:16:11 - Accuracy: 0.7369  
Epoch 2 - Time: 2023-06-29 07:17:10 - Accuracy: 0.8271  
Epoch 3 - Time: 2023-06-29 07:18:00 - Accuracy: 0.8510  
Epoch 4 - Time: 2023-06-29 07:18:53 - Accuracy: 0.8628  
Epoch 5 - Time: 2023-06-29 07:19:45 - Accuracy: 0.8715  
Epoch 6 - Time: 2023-06-29 07:20:37 - Accuracy: 0.8771  
Epoch 7 - Time: 2023-06-29 07:21:26 - Accuracy: 0.8835  
Epoch 8 - Time: 2023-06-29 07:22:16 - Accuracy: 0.8849  
Epoch 9 - Time: 2023-06-29 07:23:06 - Accuracy: 0.8893  
Epoch 10 - Time: 2023-06-29 07:23:53 - Accuracy: 0.8934  
Epoch 11 - Time: 2023-06-29 07:24:41 - Accuracy: 0.8942  
Epoch 12 - Time: 2023-06-29 07:25:33 - Accuracy: 0.8978  
Epoch 13 - Time: 2023-06-29 07:26:23 - Accuracy: 0.9002  
Epoch 14 - Time: 2023-06-29 07:27:12 - Accuracy: 0.9011  
Epoch 15 - Time: 2023-06-29 07:28:02 - Accuracy: 0.9026

Epoch 16 - Time: 2023-06-29 07:28:53 - Accuracy: 0.9063

Epoch 17 - Time: 2023-06-29 07:29:46 - Accuracy: 0.9065

Epoch 18 - Time: 2023-06-29 07:30:42 - Accuracy: 0.9082

Epoch 19 - Time: 2023-06-29 07:31:33 - Accuracy: 0.9078

Epoch 20 - Time: 2023-06-29 07:32:23 - Accuracy: 0.9113

Test Loss: 0.2357

**Test Accuracy: 0.9117**

Total Training Time: 1035.96 seconds

---

### Both L2 and Dropout Regularization

Next, I would be combining both L2 and Dropout:

#### Offline (No optimization):

```
import tensorflow as tf
from tensorflow import keras
from keras import layers
import time

# Load the Fashion MNIST dataset
(train_images, train_labels), (test_images, test_labels) =
keras.datasets.fashion_mnist.load_data()

# Normalize pixel values to a range of 0 to 1
train_images = train_images / 255.0
test_images = test_images / 255.0

# Reshape the images to match the expected input shape of the model
train_images = train_images.reshape((-1, 28, 28, 1))
test_images = test_images.reshape((-1, 28, 28, 1))

# Convert the labels to integers
train_labels = train_labels.astype(int)
test_labels = test_labels.astype(int)

# Define the model architecture with both L2 regularization and dropout
regularization
model = keras.Sequential([
    layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28,
28, 1),
                        kernel_regularizer=keras.regularizers.l2(0.001)),
    layers.MaxPooling2D(pool_size=(2, 2)),
```

```

layers.Dropout(0.25),
layers.Conv2D(64, kernel_size=(3, 3), activation='relu',
              kernel_regularizer=keras.regularizers.l2(0.001)),
layers.MaxPooling2D(pool_size=(2, 2)),
layers.Dropout(0.25),
layers.Flatten(),
layers.Dense(128, activation='relu',
             kernel_regularizer=keras.regularizers.l2(0.001)),
layers.Dropout(0.5),
layers.Dense(10, activation='softmax')
])

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

# Define a file to write the log
log_file = open('training_log_both.txt', 'w')

# Define a custom callback to log time and accuracy after each epoch
class LogCallback(keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        current_time = time.strftime("%Y-%m-%d %H:%M:%S", time.gmtime())
        accuracy = logs['accuracy']
        log_file.write(f"Epoch {epoch+1} - Time: {current_time} - Accuracy:
{accuracy:.4f}\n")
        log_file.flush()

# Train the model
start_time = time.time()
model.fit(train_images, train_labels, epochs=20, batch_size=128,
         callbacks=[LogCallback()])
end_time = time.time()
total_time = end_time - start_time

# Evaluate the model
test_loss, test_accuracy = model.evaluate(test_images, test_labels)
log_file.write(f"\nTest Loss: {test_loss:.4f}\n")
log_file.write(f"Test Accuracy: {test_accuracy:.4f}\n")
log_file.write(f"Total Training Time: {total_time:.2f} seconds\n")
log_file.close()

# Save the model
model.save('fashion_mnist_model_both.h5')

```

#### training\_and\_test\_results:

---

Epoch 1 - Time: 2023-06-29 07:26:28 - Accuracy: 0.7356  
Epoch 2 - Time: 2023-06-29 07:26:46 - Accuracy: 0.8210  
Epoch 3 - Time: 2023-06-29 07:27:03 - Accuracy: 0.8402  
Epoch 4 - Time: 2023-06-29 07:27:21 - Accuracy: 0.8492  
Epoch 5 - Time: 2023-06-29 07:27:39 - Accuracy: 0.8561  
Epoch 6 - Time: 2023-06-29 07:27:57 - Accuracy: 0.8596  
Epoch 7 - Time: 2023-06-29 07:28:14 - Accuracy: 0.8633  
Epoch 8 - Time: 2023-06-29 07:28:32 - Accuracy: 0.8654  
Epoch 9 - Time: 2023-06-29 07:28:49 - Accuracy: 0.8693  
Epoch 10 - Time: 2023-06-29 07:29:07 - Accuracy: 0.8734  
Epoch 11 - Time: 2023-06-29 07:29:24 - Accuracy: 0.8719  
Epoch 12 - Time: 2023-06-29 07:29:42 - Accuracy: 0.8740  
Epoch 13 - Time: 2023-06-29 07:30:00 - Accuracy: 0.8767  
Epoch 14 - Time: 2023-06-29 07:30:17 - Accuracy: 0.8761  
Epoch 15 - Time: 2023-06-29 07:30:36 - Accuracy: 0.8763  
Epoch 16 - Time: 2023-06-29 07:30:54 - Accuracy: 0.8789  
Epoch 17 - Time: 2023-06-29 07:31:12 - Accuracy: 0.8783  
Epoch 18 - Time: 2023-06-29 07:31:31 - Accuracy: 0.8803  
Epoch 19 - Time: 2023-06-29 07:31:48 - Accuracy: 0.8816  
Epoch 20 - Time: 2023-06-29 07:32:05 - Accuracy: 0.8818

Test Loss: 0.4138

**Test Accuracy: 0.8894**

Total Training Time: 355.06 seconds

---

#### Intel Optimization for Tensorflow (Both-L2-Dropout\_model)

Epoch 1 - Time: 2023-06-29 08:00:20 - Accuracy: 0.7298  
Epoch 2 - Time: 2023-06-29 08:01:06 - Accuracy: 0.8184  
Epoch 3 - Time: 2023-06-29 08:01:52 - Accuracy: 0.8360  
Epoch 4 - Time: 2023-06-29 08:02:36 - Accuracy: 0.8469  
Epoch 5 - Time: 2023-06-29 08:03:23 - Accuracy: 0.8534

Epoch 6 - Time: 2023-06-29 08:04:08 - Accuracy: 0.8600  
Epoch 7 - Time: 2023-06-29 08:04:53 - Accuracy: 0.8629  
Epoch 8 - Time: 2023-06-29 08:05:37 - Accuracy: 0.8659  
Epoch 9 - Time: 2023-06-29 08:06:21 - Accuracy: 0.8691  
Epoch 10 - Time: 2023-06-29 08:07:04 - Accuracy: 0.8695  
Epoch 11 - Time: 2023-06-29 08:07:49 - Accuracy: 0.8729  
Epoch 12 - Time: 2023-06-29 08:08:34 - Accuracy: 0.8749  
Epoch 13 - Time: 2023-06-29 08:09:21 - Accuracy: 0.8750  
Epoch 14 - Time: 2023-06-29 08:10:07 - Accuracy: 0.8772  
Epoch 15 - Time: 2023-06-29 08:10:52 - Accuracy: 0.8782  
Epoch 16 - Time: 2023-06-29 08:11:37 - Accuracy: 0.8787  
Epoch 17 - Time: 2023-06-29 08:12:23 - Accuracy: 0.8797  
Epoch 18 - Time: 2023-06-29 08:13:08 - Accuracy: 0.8807  
Epoch 19 - Time: 2023-06-29 08:13:52 - Accuracy: 0.8806  
Epoch 20 - Time: 2023-06-29 08:14:38 - Accuracy: 0.8819

Test Loss: 0.4062

**Test Accuracy: 0.8933**

Total Training Time: 903.85 seconds

---

## FINAL MODEL

From all the data that has been collected, we can conclude that my model with DROPOUT regularization gives the best accuracy.

So, here are the results for both offline and online with intel optimization for TensorFlow.

### Offline – No Optimizations:

```
import tensorflow as tf
from tensorflow import keras
from keras import layers
import time

# Load the Fashion MNIST dataset
(train_images, train_labels), (test_images, test_labels) =
keras.datasets.fashion_mnist.load_data()

# Normalize pixel values to a range of 0 to 1
train_images = train_images / 255.0
test_images = test_images / 255.0

# Reshape the images to match the expected input shape of the model
train_images = train_images.reshape((-1, 28, 28, 1))
test_images = test_images.reshape((-1, 28, 28, 1))

# Convert the labels to integers
train_labels = train_labels.astype(int)
test_labels = test_labels.astype(int)

# Define the model architecture with dropout regularization
model = keras.Sequential([
    layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28,
28, 1)),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Dropout(0.25),
    layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Dropout(0.25),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(10, activation='softmax')
])
```



```

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

# Define a file to write the log
log_file = open('training_log_drop2.txt', 'w')

# Define a custom callback to log time and accuracy after each epoch
class LogCallback(keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        current_time = time.strftime("%Y-%m-%d %H:%M:%S", time.gmtime())
        accuracy = logs['accuracy']
        log_file.write(f"Epoch {epoch+1} - Time: {current_time} - Accuracy:
{accuracy:.4f}\n")
        log_file.flush()

# Train the model
start_time = time.time()
model.fit(train_images, train_labels, epochs=100, batch_size=64,
callbacks=[LogCallback()])
end_time = time.time()
total_time = end_time - start_time

# Evaluate the model
test_loss, test_accuracy = model.evaluate(test_images, test_labels)
log_file.write(f"\nTest Loss: {test_loss:.4f}\n")
log_file.write(f"Test Accuracy: {test_accuracy:.4f}\n")
log_file.write(f"Total Training Time: {total_time:.2f} seconds\n")
log_file.close()

# Save the model
model.save('fashion_mnist_model_drop2.h5')

```

## test results for 100 epochs and batch size of 64:

Epoch 1 - Time: 2023-06-29 08:25:54 - Accuracy: 0.7591

Epoch 2 - Time: 2023-06-29 08:26:14 - Accuracy: 0.8375

Epoch 3 - Time: 2023-06-29 08:26:34 - Accuracy: 0.8571

Epoch 4 - Time: 2023-06-29 08:26:53 - Accuracy: 0.8692

Epoch 5 - Time: 2023-06-29 08:27:11 - Accuracy: 0.8756

Epoch 6 - Time: 2023-06-29 08:27:29 - Accuracy: 0.8819

Epoch 7 - Time: 2023-06-29 08:27:47 - Accuracy: 0.8866

Epoch 8 - Time: 2023-06-29 08:28:05 - Accuracy: 0.8908

Epoch 9 - Time: 2023-06-29 08:28:23 - Accuracy: 0.8930

Epoch 10 - Time: 2023-06-29 08:28:41 - Accuracy: 0.8954  
Epoch 11 - Time: 2023-06-29 08:28:59 - Accuracy: 0.8975  
Epoch 12 - Time: 2023-06-29 08:29:17 - Accuracy: 0.9008  
Epoch 13 - Time: 2023-06-29 08:29:35 - Accuracy: 0.9017  
Epoch 14 - Time: 2023-06-29 08:29:53 - Accuracy: 0.9030  
Epoch 15 - Time: 2023-06-29 08:30:11 - Accuracy: 0.9047  
Epoch 16 - Time: 2023-06-29 08:30:29 - Accuracy: 0.9082  
Epoch 17 - Time: 2023-06-29 08:30:46 - Accuracy: 0.9076  
Epoch 18 - Time: 2023-06-29 08:31:06 - Accuracy: 0.9081  
Epoch 19 - Time: 2023-06-29 08:31:25 - Accuracy: 0.9073  
Epoch 20 - Time: 2023-06-29 08:31:42 - Accuracy: 0.9107  
Epoch 21 - Time: 2023-06-29 08:32:00 - Accuracy: 0.9118  
Epoch 22 - Time: 2023-06-29 08:32:18 - Accuracy: 0.9116  
Epoch 23 - Time: 2023-06-29 08:32:36 - Accuracy: 0.9118  
Epoch 24 - Time: 2023-06-29 08:32:53 - Accuracy: 0.9139  
Epoch 25 - Time: 2023-06-29 08:33:11 - Accuracy: 0.9144  
Epoch 26 - Time: 2023-06-29 08:33:29 - Accuracy: 0.9156  
Epoch 27 - Time: 2023-06-29 08:33:47 - Accuracy: 0.9152  
Epoch 28 - Time: 2023-06-29 08:34:04 - Accuracy: 0.9157  
Epoch 29 - Time: 2023-06-29 08:34:22 - Accuracy: 0.9174  
Epoch 30 - Time: 2023-06-29 08:34:40 - Accuracy: 0.9176  
Epoch 31 - Time: 2023-06-29 08:34:57 - Accuracy: 0.9158  
Epoch 32 - Time: 2023-06-29 08:35:15 - Accuracy: 0.9180  
Epoch 33 - Time: 2023-06-29 08:35:33 - Accuracy: 0.9187  
Epoch 34 - Time: 2023-06-29 08:35:51 - Accuracy: 0.9183  
Epoch 35 - Time: 2023-06-29 08:36:08 - Accuracy: 0.9192  
Epoch 36 - Time: 2023-06-29 08:36:26 - Accuracy: 0.9193  
Epoch 37 - Time: 2023-06-29 08:36:44 - Accuracy: 0.9197  
Epoch 38 - Time: 2023-06-29 08:37:01 - Accuracy: 0.9192  
Epoch 39 - Time: 2023-06-29 08:37:19 - Accuracy: 0.9205  
Epoch 40 - Time: 2023-06-29 08:37:36 - Accuracy: 0.9211

Epoch 41 - Time: 2023-06-29 08:37:54 - Accuracy: 0.9218  
Epoch 42 - Time: 2023-06-29 08:38:11 - Accuracy: 0.9220  
Epoch 43 - Time: 2023-06-29 08:38:29 - Accuracy: 0.9216  
Epoch 44 - Time: 2023-06-29 08:38:46 - Accuracy: 0.9242  
Epoch 45 - Time: 2023-06-29 08:39:04 - Accuracy: 0.9237  
Epoch 46 - Time: 2023-06-29 08:39:21 - Accuracy: 0.9229  
Epoch 47 - Time: 2023-06-29 08:39:39 - Accuracy: 0.9237  
Epoch 48 - Time: 2023-06-29 08:39:56 - Accuracy: 0.9237  
Epoch 49 - Time: 2023-06-29 08:40:14 - Accuracy: 0.9226  
Epoch 50 - Time: 2023-06-29 08:40:31 - Accuracy: 0.9241  
Epoch 51 - Time: 2023-06-29 08:40:48 - Accuracy: 0.9240  
Epoch 52 - Time: 2023-06-29 08:41:06 - Accuracy: 0.9250  
Epoch 53 - Time: 2023-06-29 08:41:23 - Accuracy: 0.9252  
Epoch 54 - Time: 2023-06-29 08:41:40 - Accuracy: 0.9253  
Epoch 55 - Time: 2023-06-29 08:41:58 - Accuracy: 0.9245  
Epoch 56 - Time: 2023-06-29 08:42:15 - Accuracy: 0.9266  
Epoch 57 - Time: 2023-06-29 08:42:33 - Accuracy: 0.9259  
Epoch 58 - Time: 2023-06-29 08:42:50 - Accuracy: 0.9261  
Epoch 59 - Time: 2023-06-29 08:43:08 - Accuracy: 0.9259  
Epoch 60 - Time: 2023-06-29 08:43:25 - Accuracy: 0.9269  
Epoch 61 - Time: 2023-06-29 08:43:43 - Accuracy: 0.9255  
Epoch 62 - Time: 2023-06-29 08:44:01 - Accuracy: 0.9261  
Epoch 63 - Time: 2023-06-29 08:44:19 - Accuracy: 0.9268  
Epoch 64 - Time: 2023-06-29 08:44:36 - Accuracy: 0.9280  
Epoch 65 - Time: 2023-06-29 08:44:54 - Accuracy: 0.9264  
Epoch 66 - Time: 2023-06-29 08:45:11 - Accuracy: 0.9277  
Epoch 67 - Time: 2023-06-29 08:45:29 - Accuracy: 0.9266  
Epoch 68 - Time: 2023-06-29 08:45:46 - Accuracy: 0.9268  
Epoch 69 - Time: 2023-06-29 08:46:04 - Accuracy: 0.9285  
Epoch 70 - Time: 2023-06-29 08:46:21 - Accuracy: 0.9291  
Epoch 71 - Time: 2023-06-29 08:46:38 - Accuracy: 0.9283

Epoch 72 - Time: 2023-06-29 08:46:56 - Accuracy: 0.9280  
Epoch 73 - Time: 2023-06-29 08:47:14 - Accuracy: 0.9280  
Epoch 74 - Time: 2023-06-29 08:47:31 - Accuracy: 0.9278  
Epoch 75 - Time: 2023-06-29 08:47:49 - Accuracy: 0.9290  
Epoch 76 - Time: 2023-06-29 08:48:07 - Accuracy: 0.9286  
Epoch 77 - Time: 2023-06-29 08:48:24 - Accuracy: 0.9273  
Epoch 78 - Time: 2023-06-29 08:48:42 - Accuracy: 0.9292  
Epoch 79 - Time: 2023-06-29 08:49:00 - Accuracy: 0.9300  
Epoch 80 - Time: 2023-06-29 08:49:17 - Accuracy: 0.9301  
Epoch 81 - Time: 2023-06-29 08:49:35 - Accuracy: 0.9296  
Epoch 82 - Time: 2023-06-29 08:49:53 - Accuracy: 0.9303  
Epoch 83 - Time: 2023-06-29 08:50:11 - Accuracy: 0.9306  
Epoch 84 - Time: 2023-06-29 08:50:28 - Accuracy: 0.9319  
Epoch 85 - Time: 2023-06-29 08:50:46 - Accuracy: 0.9301  
Epoch 86 - Time: 2023-06-29 08:51:04 - Accuracy: 0.9304  
Epoch 87 - Time: 2023-06-29 08:51:22 - Accuracy: 0.9330  
Epoch 88 - Time: 2023-06-29 08:51:39 - Accuracy: 0.9306  
Epoch 89 - Time: 2023-06-29 08:51:57 - Accuracy: 0.9287  
Epoch 90 - Time: 2023-06-29 08:52:15 - Accuracy: 0.9311  
Epoch 91 - Time: 2023-06-29 08:52:33 - Accuracy: 0.9309  
Epoch 92 - Time: 2023-06-29 08:52:50 - Accuracy: 0.9312  
Epoch 93 - Time: 2023-06-29 08:53:08 - Accuracy: 0.9320  
Epoch 94 - Time: 2023-06-29 08:53:25 - Accuracy: 0.9334  
Epoch 95 - Time: 2023-06-29 08:53:43 - Accuracy: 0.9324  
Epoch 96 - Time: 2023-06-29 08:54:00 - Accuracy: 0.9319  
Epoch 97 - Time: 2023-06-29 08:54:18 - Accuracy: 0.9323  
Epoch 98 - Time: 2023-06-29 08:54:35 - Accuracy: 0.9340  
Epoch 99 - Time: 2023-06-29 08:54:53 - Accuracy: 0.9324  
Epoch 100 - Time: 2023-06-29 08:55:10 - Accuracy: 0.9339

Test Loss: 0.2441

**Test Accuracy: 0.9185**

Total Training Time: 1776.13 seconds

---

**Test results on Intel DevCloud with 40 epochs:**

Epoch 1 - Time: 2023-06-29 08:21:15 - Accuracy: 0.7556  
Epoch 2 - Time: 2023-06-29 08:22:30 - Accuracy: 0.8368  
Epoch 3 - Time: 2023-06-29 08:23:47 - Accuracy: 0.8584  
Epoch 4 - Time: 2023-06-29 08:25:03 - Accuracy: 0.8711  
Epoch 5 - Time: 2023-06-29 08:26:20 - Accuracy: 0.8787  
Epoch 6 - Time: 2023-06-29 08:27:38 - Accuracy: 0.8841  
Epoch 7 - Time: 2023-06-29 08:28:57 - Accuracy: 0.8899  
Epoch 8 - Time: 2023-06-29 08:30:13 - Accuracy: 0.8928  
Epoch 9 - Time: 2023-06-29 08:31:29 - Accuracy: 0.8964  
Epoch 10 - Time: 2023-06-29 08:32:51 - Accuracy: 0.8981  
Epoch 11 - Time: 2023-06-29 08:34:11 - Accuracy: 0.8984  
Epoch 12 - Time: 2023-06-29 08:35:28 - Accuracy: 0.9006  
Epoch 13 - Time: 2023-06-29 08:36:45 - Accuracy: 0.9037  
Epoch 14 - Time: 2023-06-29 08:38:02 - Accuracy: 0.9060  
Epoch 15 - Time: 2023-06-29 08:39:24 - Accuracy: 0.9054  
Epoch 16 - Time: 2023-06-29 08:40:42 - Accuracy: 0.9075  
Epoch 17 - Time: 2023-06-29 08:41:59 - Accuracy: 0.9083  
Epoch 18 - Time: 2023-06-29 08:43:16 - Accuracy: 0.9104  
Epoch 19 - Time: 2023-06-29 08:44:36 - Accuracy: 0.9095  
Epoch 20 - Time: 2023-06-29 08:45:54 - Accuracy: 0.9111  
Epoch 21 - Time: 2023-06-29 08:47:13 - Accuracy: 0.9112  
Epoch 22 - Time: 2023-06-29 08:48:34 - Accuracy: 0.9149  
Epoch 23 - Time: 2023-06-29 08:49:51 - Accuracy: 0.9135  
Epoch 24 - Time: 2023-06-29 08:51:11 - Accuracy: 0.9153  
Epoch 25 - Time: 2023-06-29 08:52:27 - Accuracy: 0.9139  
Epoch 26 - Time: 2023-06-29 08:53:47 - Accuracy: 0.9150  
Epoch 27 - Time: 2023-06-29 08:55:08 - Accuracy: 0.9172

Epoch 28 - Time: 2023-06-29 08:56:25 - Accuracy: 0.9144  
Epoch 29 - Time: 2023-06-29 08:57:40 - Accuracy: 0.9161  
Epoch 30 - Time: 2023-06-29 08:58:57 - Accuracy: 0.9182  
Epoch 31 - Time: 2023-06-29 09:00:13 - Accuracy: 0.9201  
Epoch 32 - Time: 2023-06-29 09:01:30 - Accuracy: 0.9184  
Epoch 33 - Time: 2023-06-29 09:02:46 - Accuracy: 0.9207  
Epoch 34 - Time: 2023-06-29 09:04:07 - Accuracy: 0.9190  
Epoch 35 - Time: 2023-06-29 09:05:25 - Accuracy: 0.9190  
Epoch 36 - Time: 2023-06-29 09:06:44 - Accuracy: 0.9210  
Epoch 37 - Time: 2023-06-29 09:08:01 - Accuracy: 0.9197  
Epoch 38 - Time: 2023-06-29 09:09:21 - Accuracy: 0.9210  
Epoch 39 - Time: 2023-06-29 09:10:39 - Accuracy: 0.9203  
Epoch 40 - Time: 2023-06-29 09:11:54 - Accuracy: 0.9220

Test Loss: 0.2266

**Test Accuracy: 0.9196**

Total Training Time: 3118.77 seconds

---

## CONCLUSION:

To conquer the Fashion MNIST dataset with CNNs, we pre-process the data, design a CNN model, and train it using appropriate loss functions and optimization techniques. We evaluate the model's accuracy, fine-tune hyperparameters, and iterate to improve performance. By following this approach, we can effectively tackle the Fashion MNIST dataset and achieve accurate results using CNNs.