DL_spam_shield

March 6, 2025

0.1 Load and inspect the dataset

[1]:
```
import pandas as pd
import numpy as np

df = pd.read_csv('spam.csv', encoding='latin-1')

print(df.head()) # printing the first 5 rows of the dataframe

print(df.info()) # printing the info of the dataframe

print(df.describe())
```

```
                                                text  spam
0  Subject: naturally irresistible your corporate…     1
1  Subject: the stock trading gunslinger  fanny i…     1
2  Subject: unbelievable new homes made easy  im …     1
3  Subject: 4 color printing special  request add…     1
4  Subject: do not have money , get software cds …     1
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5728 entries, 0 to 5727
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   text    5728 non-null   object
 1   spam    5728 non-null   int64
dtypes: int64(1), object(1)
memory usage: 89.6+ KB
None
              spam
count  5728.000000
mean      0.238827
std       0.426404
min       0.000000
25%       0.000000
50%       0.000000
75%       0.000000
max       1.000000
```

```
[2]: print(df.isnull().sum()) # check for missing values
```

```
text    0
spam    0
dtype: int64
```

```
[3]: df['text'] = pd.Series(text[9:] for text in df['text']) # removing (Subject:)␣
     ↪from the text column
```

0.2 Visualizing Spam Message Data Using Word Clouds

```
[4]: spam_df = df[df.spam == 1] # filtering the spam messages
     spam_messages = spam_df['text'] # getting the spam messages
```

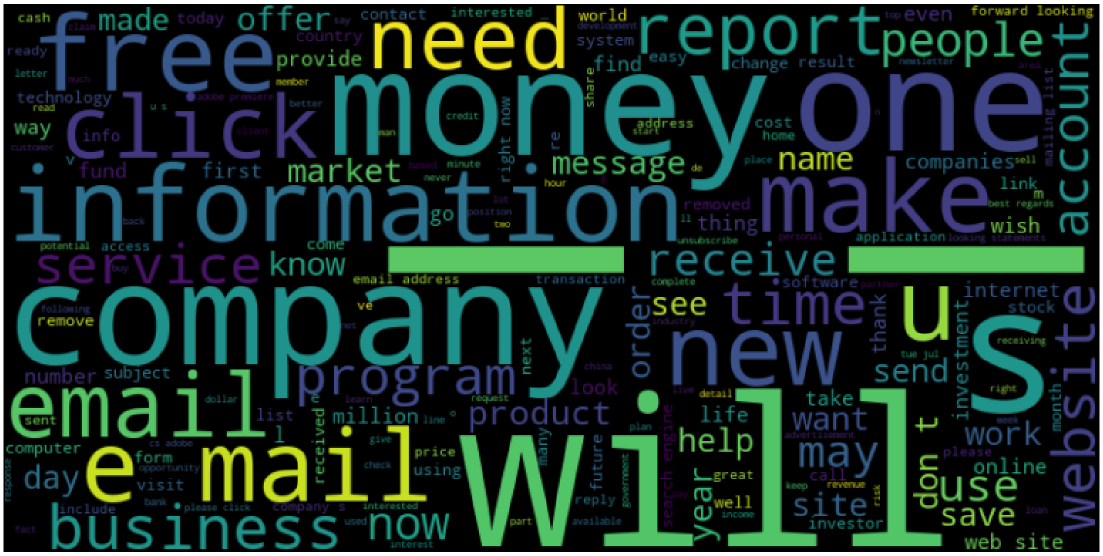
```
[5]: all_spam = " ".join(message for message in spam_messages)
     print(f"There are {len(all_spam)} words in the combination of all spam messages.
     ↪")
```

```
There are 1791063 words in the combination of all spam messages.
```

```
[6]: from wordcloud import WordCloud
     import matplotlib.pyplot as plt

     # Generate word cloud
     wordcloud = WordCloud(width = 800, height = 400, background_color ='black').
     ↪generate(all_spam)

     # Display the word cloud using Matplotlib
     plt.figure(figsize=(10, 5))
     plt.imshow(wordcloud, interpolation='bilinear')
     plt.axis('off')  # axes not shown to keep it clean
     plt.show()
```



0.3 Preprocessing and Feature Extraction

```
[11]: import re
import nltk
from nltk.corpus import stopwords

nltk.download('stopwords')

def clean_text(text):
    # Removing non-letters
    text = re.sub(r'\s+', ' ', text) # replacing multiple spaces with a single space
    letters_only = re.sub("[^a-zA-Z]", " ", text)
    # Convert to lower case and split into words
    words = letters_only.lower().split()
    # Removing stopwords
    stops = set(stopwords.words("english"))
    meaningful_words = [w for w in words if not w in stops]
    # Joining the words back into one string separated by space and return the result
    return " ".join(meaningful_words)

df['clean_text'] = df['text'].apply(clean_text)
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\adhir\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[ ]:
```python
from sklearn.feature_extraction.text import TfidfVectorizer

# Initializing the TF-IDF vectorizer
vectorizer = TfidfVectorizer(max_features=5000)
X = vectorizer.fit_transform(df['clean_text'])

df['label'] = df['spam'].map({0: 'ham', 1: 'spam'})

# Getting the labels
y = df['spam']
```

[13]:
```python
from sklearn.model_selection import train_test_split

# Splitting the data into a training set and a test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

0.4 Building and Compiling a Neural Network

[14]:
```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.metrics import Precision, Recall, AUC
```

[163]:
```python
model = Sequential([
    # Input layer and first hidden layer
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.7),

    # Second hidden layer
    Dense(64, activation='relu'),
    Dropout(0.6),

    # Output layer
    Dense(1, activation='sigmoid')  # Output layer with sigmoid activation for␣
↪binary classification
])
```

[164]:
```python
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',  # Appropriate loss function for binary␣
↪classification
    metrics=['accuracy', Precision(name='precision'), Recall(name='recall'),␣
↪AUC(name='auc')]
)
```

[165]:
```python
model.summary()
```

```
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
dense_6 (Dense)	(None, 128)	640,128
dropout_4 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 64)	8,256
dropout_5 (Dropout)	(None, 64)	0
dense_8 (Dense)	(None, 1)	65

```
 Total params: 648,449 (2.47 MB)

 Trainable params: 648,449 (2.47 MB)

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

0.5 Training a Neural Network with Early Stopping

[166]:
```python
from tensorflow.keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(
    monitor='val_auc',
    patience=10,          # Number of epochs to wait after min has been reached
    restore_best_weights=True  # Restoring model weights from the epoch with␣
 ↪the lowest validation loss
    )

history = model.fit(
    X_train,
    y_train,
    epochs=100,  # Max number of epochs
    callbacks=[early_stopping],
    batch_size=64,  # Batch size for training
    validation_split=0.2
)
```

```
Epoch 1/100
58/58                  4s 23ms/step -
accuracy: 0.7028 - auc: 0.6135 - loss: 0.6140 - precision: 0.3171 - recall:
```

```
0.1563 - val_accuracy: 0.7819 - val_auc: 0.9957 - val_loss: 0.3012 -
val_precision: 1.0000 - val_recall: 0.0196
Epoch 2/100
58/58            1s 14ms/step -
accuracy: 0.8489 - auc: 0.9939 - loss: 0.2618 - precision: 0.9957 - recall:
0.4008 - val_accuracy: 0.9815 - val_auc: 0.9987 - val_loss: 0.0722 -
val_precision: 0.9606 - val_recall: 0.9559
Epoch 3/100
58/58            1s 11ms/step -
accuracy: 0.9900 - auc: 0.9995 - loss: 0.0589 - precision: 0.9881 - recall:
0.9690 - val_accuracy: 0.9869 - val_auc: 0.9993 - val_loss: 0.0300 -
val_precision: 0.9660 - val_recall: 0.9755
Epoch 4/100
58/58            1s 10ms/step -
accuracy: 0.9963 - auc: 0.9999 - loss: 0.0201 - precision: 0.9928 - recall:
0.9920 - val_accuracy: 0.9902 - val_auc: 0.9995 - val_loss: 0.0254 -
val_precision: 0.9803 - val_recall: 0.9755
Epoch 5/100
58/58            1s 10ms/step -
accuracy: 0.9984 - auc: 1.0000 - loss: 0.0107 - precision: 0.9978 - recall:
0.9959 - val_accuracy: 0.9891 - val_auc: 0.9996 - val_loss: 0.0224 -
val_precision: 0.9755 - val_recall: 0.9755
Epoch 6/100
58/58            1s 11ms/step -
accuracy: 0.9990 - auc: 0.9999 - loss: 0.0087 - precision: 0.9963 - recall:
0.9993 - val_accuracy: 0.9902 - val_auc: 0.9996 - val_loss: 0.0224 -
val_precision: 0.9756 - val_recall: 0.9804
Epoch 7/100
58/58            1s 14ms/step -
accuracy: 0.9996 - auc: 1.0000 - loss: 0.0041 - precision: 1.0000 - recall:
0.9982 - val_accuracy: 0.9902 - val_auc: 0.9997 - val_loss: 0.0215 -
val_precision: 0.9756 - val_recall: 0.9804
Epoch 8/100
58/58            1s 9ms/step -
accuracy: 0.9996 - auc: 1.0000 - loss: 0.0032 - precision: 0.9982 - recall:
1.0000 - val_accuracy: 0.9902 - val_auc: 0.9997 - val_loss: 0.0207 -
val_precision: 0.9756 - val_recall: 0.9804
Epoch 9/100
58/58            1s 9ms/step -
accuracy: 0.9995 - auc: 1.0000 - loss: 0.0030 - precision: 0.9994 - recall:
0.9985 - val_accuracy: 0.9924 - val_auc: 0.9997 - val_loss: 0.0188 -
val_precision: 0.9852 - val_recall: 0.9804
Epoch 10/100
58/58            1s 12ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 0.0017 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9945 - val_auc: 0.9997 - val_loss: 0.0189 -
val_precision: 0.9854 - val_recall: 0.9902
Epoch 11/100
```

```
58/58            1s 12ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 0.0013 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9924 - val_auc: 0.9997 - val_loss: 0.0190 -
val_precision: 0.9852 - val_recall: 0.9804
Epoch 12/100
58/58            1s 11ms/step -
accuracy: 0.9997 - auc: 1.0000 - loss: 0.0018 - precision: 1.0000 - recall:
0.9988 - val_accuracy: 0.9924 - val_auc: 0.9997 - val_loss: 0.0203 -
val_precision: 0.9758 - val_recall: 0.9902
Epoch 13/100
58/58            1s 11ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 0.0011 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9924 - val_auc: 0.9998 - val_loss: 0.0203 -
val_precision: 0.9758 - val_recall: 0.9902
Epoch 14/100
58/58            1s 10ms/step -
accuracy: 0.9999 - auc: 1.0000 - loss: 0.0011 - precision: 0.9997 - recall:
0.9999 - val_accuracy: 0.9913 - val_auc: 0.9973 - val_loss: 0.0212 -
val_precision: 0.9757 - val_recall: 0.9853
Epoch 15/100
58/58            1s 10ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 7.6619e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9935 - val_auc: 0.9973 - val_loss: 0.0210 -
val_precision: 0.9853 - val_recall: 0.9853
Epoch 16/100
58/58            1s 10ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 6.8579e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9924 - val_auc: 0.9974 - val_loss: 0.0210 -
val_precision: 0.9805 - val_recall: 0.9853
Epoch 17/100
58/58            1s 11ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 5.7301e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9935 - val_auc: 0.9974 - val_loss: 0.0200 -
val_precision: 0.9853 - val_recall: 0.9853
Epoch 18/100
58/58            1s 11ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 7.0712e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9935 - val_auc: 0.9967 - val_loss: 0.0207 -
val_precision: 0.9806 - val_recall: 0.9902
Epoch 19/100
58/58            1s 9ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 3.9256e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9935 - val_auc: 0.9967 - val_loss: 0.0210 -
val_precision: 0.9806 - val_recall: 0.9902
Epoch 20/100
58/58            1s 10ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 3.4339e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9935 - val_auc: 0.9974 - val_loss: 0.0209 -
```

```
val_precision: 0.9853 - val_recall: 0.9853
Epoch 21/100
58/58            1s 12ms/step -
accuracy: 0.9988 - auc: 1.0000 - loss: 0.0028 - precision: 0.9971 - recall:
0.9984 - val_accuracy: 0.9935 - val_auc: 0.9974 - val_loss: 0.0204 -
val_precision: 0.9853 - val_recall: 0.9853
Epoch 22/100
58/58            1s 11ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 5.9492e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9924 - val_auc: 0.9974 - val_loss: 0.0213 -
val_precision: 0.9805 - val_recall: 0.9853
Epoch 23/100
58/58            1s 11ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 3.3652e-04 - precision: 1.0000 - recall:
1.0000 - val_accuracy: 0.9924 - val_auc: 0.9974 - val_loss: 0.0218 -
val_precision: 0.9805 - val_recall: 0.9853
```

0.6 Evaluating the Performance of the Classification Model

[167]:

```python
predictions = model.predict(X_test)
predictions = (predictions > 0.5).astype(int)  # Converting probabilities to␣
 ↪binary output
```

```
36/36            0s 5ms/step
```

[168]:

```python
from sklearn.metrics import classification_report, confusion_matrix

report = classification_report(y_test, predictions, target_names=['Ham',␣
 ↪'Spam'])
print(report)
```

```
              precision    recall  f1-score   support

         Ham       0.99      1.00      1.00       856
        Spam       0.99      0.98      0.99       290

    accuracy                           0.99      1146
   macro avg       0.99      0.99      0.99      1146
weighted avg       0.99      0.99      0.99      1146
```

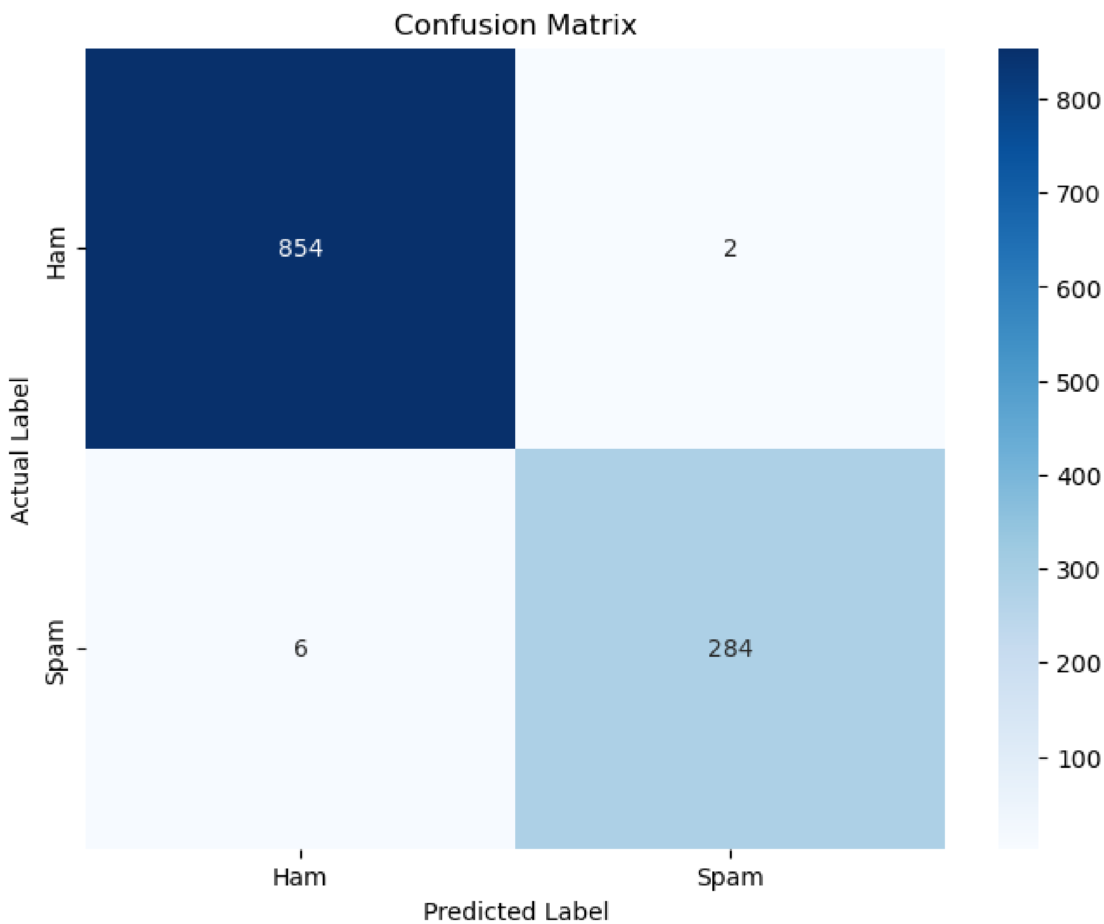
[169]:

```python
# Generate confusion matrix
conf_matrix = confusion_matrix(y_test, predictions)
print(conf_matrix)
```

```
[[854   2]
 [  6 284]]
```

[170]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap='Blues', xticklabels=['Ham',␣
↪'Spam'], yticklabels=['Ham', 'Spam'])
plt.ylabel('Actual Label')
plt.xlabel('Predicted Label')
plt.title('Confusion Matrix')
plt.show()
```



0.7 Visualizing Comprehensive Performance Metrics

[171]:
```
import matplotlib.pyplot as plt

# Extracting the data from the history object
acc = history.history['accuracy']
```

```
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
precision = history.history['precision']
val_precision = history.history['val_precision']
recall = history.history['recall']
val_recall = history.history['val_recall']
auc = history.history['auc']
val_auc = history.history['val_auc']
epochs = range(1, len(acc) + 1)
```

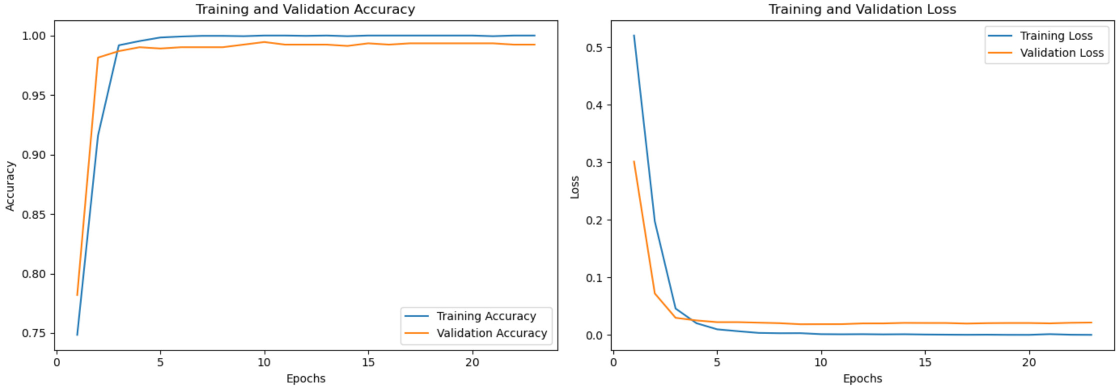
[172]:

```
plt.figure(figsize=(14, 5))

# Plotting training and validation accuracy
plt.subplot(1, 2, 1)
plt.plot(epochs, acc, label='Training Accuracy')
plt.plot(epochs, val_acc, label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Plotting training and validation loss
plt.subplot(1, 2, 2)
plt.plot(epochs, loss, label='Training Loss')
plt.plot(epochs, val_loss, label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

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



[173]:

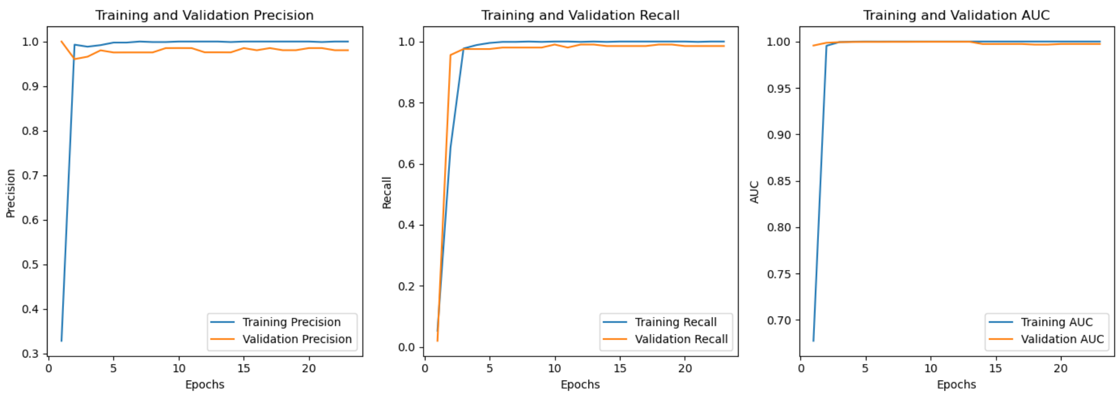
```
plt.figure(figsize=(14, 5))

# Plotting precision
plt.subplot(1, 3, 1)
plt.plot(epochs, precision, label='Training Precision')
plt.plot(epochs, val_precision, label='Validation Precision')
plt.title('Training and Validation Precision')
plt.xlabel('Epochs')
plt.ylabel('Precision')
plt.legend()

# Plotting recall
plt.subplot(1, 3, 2)
plt.plot(epochs, recall, label='Training Recall')
plt.plot(epochs, val_recall, label='Validation Recall')
plt.title('Training and Validation Recall')
plt.xlabel('Epochs')
plt.ylabel('Recall')
plt.legend()

# Plotting AUC
plt.subplot(1, 3, 3)
plt.plot(epochs, auc, label='Training AUC')
plt.plot(epochs, val_auc, label='Validation AUC')
plt.title('Training and Validation AUC')
plt.xlabel('Epochs')
plt.ylabel('AUC')
plt.legend()

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



0.8 Hyperparameter Optimization for Neural Network

[152]:
```
from kerastuner import HyperModel
from kerastuner.tuners import Hyperband
from tensorflow.keras.optimizers import Adam

class SpamClassifierHyperModel(HyperModel):
    def __init__(self, input_dim):
        self.input_dim = input_dim

    def build(self, hp):
        model = Sequential([
            Dense(
                units=hp.Int('input_units', min_value=32, max_value=512,␣
↪step=32),
                activation='relu',
                input_shape=(self.input_dim,)
            ),
            Dropout(rate=hp.Float('dropout1', min_value=0.0, max_value=0.7,␣
↪default=0.25, step=0.05)),
            Dense(
                units=hp.Int('hidden_units', min_value=32, max_value=128,␣
↪step=32),
                activation='relu'
            ),
            Dropout(rate=hp.Float('dropout2', min_value=0.0, max_value=0.6,␣
↪default=0.25, step=0.05)),
            Dense(1, activation='sigmoid')
        ])
        model.compile(
            optimizer=Adam(learning_rate=hp.Choice('learning_rate',␣
↪values=[1e-2, 1e-3, 1e-4])),
            loss='binary_crossentropy',
            metrics=['accuracy', tf.keras.metrics.AUC(name='auc')]
        )
        return model
```

[154]:
```
hypermodel = SpamClassifierHyperModel(input_dim=X_train.shape[1])

tuner = Hyperband(
    hypermodel,
    objective='val_auc',
    max_epochs=50,
    factor=3,
    directory='hyperband',
    project_name='spam_classification2'
)
```

```
c:\UoS_Lab\Anaconda\envs\com6018\Lib\site-
packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

[155]:
```python
early_stopping = EarlyStopping(monitor='val_auc', patience=5,␣
 ↪restore_best_weights=True)
tuner.search(
    X_train, y_train,
    epochs=50,
    validation_split=0.2,
    callbacks=[early_stopping]
)
```

```
Trial 90 Complete [00h 02m 55s]
val_auc: 0.9997971653938293

Best val_auc So Far: 0.9999106526374817
Total elapsed time: 00h 19m 40s
```

[156]:
```python
best_model = tuner.get_best_models(num_models=1)[0]
best_hyperparameters = tuner.get_best_hyperparameters(num_trials=1)[0]

print('Best model summary:')
best_model.summary()
print('Best hyperparameters:', best_hyperparameters.values)
```

```
Best model summary:
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 192)	960,192
dropout (Dropout)	(None, 192)	0
dense_1 (Dense)	(None, 32)	6,176
dropout_1 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 1)	33

Total params: 966,401 (3.69 MB)

Trainable params: 966,401 (3.69 MB)

Non-trainable params: 0 (0.00 B)

Best hyperparameters: {'input_units': 192, 'dropout1': 0.35000000000000003, 'hidden_units': 32, 'dropout2': 0.05, 'learning_rate': 0.01, 'tuner/epochs': 6, 'tuner/initial_epoch': 0, 'tuner/bracket': 2, 'tuner/round': 0}

0.9 Save a Tuned Neural Network Model for Text Classification

[157]:
```python
def build_model(best_hyperparameters):
    model = Sequential([
        Dense(best_hyperparameters.get('input_units'), activation='relu',␣
↪input_shape=(X_train.shape[1],)),
        Dropout(best_hyperparameters.get('dropout1')),
        Dense(best_hyperparameters.get('hidden_units'), activation='relu',␣
↪input_shape=(X_train.shape[1],)),
        Dropout(best_hyperparameters.get('dropout2')),
        Dense(1, activation='sigmoid')
    ])
    model.compile(
        optimizer=Adam(learning_rate=best_hyperparameters.get('learning_rate')),
        loss='binary_crossentropy',
        metrics=['accuracy', tf.keras.metrics.AUC(name='auc')]
    )
    return model

# Build the model using the best hyperparameters
model = build_model(best_hyperparameters)
```

[158]:
```python
early_stopping = EarlyStopping(monitor='val_auc', patience=5,␣
↪restore_best_weights=True)
history = model.fit(X_train, y_train, epochs=50, batch_size=64,␣
↪callbacks=[early_stopping], validation_split=0.2)
```

```
Epoch 1/50
58/58                 3s 18ms/step -
accuracy: 0.8466 - auc: 0.9005 - loss: 0.2876 - val_accuracy: 0.9858 - val_auc:
0.9972 - val_loss: 0.0584
Epoch 2/50
58/58                 1s 12ms/step -
accuracy: 0.9976 - auc: 1.0000 - loss: 0.0061 - val_accuracy: 0.9891 - val_auc:
0.9947 - val_loss: 0.0432
Epoch 3/50
58/58                 1s 12ms/step -
accuracy: 0.9994 - auc: 1.0000 - loss: 9.5791e-04 - val_accuracy: 0.9902 -
val_auc: 0.9941 - val_loss: 0.0363
```

```
Epoch 4/50
58/58            1s 11ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 1.4389e-04 - val_accuracy: 0.9902 -
val_auc: 0.9966 - val_loss: 0.0353
Epoch 5/50
58/58            1s 14ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 9.2901e-05 - val_accuracy: 0.9902 -
val_auc: 0.9966 - val_loss: 0.0351
Epoch 6/50
58/58            1s 12ms/step -
accuracy: 1.0000 - auc: 1.0000 - loss: 2.5539e-05 - val_accuracy: 0.9902 -
val_auc: 0.9966 - val_loss: 0.0355
```

[159]:

```python
evaluation = model.evaluate(X_test, y_test)
print(f"Test Loss: {evaluation[0]}, Test Accuracy: {evaluation[1]}")
```

```
36/36            0s 2ms/step -
accuracy: 0.9875 - auc: 0.9886 - loss: 0.0758
Test Loss: 0.04198630899190903, Test Accuracy: 0.9904013872146606
```

[160]:

```python
model.save('spam_classifier_model.h5')  # Saves the model in HDF5 format
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

[161]:

```python
from tensorflow.keras.models import load_model

loaded_model = load_model('spam_classifier_model.h5')
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be
built. `model.compile_metrics` will be empty until you train or evaluate the
model.
```

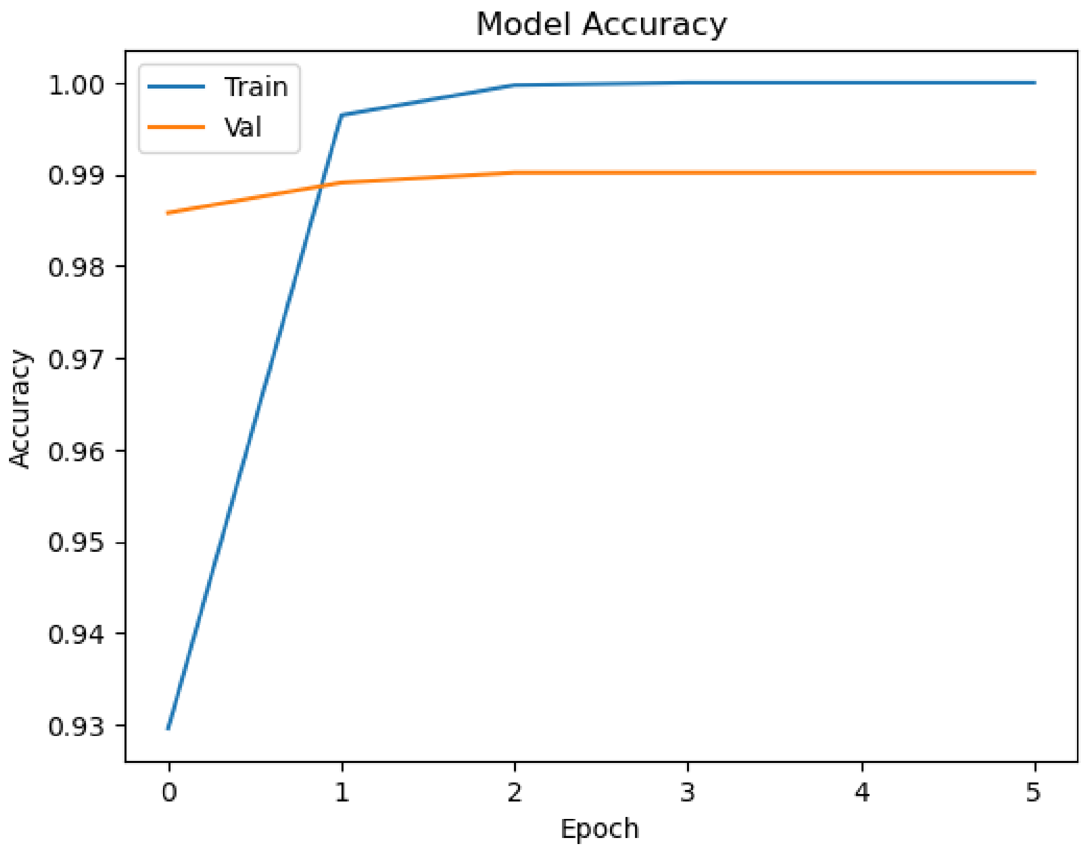
[162]:

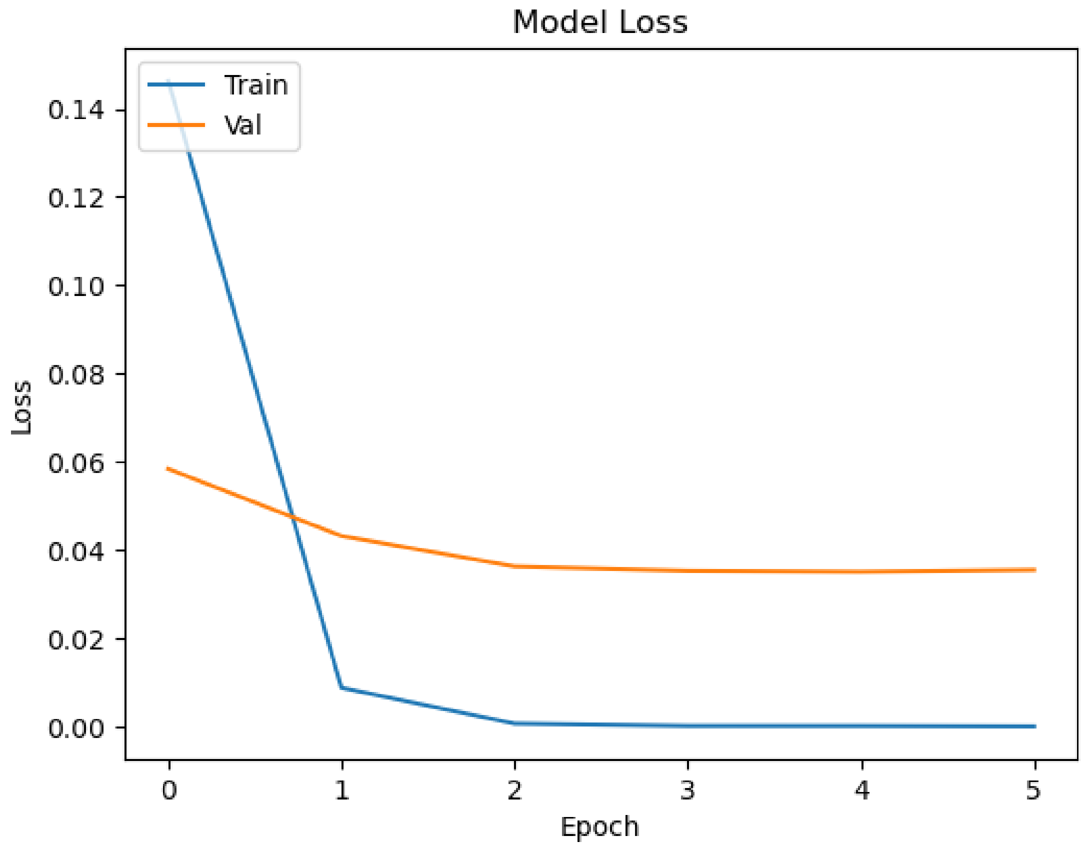
```python
import matplotlib.pyplot as plt

# Plot training & validation accuracy values
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()

# Plot training & validation loss values
plt.plot(history.history['loss'])
```

```
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()
```




Model Loss
Train
Val
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Loss
0
1
2
3
4
5
Epoch