CS 4375 Intro to Machine Learning

Objectives:

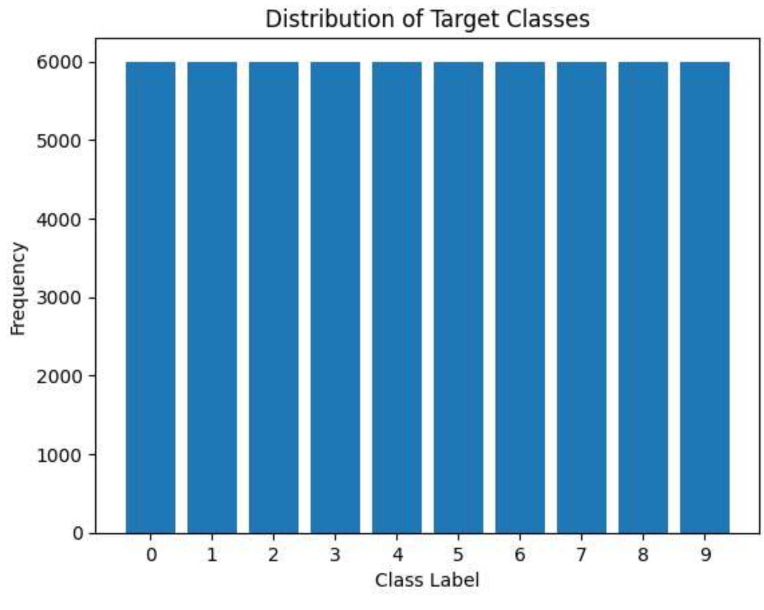
- Gain experience with Keras
- Gain experience with image classification
- Gain experience with deep learning model variations and embedding

1.

```
from keras.datasets import fashion_mnist
from sklearn.model_selection import train_test_split
from keras.models import Sequential,save_model, load_model
from keras.layers import Dense, Flatten, Conv2D, MaxPooling2D,LSTM
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# Load the Fashion-MNIST dataset from Keras
(train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()


print("Train data shape: ", train_images.shape, train_labels.shape)
print("Test data shape: ", test_images.shape, test_labels.shape)
```

```
Train data shape:  (60000, 28, 28) (60000,)
Test data shape:  (10000, 28, 28) (10000,)
```

```
# Plot the distribution of target classes
plt.hist(train_labels, bins=np.arange(11)-0.5, rwidth=0.8)
plt.xticks(range(10))
plt.xlabel('Class Label')
plt.ylabel('Frequency')
plt.title('Distribution of Target Classes')
plt.show()
```



The Fashion-MNIST dataset consists of 70,000 28x28 pixel grayscale images that have been divided into 10 classes of apparel items. The dataset is designed for image classification problems, with the goal of teaching a model to correctly categorize fresh photographs of apparel items into one of the 10 groups.

The dataset is frequently used as a benchmark to assess how well deep learning and machine learning models perform in classifying images. The goal is to train a model that, using the patterns and features discovered from the training set, can correctly predict the class of a new image of apparel.

Given that the photos are low-resolution, grayscale, and may be confusing or contain noise, the process is difficult. Furthermore, some of the apparel items in the dataset, including pullovers and sweaters or sandals and shoes, are visually identical, making categorization challenging even for human observers.

The Fashion-MNIST dataset, which has gained popularity among researchers and practitioners in the field of computer vision, offers a realistic and difficult benchmark for creating and assessing picture categorization algorithms.

2.

```
# Preprocess the data
train_images_SQ = train_images / 255.0
test_images_SQ = test_images / 255.0

# Create a sequential model
model = Sequential([
    Flatten(input_shape=(28, 28)),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])

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

# Train the model on the training data
model.fit(train_images_SQ, train_labels, epochs=10, validation_split=0.2)

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(test_images_SQ, test_labels)
print('Test accuracy:', test_acc)
```

```
Epoch 1/10
1500/1500 [==============================] - 6s 3ms/step - loss: 0.5131 - accuracy: 0.8200 - val_loss: 0.4188 - val_accuracy: 0.852
Epoch 2/10
1500/1500 [==============================] - 4s 3ms/step - loss: 0.3830 - accuracy: 0.8632 - val_loss: 0.3884 - val_accuracy: 0.858
Epoch 3/10
1500/1500 [==============================] - 5s 3ms/step - loss: 0.3441 - accuracy: 0.8753 - val_loss: 0.3745 - val_accuracy: 0.870
Epoch 4/10
1500/1500 [==============================] - 5s 3ms/step - loss: 0.3192 - accuracy: 0.8829 - val_loss: 0.4106 - val_accuracy: 0.845
Epoch 5/10
1500/1500 [==============================] - 4s 3ms/step - loss: 0.2979 - accuracy: 0.8902 - val_loss: 0.3475 - val_accuracy: 0.879
Epoch 6/10
1500/1500 [==============================] - 5s 3ms/step - loss: 0.2832 - accuracy: 0.8959 - val_loss: 0.3398 - val_accuracy: 0.881
Epoch 7/10
1500/1500 [==============================] - 5s 3ms/step - loss: 0.2735 - accuracy: 0.8988 - val_loss: 0.3348 - val_accuracy: 0.884
Epoch 8/10
1500/1500 [==============================] - 6s 4ms/step - loss: 0.2615 - accuracy: 0.9030 - val_loss: 0.3229 - val_accuracy: 0.888
Epoch 9/10
1500/1500 [==============================] - 5s 3ms/step - loss: 0.2514 - accuracy: 0.9082 - val_loss: 0.3568 - val_accuracy: 0.873
Epoch 10/10
1500/1500 [==============================] - 5s 4ms/step - loss: 0.2418 - accuracy: 0.9097 - val_loss: 0.3279 - val_accuracy: 0.882
313/313 [==============================] - 1s 2ms/step - loss: 0.3539 - accuracy: 0.8752
Test accuracy: 0.8751999735832214
```

3.

```
# Preprocess the data
train_images_CNN = train_images.reshape(train_images.shape[0], 28, 28, 1) / 255.0
test_images_CNN = test_images.reshape(test_images.shape[0], 28, 28, 1) / 255.0

# Create a CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])

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

# Train the model on the training data
model.fit(train_images_CNN, train_labels, epochs=10, validation_split=0.2)

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(test_images_CNN, test_labels)
print('Test accuracy:', test_acc)
```

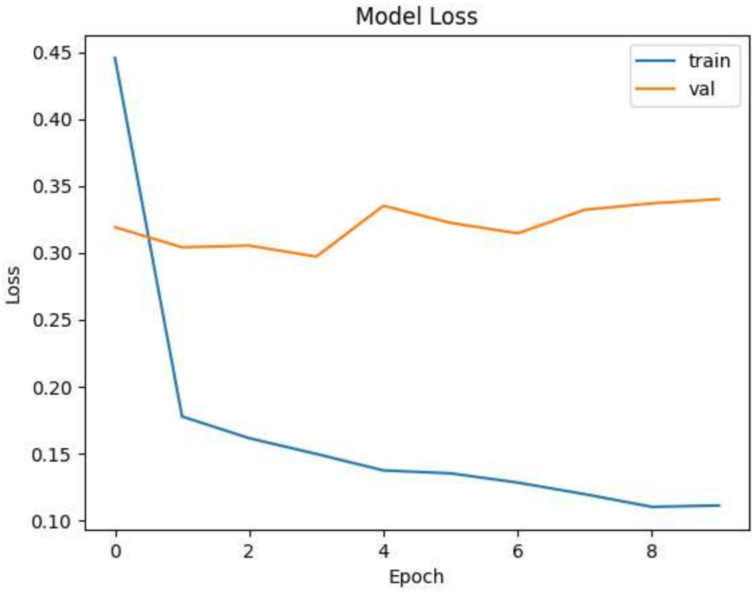
```
Epoch 1/10
1500/1500 [==============================] - 9s 5ms/step - loss: 0.5426 - accuracy: 0.7999 - val_loss: 0.3742 - val_accuracy: 0.863
```

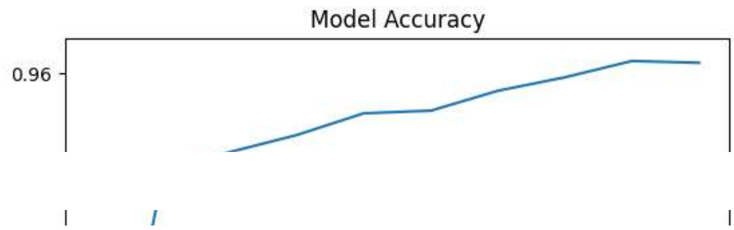
```
Epoch 2/10
1500/1500 [==============================] - 7s 5ms/step - loss: 0.3524 - accuracy: 0.8723 - val_loss: 0.3413 - val_accuracy: 0.872
Epoch 3/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.2993 - accuracy: 0.8911 - val_loss: 0.3069 - val_accuracy: 0.887
Epoch 4/10
1500/1500 [==============================] - 7s 5ms/step - loss: 0.2666 - accuracy: 0.9017 - val_loss: 0.2794 - val_accuracy: 0.899
Epoch 5/10
1500/1500 [==============================] - 7s 5ms/step - loss: 0.2426 - accuracy: 0.9106 - val_loss: 0.2793 - val_accuracy: 0.898
Epoch 6/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.2212 - accuracy: 0.9182 - val_loss: 0.2665 - val_accuracy: 0.900
Epoch 7/10
1500/1500 [==============================] - 7s 5ms/step - loss: 0.2026 - accuracy: 0.9260 - val_loss: 0.2748 - val_accuracy: 0.904
Epoch 8/10
1500/1500 [==============================] - 7s 4ms/step - loss: 0.1877 - accuracy: 0.9307 - val_loss: 0.2544 - val_accuracy: 0.908
Epoch 9/10
1500/1500 [==============================] - 7s 5ms/step - loss: 0.1731 - accuracy: 0.9361 - val_loss: 0.2657 - val_accuracy: 0.904
Epoch 10/10
1500/1500 [==============================] - 6s 4ms/step - loss: 0.1580 - accuracy: 0.9412 - val_loss: 0.2670 - val_accuracy: 0.909
313/313 [==============================] - 1s 3ms/step - loss: 0.2819 - accuracy: 0.9057
Test accuracy: 0.9057000279426575
```

4.

```
#Transfer learning
# Saving the initial trained model of CNN architecture
model.save('initial_model.h5')

# Loading the saved model
loaded_model = load_model('initial_model.h5')

# Adding new layers on top of the loaded model
loaded_model.add(Dense(64, activation='relu'))
loaded_model.add(Dense(10, activation='softmax'))

# Compiling the model with added layers
loaded_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Training the model with added layers
history = loaded_model.fit(train_images_CNN, train_labels, epochs=10, validation_split=0.2)


# Evaluating the model on test data
test_loss, test_acc = loaded_model.evaluate(test_images_CNN, test_labels)
print('Test accuracy:', test_acc)

# Plot the training loss and accuracy
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['train', 'val'], loc='upper right')
plt.show()

plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['train', 'val'], loc='lower right')
plt.show()
```

```
Epoch 1/10
1500/1500 [==============================] - 10s 5ms/step - loss: 0.4456 - accuracy: 0.8795
Epoch 2/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1776 - accuracy: 0.9411 -
Epoch 3/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1614 - accuracy: 0.9454 -
Epoch 4/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1496 - accuracy: 0.9486 -
Epoch 5/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1373 - accuracy: 0.9526 -
Epoch 6/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1351 - accuracy: 0.9531 -
Epoch 7/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1282 - accuracy: 0.9567 -
Epoch 8/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1195 - accuracy: 0.9592 -
Epoch 9/10
1500/1500 [==============================] - 8s 5ms/step - loss: 0.1100 - accuracy: 0.9622 -
Epoch 10/10
1500/1500 [==============================] - 7s 5ms/step - loss: 0.1111 - accuracy: 0.9619 -
313/313 [==============================] - 1s 3ms/step - loss: 0.3560 - accuracy: 0.8986
Test accuracy: 0.8985999822616577
```





3.

```
# Preprocess the data
train_images_RNN = train_images.reshape(train_images.shape[0], -1, 1) / 255.0
test_images_RNN = test_images.reshape(test_images.shape[0], -1, 1) / 255.0

# Create an LSTM model
model = Sequential([
    LSTM(32, input_shape=(784, 1)),
    Dense(10, activation='softmax')
])

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

# Train the model on the training data
model.fit(train_images_RNN, train_labels, epochs=10, validation_split=0.2)

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(test_images_RNN, test_labels)
print('Test accuracy:', test_acc)
```

```
Epoch 1/10
1500/1500 [==============================] - 38s 23ms/step - loss: 1.6883 - accuracy: 0.3402 - val_loss: 1.4599 - val_accuracy: 0.4
Epoch 2/10
1500/1500 [==============================] - 37s 24ms/step - loss: 1.5004 - accuracy: 0.4061 - val_loss: 1.3448 - val_accuracy: 0.4
Epoch 3/10
1500/1500 [==============================] - 35s 24ms/step - loss: 1.3167 - accuracy: 0.4836 - val_loss: 1.2399 - val_accuracy: 0.5
Epoch 4/10
```

```
1500/1500 [==============================] - 38s 25ms/step - loss: 1.9130 - accuracy: 0.2931 - val_loss: 1.9748 - val_accuracy: 0.2
Epoch 5/10
1500/1500 [==============================] - 37s 25ms/step - loss: 1.6778 - accuracy: 0.3556 - val_loss: 1.5389 - val_accuracy: 0.3
Epoch 6/10
1500/1500 [==============================] - 35s 24ms/step - loss: 1.5075 - accuracy: 0.4067 - val_loss: 1.4551 - val_accuracy: 0.4
Epoch 7/10
1500/1500 [==============================] - 35s 24ms/step - loss: 1.4406 - accuracy: 0.4488 - val_loss: 1.4300 - val_accuracy: 0.4
Epoch 8/10
1500/1500 [==============================] - 35s 23ms/step - loss: 1.4744 - accuracy: 0.4342 - val_loss: 1.4688 - val_accuracy: 0.4
Epoch 9/10
1500/1500 [==============================] - 35s 23ms/step - loss: 1.3844 - accuracy: 0.4639 - val_loss: 1.5425 - val_accuracy: 0.4
Epoch 10/10
1500/1500 [==============================] - 35s 23ms/step - loss: 2.5256 - accuracy: 0.1351 - val_loss: 2.1980 - val_accuracy: 0.1
313/313 [==============================] - 5s 13ms/step - loss: 2.1977 - accuracy: 0.1732
Test accuracy: 0.17319999635219574
```

5.

Performance Analysis:

1. Sequential Model: The Sequential Model is a basic neural network architecture that consists of a linear stack of layers. It is simple and easy to implement, making it suitable for small-scale image classification tasks. However, it may not perform well on more complex tasks that require capturing spatial dependencies or handling large image datasets with varying sizes and resolutions.
2. Convolutional Neural Networks (CNNs): CNNs are specifically designed for image recognition tasks and can capture local patterns and spatial dependencies in images. They use convolutional layers for feature extraction and pooling layers for spatial downsampling. CNNs are more complex than Sequential Models and can learn complex hierarchical features from images, making them more suitable for larger image datasets and tasks that require high accuracy.
3. Recurrent Neural Networks (RNNs): RNNs are designed to handle sequential data, making them suitable for tasks that require capturing temporal dependencies, such as time-series data or text data. RNNs have a feedback loop that allows them to remember previous states, making them capable of modeling long-term dependencies. However, RNNs may suffer from the vanishing gradient problem and may not perform well on image classification tasks compared to CNNs.
4. Transfer Learning: Transfer Learning is a technique that allows pre-trained models, usually trained on large datasets, to be used as a starting point for a new task with limited data. Transfer Learning can save training time and improve performance, especially when the new task has limited data. By leveraging features learned from pre-trained models, Transfer Learning can achieve good performance with smaller datasets compared to training from scratch. It is particularly useful in scenarios where you don't have access to large amounts of labeled data.