Group No: 9

Group Member Name:

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1. Import the required libraries

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import string
from tensorflow.keras.layers import Embedding, Dense, Flatten
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
from sklearn.metrics import confusion_matrix
import seaborn as sns
from tensorflow.keras.layers import Dropout
from tensorflow.keras.regularizers import l2
```

2. Data Acquisition

2.1 Code for converting the above downloaded data into a dataframe

```
def load_reviews(directory):
    reviews = []
    labels = []
    for label in ['pos', 'neg']:
        path = os.path.join(directory, label)
        for filename in os.listdir(path):
            with open(os.path.join(path, filename), 'r',
encoding='utf-8') as file:
                text = file.read()
```

```
                reviews.append(text)
                labels.append(1 if label == 'pos' else 0)
    return reviews, labels

train_reviews, train_labels = load_reviews('/kaggle/input/imdb-reviews/aclImdb/train')
test_reviews, test_labels =
load_reviews('/kaggle/input/imdb-reviews/aclImdb/test')

train_df = pd.DataFrame({'text': train_reviews, 'label':
train_labels})
test_df = pd.DataFrame({'text': test_reviews, 'label': test_labels})

train_df
```

```
                                                    text  label
0      This was one of those wonderful rare moments i...      1
1      Have you seen The Graduate? It was hailed as t...      1
2      I don't watch a lot of TV, except for The Offi...      1
3      Kubrick again puts on display his stunning abi...      1
4      First of all, I liked very much the central id...      1
...                                                  ...    ...
24995  The first hour of the movie was boring as hell...      0
24996  A fun concept, but poorly executed. Except for...      0
24997  I honestly don't understand how tripe like thi...      0
24998  This remake of the 1962 orginal film'o the boo...      0
24999  La Sanguisuga Conduce la Danza, or The Bloodsu...      0

[25000 rows x 2 columns]
```

Size of the dataset

```
train_df.shape
```

```
(25000, 2)
```

Type of data attributes

```
data_attributes = train_df.columns.tolist()
print("Data attributes:", data_attributes)
```

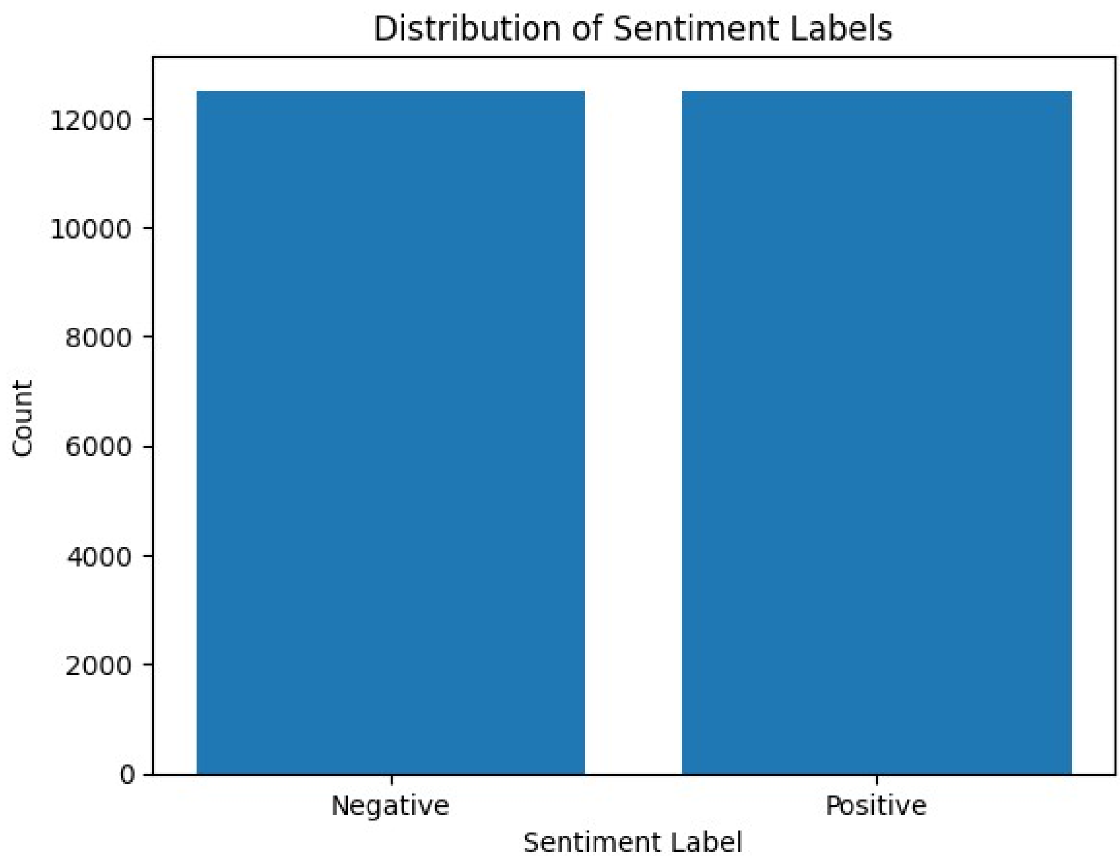
```
Data attributes: ['text', 'label']
```

Plot the distribution of the categories of the label.

```
target = train_df['label'].value_counts()

plt.bar(target.index, target.values)
plt.xlabel('Sentiment Label')
plt.ylabel('Count')
```

```
plt.xticks([0, 1], ['Negative', 'Positive'])
plt.title('Distribution of Sentiment Labels')
plt.show()
```



3. Data Preparation

3.1 Pre-processing techiniques

- Stop word removal
- Word tokenize
- Lower the text
- Remove punctuation
- Vectorization
- Padding

```
def preprocess_text(text):
    text = text.lower()
    words = word_tokenize(text)
    stop_words = set(stopwords.words('english'))
    words = [word for word in words if word not in stop_words and word
```

```
not in string.punctuation]
    return ' '.join(words)

train_df['text'] = train_df['text'].apply(preprocess_text)
test_df['text'] = test_df['text'].apply(preprocess_text)

max_words = 10000
max_sequence_length = 200

tokenizer = Tokenizer(num_words=max_words, oov_token="<OOV>")
tokenizer.fit_on_texts(train_df['text'])

train_sequences = tokenizer.texts_to_sequences(train_df['text'])
test_sequences = tokenizer.texts_to_sequences(test_df['text'])

train_sequences = pad_sequences(train_sequences,
maxlen=max_sequence_length, padding='post', truncating='post')
test_sequences = pad_sequences(test_sequences,
maxlen=max_sequence_length, padding='post', truncating='post')
```

3.2 Spliting the data into training set and testing set

```
X_train, X_val, y_train, y_val = train_test_split(train_sequences,
train_df['label'], test_size=0.2, random_state=42)
```

3.3 Preprocessing report

```
X_train.shape[0]
```

```
20000
```

```
X_val.shape[0]
```

```
5000
```

4. Deep Neural Network Architecture

4.1 Architecture design

The layers used for my models are,

Dense Layer :

A dense layer is a fundamental layer in DNNs where each neuron is connected to every neuron in the previous layer.It performs a linear transformation followed by an activation function (e.g., ReLU or sigmoid).Dense layers are used for feature extraction and representation learning.They can have varying numbers of neurons, allowing you to control the model's capacity.

Flatten Layer:

A flatten layer is used to transform multi-dimensional input (e.g., image tensors) into a 1D vector.

Embeddng Layer:

In a Deep Neural Network (DNN), an "Embedding Layer" is a type of layer that is commonly used when working with categorical data or text data. It is particularly useful for converting discrete inputs into continuous vector representations that the neural network can work with.

```
model = tf.keras.Sequential([
    Embedding(input_dim=max_words, output_dim=16,
input_length=max_sequence_length),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1, activation='sigmoid')
])
```

4.2 DNN Report

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 200, 16)           160000

 flatten (Flatten)           (None, 3200)              0

 dense_2 (Dense)             (None, 64)                204864

 dense_3 (Dense)             (None, 1)                 65

=================================================================
Total params: 364,929
Trainable params: 364,929
Non-trainable params: 0
_________________________________________________________________
```

5. Training the model

5.1 Configure the training

```
model.compile(optimizer='sgd', loss='binary_crossentropy',
metrics=['accuracy'])
```

5.2 Train the model

```
batch_size = 64
epochs = 20
history = model.fit(X_train,y_train,validation_data=(X_val, y_val),
epochs=epochs,batch_size=batch_size)
```

```
Epoch 1/20
313/313 [==============================] - 5s 11ms/step - loss: 0.6930
- accuracy: 0.5087 - val_loss: 0.6923 - val_accuracy: 0.5216
Epoch 2/20
313/313 [==============================] - 3s 11ms/step - loss: 0.6925
- accuracy: 0.5201 - val_loss: 0.6920 - val_accuracy: 0.5274
Epoch 3/20
313/313 [==============================] - 4s 12ms/step - loss: 0.6921
- accuracy: 0.5276 - val_loss: 0.6918 - val_accuracy: 0.5268
Epoch 4/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6916
- accuracy: 0.5293 - val_loss: 0.6915 - val_accuracy: 0.5340
Epoch 5/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6911
- accuracy: 0.5339 - val_loss: 0.6913 - val_accuracy: 0.5294
Epoch 6/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6907
- accuracy: 0.5337 - val_loss: 0.6911 - val_accuracy: 0.5308
Epoch 7/20
313/313 [==============================] - 3s 11ms/step - loss: 0.6903
- accuracy: 0.5340 - val_loss: 0.6908 - val_accuracy: 0.5302
Epoch 8/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6899
- accuracy: 0.5351 - val_loss: 0.6906 - val_accuracy: 0.5308
Epoch 9/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6895
- accuracy: 0.5376 - val_loss: 0.6903 - val_accuracy: 0.5296
Epoch 10/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6891
- accuracy: 0.5372 - val_loss: 0.6901 - val_accuracy: 0.5308
Epoch 11/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6886
- accuracy: 0.5403 - val_loss: 0.6900 - val_accuracy: 0.5272
Epoch 12/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6881
- accuracy: 0.5429 - val_loss: 0.6896 - val_accuracy: 0.5312
Epoch 13/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6875
- accuracy: 0.5444 - val_loss: 0.6892 - val_accuracy: 0.5380
Epoch 14/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6869
- accuracy: 0.5446 - val_loss: 0.6886 - val_accuracy: 0.5420
Epoch 15/20
```

```
313/313 [==============================] - 3s 10ms/step - loss: 0.6862
- accuracy: 0.5513 - val_loss: 0.6881 - val_accuracy: 0.5336
Epoch 16/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6855
- accuracy: 0.5509 - val_loss: 0.6873 - val_accuracy: 0.5446
Epoch 17/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6844
- accuracy: 0.5572 - val_loss: 0.6864 - val_accuracy: 0.5518
Epoch 18/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6833
- accuracy: 0.5650 - val_loss: 0.6852 - val_accuracy: 0.5508
Epoch 19/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6818
- accuracy: 0.5738 - val_loss: 0.6838 - val_accuracy: 0.5588
Epoch 20/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6802
- accuracy: 0.5817 - val_loss: 0.6824 - val_accuracy: 0.5624
```

6. Testing the model

```
input_text = "this movie is good"
input_text= preprocess_text(input_text)

input_sequence = tokenizer.texts_to_sequences([input_text])
input_sequence = pad_sequences(input_sequence,
maxlen=max_sequence_length, padding='post', truncating='post')

prediction = model.predict(input_sequence)[0, 0]

if prediction >= 0.5:
    print("Positive sentiment")
else:
    print("Negative sentiment")

1/1 [==============================] - 0s 26ms/step
Positive sentiment
```

7. Intermediate result

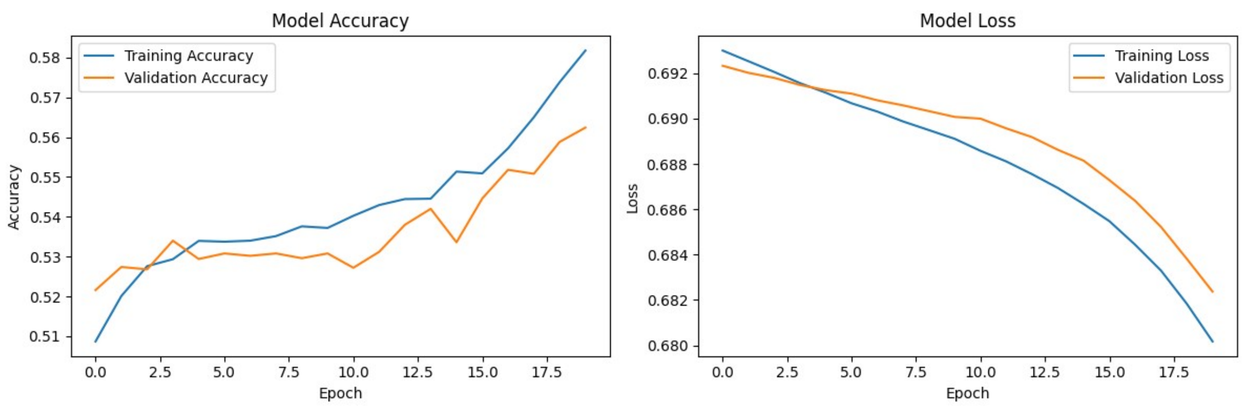
.

7.1 The training and validation loss history,Plot the training and validation accuracy history and Report the testing accuracy and loss.

```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()


plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

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



7.2 Confusion Matrix for testing dataset.

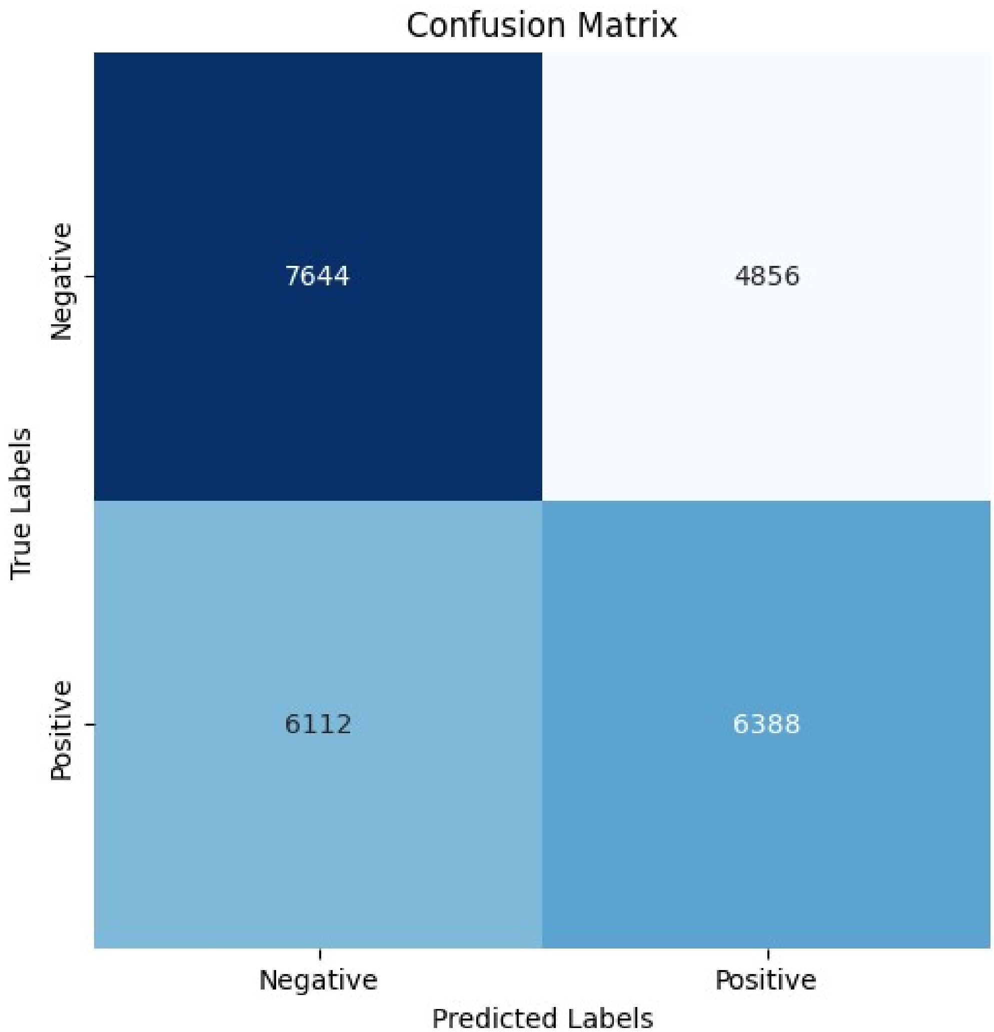
```
test_predictions = model.predict(test_sequences)
test_predictions = (test_predictions >= 0.5).astype(int)


confusion = confusion_matrix(test_df['label'], test_predictions)

plt.figure(figsize=(6, 6))
```

```
sns.heatmap(confusion, annot=True, fmt="d", cmap="Blues", cbar=False,
square=True,
            xticklabels=['Negative', 'Positive'],
yticklabels=['Negative', 'Positive'])
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()

782/782 [==============================] - 2s 3ms/step
```



7.3 Preformance study metrics like accuracy, precision, recall, F1 Score.

```
accuracy = accuracy_score(test_df['label'], test_predictions)
precision = precision_score(test_df['label'], test_predictions)
recall = recall_score(test_df['label'], test_predictions)
```

```
f1 = f1_score(test_df['label'], test_predictions)

print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')

Accuracy: 0.5613
Precision: 0.5681
Recall: 0.5110
F1 Score: 0.5381
```

8. Model architecture

8.1.1 Modify the architecture designed in section 4.1

1. By decreasing one layer

```
model1 = tf.keras.Sequential([
    Embedding(input_dim=max_words, output_dim=16,
input_length=max_sequence_length),
    Flatten(),
    Dense(1, activation='sigmoid')
])

model1.compile(optimizer='sgd', loss='binary_crossentropy',
metrics=['accuracy'])

batch_size = 64
epochs = 20

history1 = model1.fit(X_train,y_train,validation_data=(X_val, y_val),
epochs=epochs,batch_size=batch_size)

Epoch 1/20
313/313 [==============================] - 3s 8ms/step - loss: 0.6928
- accuracy: 0.5120 - val_loss: 0.6930 - val_accuracy: 0.5114
Epoch 2/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6923
- accuracy: 0.5185 - val_loss: 0.6928 - val_accuracy: 0.5132
Epoch 3/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6919
- accuracy: 0.5222 - val_loss: 0.6925 - val_accuracy: 0.5166
Epoch 4/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6916
- accuracy: 0.5249 - val_loss: 0.6924 - val_accuracy: 0.5200
Epoch 5/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6912
- accuracy: 0.5292 - val_loss: 0.6922 - val_accuracy: 0.5164
```

```
Epoch 6/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6909
- accuracy: 0.5297 - val_loss: 0.6920 - val_accuracy: 0.5208
Epoch 7/20
313/313 [==============================] - 3s 8ms/step - loss: 0.6905
- accuracy: 0.5333 - val_loss: 0.6919 - val_accuracy: 0.5216
Epoch 8/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6902
- accuracy: 0.5350 - val_loss: 0.6917 - val_accuracy: 0.5230
Epoch 9/20
313/313 [==============================] - 3s 8ms/step - loss: 0.6899
- accuracy: 0.5307 - val_loss: 0.6915 - val_accuracy: 0.5246
Epoch 10/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6895
- accuracy: 0.5342 - val_loss: 0.6914 - val_accuracy: 0.5258
Epoch 11/20
313/313 [==============================] - 3s 8ms/step - loss: 0.6891
- accuracy: 0.5386 - val_loss: 0.6911 - val_accuracy: 0.5262
Epoch 12/20
313/313 [==============================] - 2s 7ms/step - loss: 0.6888
- accuracy: 0.5376 - val_loss: 0.6908 - val_accuracy: 0.5274
Epoch 13/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6884
- accuracy: 0.5395 - val_loss: 0.6905 - val_accuracy: 0.5326
Epoch 14/20
313/313 [==============================] - 2s 7ms/step - loss: 0.6879
- accuracy: 0.5419 - val_loss: 0.6901 - val_accuracy: 0.5342
Epoch 15/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6873
- accuracy: 0.5451 - val_loss: 0.6898 - val_accuracy: 0.5334
Epoch 16/20
313/313 [==============================] - 2s 7ms/step - loss: 0.6868
- accuracy: 0.5457 - val_loss: 0.6892 - val_accuracy: 0.5376
Epoch 17/20
313/313 [==============================] - 2s 7ms/step - loss: 0.6862
- accuracy: 0.5501 - val_loss: 0.6887 - val_accuracy: 0.5330
Epoch 18/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6854
- accuracy: 0.5548 - val_loss: 0.6882 - val_accuracy: 0.5314
Epoch 19/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6847
- accuracy: 0.5567 - val_loss: 0.6875 - val_accuracy: 0.5350
Epoch 20/20
313/313 [==============================] - 2s 8ms/step - loss: 0.6839
- accuracy: 0.5599 - val_loss: 0.6866 - val_accuracy: 0.5480
```

8.1.2 Modify the architecture designed in section 4.1

1. By Increasing one layer

```
model2 = tf.keras.Sequential([
    Embedding(input_dim=max_words, output_dim=16,
input_length=max_sequence_length),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')
])

model2.compile(optimizer='sgd', loss='binary_crossentropy',
metrics=['accuracy'])

batch_size = 64
epochs = 20

history2 = model2.fit(X_train,y_train,validation_data=(X_val, y_val),
epochs=epochs,batch_size=batch_size)
```

```
Epoch 1/20
313/313 [==============================] - 4s 11ms/step - loss: 0.6930
- accuracy: 0.5113 - val_loss: 0.6931 - val_accuracy: 0.5044
Epoch 2/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6926
- accuracy: 0.5166 - val_loss: 0.6930 - val_accuracy: 0.5142
Epoch 3/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6923
- accuracy: 0.5237 - val_loss: 0.6927 - val_accuracy: 0.5126
Epoch 4/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6919
- accuracy: 0.5252 - val_loss: 0.6926 - val_accuracy: 0.5196
Epoch 5/20
313/313 [==============================] - 3s 11ms/step - loss: 0.6916
- accuracy: 0.5329 - val_loss: 0.6924 - val_accuracy: 0.5240
Epoch 6/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6912
- accuracy: 0.5329 - val_loss: 0.6922 - val_accuracy: 0.5246
Epoch 7/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6909
- accuracy: 0.5347 - val_loss: 0.6921 - val_accuracy: 0.5212
Epoch 8/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6906
- accuracy: 0.5361 - val_loss: 0.6919 - val_accuracy: 0.5250
Epoch 9/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6903
- accuracy: 0.5375 - val_loss: 0.6918 - val_accuracy: 0.5242
Epoch 10/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6899
- accuracy: 0.5383 - val_loss: 0.6917 - val_accuracy: 0.5214
Epoch 11/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6896
```

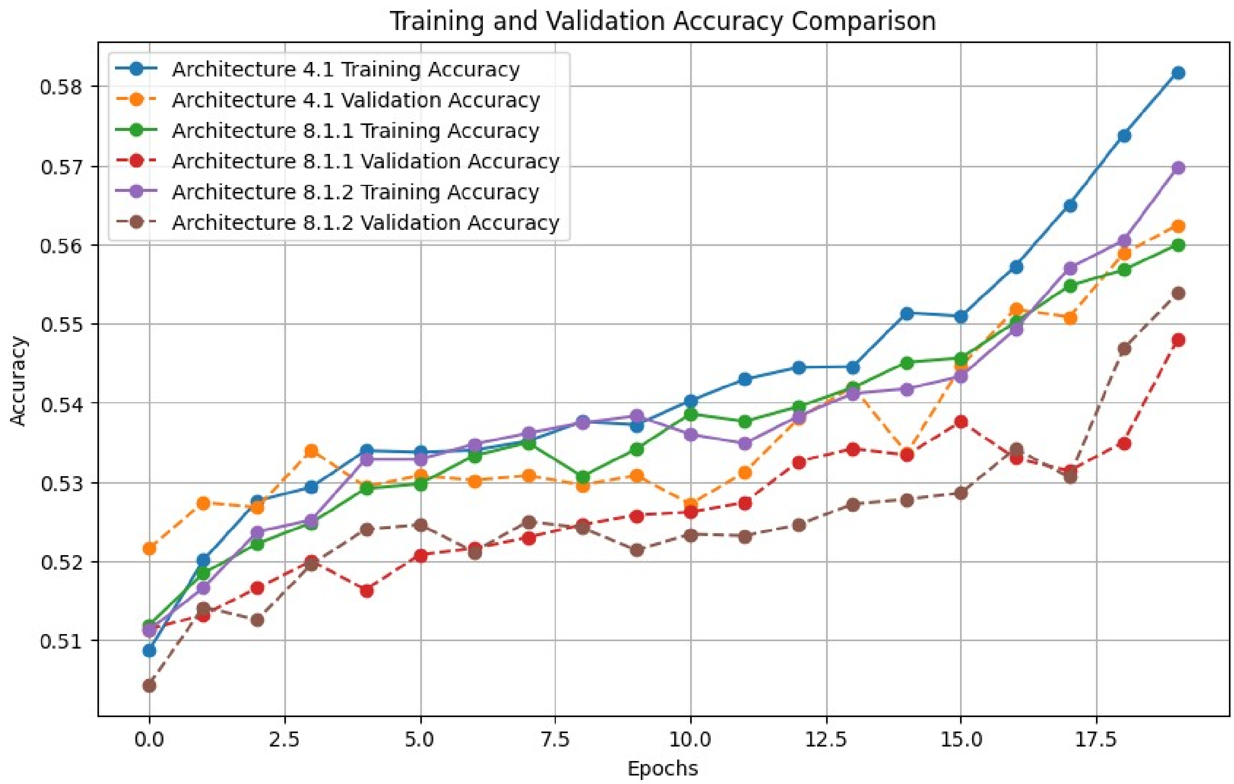
```
- accuracy: 0.5360 - val_loss: 0.6915 - val_accuracy: 0.5234
Epoch 12/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6893
- accuracy: 0.5349 - val_loss: 0.6913 - val_accuracy: 0.5232
Epoch 13/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6889
- accuracy: 0.5383 - val_loss: 0.6910 - val_accuracy: 0.5246
Epoch 14/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6885
- accuracy: 0.5411 - val_loss: 0.6908 - val_accuracy: 0.5272
Epoch 15/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6880
- accuracy: 0.5418 - val_loss: 0.6904 - val_accuracy: 0.5278
Epoch 16/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6874
- accuracy: 0.5433 - val_loss: 0.6899 - val_accuracy: 0.5286
Epoch 17/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6867
- accuracy: 0.5493 - val_loss: 0.6894 - val_accuracy: 0.5342
Epoch 18/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6857
- accuracy: 0.5570 - val_loss: 0.6887 - val_accuracy: 0.5306
Epoch 19/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6847
- accuracy: 0.5605 - val_loss: 0.6876 - val_accuracy: 0.5468
Epoch 20/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6832
- accuracy: 0.5697 - val_loss: 0.6864 - val_accuracy: 0.5538
```

8.2 The comparison of the training and validation accuracy of the three architecure

```
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Architecture 4.1 Training
Accuracy', linestyle='-', marker='o')
plt.plot(history.history['val_accuracy'], label='Architecture 4.1
Validation Accuracy', linestyle='--', marker='o')
plt.plot(history1.history['accuracy'], label='Architecture 8.1.1
Training Accuracy', linestyle='-', marker='o')
plt.plot(history1.history['val_accuracy'], label='Architecture 8.1.1
Validation Accuracy', linestyle='--', marker='o')
plt.plot(history2.history['accuracy'], label='Architecture 8.1.2
Training Accuracy', linestyle='-', marker='o')
plt.plot(history2.history['val_accuracy'], label='Architecture 8.1.2
Validation Accuracy', linestyle='--', marker='o')

plt.xlabel('Epochs')
plt.ylabel('Accuracy')
```

```
plt.title('Training and Validation Accuracy Comparison')
plt.legend()
plt.grid(True)
plt.show()
```



9. Regularisations

Regularization in Deep Learning (DL) refers to a set of techniques used to prevent a neural network from overfitting the training data. Overfitting occurs when a model learns to perform exceptionally well on the training data but fails to generalize to unseen data. Regularization methods aim to encourage the neural network to have a simpler, more generalized representation rather than memorizing the training data.

9.1.1 Modify the architecture designed in section 4.1

1. Dropout of ratio 0.25

Dropout layer: The Dropout layer is a regularization technique used in Deep Neural Networks (DNNs) to reduce overfitting. Overfitting occurs when a model learns to perform exceptionally well on the training data but fails to generalize to unseen data. Dropout is a simple yet effective method to combat overfitting by preventing the network from relying too heavily on any one neuron or feature.

```
model3 = tf.keras.Sequential([
    Embedding(input_dim=max_words, output_dim=16,
input_length=max_sequence_length),
    Flatten(),
    Dense(64, activation='relu'),
    Dropout(0.25),
    Dense(1, activation='sigmoid')
])

model3.compile(optimizer='sgd', loss='binary_crossentropy',
metrics=['accuracy'])

history3 = model3.fit(X_train,y_train,validation_data=(X_val, y_val),
epochs=epochs,batch_size=batch_size)
```

```
Epoch 1/20
313/313 [==============================] - 4s 10ms/step - loss: 0.6935
- accuracy: 0.4976 - val_loss: 0.6935 - val_accuracy: 0.4934
Epoch 2/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6930
- accuracy: 0.5094 - val_loss: 0.6932 - val_accuracy: 0.5002
Epoch 3/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6928
- accuracy: 0.5093 - val_loss: 0.6930 - val_accuracy: 0.5166
Epoch 4/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6926
- accuracy: 0.5159 - val_loss: 0.6929 - val_accuracy: 0.5066
Epoch 5/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6923
- accuracy: 0.5211 - val_loss: 0.6927 - val_accuracy: 0.5188
Epoch 6/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6919
- accuracy: 0.5270 - val_loss: 0.6925 - val_accuracy: 0.5206
Epoch 7/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6919
- accuracy: 0.5248 - val_loss: 0.6923 - val_accuracy: 0.5178
Epoch 8/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6914
- accuracy: 0.5254 - val_loss: 0.6922 - val_accuracy: 0.5252
Epoch 9/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6912
- accuracy: 0.5296 - val_loss: 0.6921 - val_accuracy: 0.5194
Epoch 10/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6905
- accuracy: 0.5360 - val_loss: 0.6919 - val_accuracy: 0.5244
Epoch 11/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6903
- accuracy: 0.5356 - val_loss: 0.6920 - val_accuracy: 0.5170
Epoch 12/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6900
```

```
- accuracy: 0.5321 - val_loss: 0.6917 - val_accuracy: 0.5272
Epoch 13/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6898
- accuracy: 0.5361 - val_loss: 0.6916 - val_accuracy: 0.5242
Epoch 14/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6897
- accuracy: 0.5348 - val_loss: 0.6915 - val_accuracy: 0.5234
Epoch 15/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6894
- accuracy: 0.5372 - val_loss: 0.6913 - val_accuracy: 0.5246
Epoch 16/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6892
- accuracy: 0.5376 - val_loss: 0.6912 - val_accuracy: 0.5236
Epoch 17/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6886
- accuracy: 0.5406 - val_loss: 0.6910 - val_accuracy: 0.5302
Epoch 18/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6883
- accuracy: 0.5443 - val_loss: 0.6908 - val_accuracy: 0.5256
Epoch 19/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6878
- accuracy: 0.5423 - val_loss: 0.6905 - val_accuracy: 0.5270
Epoch 20/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6877
- accuracy: 0.5440 - val_loss: 0.6902 - val_accuracy: 0.5296
```

9.1.2 Modify the architecture designed in section 4.1

1. Dropout of ratio 0.25 with L2 regulariser with factor 1e−04.

L2 regularization adds a penalty term that encourages the model's weights to be small but does not enforce sparsity. These techniques help prevent overfitting by discouraging overly complex models.

```
model4 = tf.keras.Sequential([
    Embedding(input_dim=max_words, output_dim=16,
input_length=max_sequence_length),
    Flatten(),
    Dense(64, activation='relu'),
    Dropout(0.25),
    Dense(1, activation='sigmoid', kernel_regularizer=l2(1e-04))
])

model4.compile(optimizer='sgd', loss='binary_crossentropy',
metrics=['accuracy'])

history4 = model4.fit(X_train,y_train,validation_data=(X_val, y_val),
epochs=epochs,batch_size=batch_size)
```

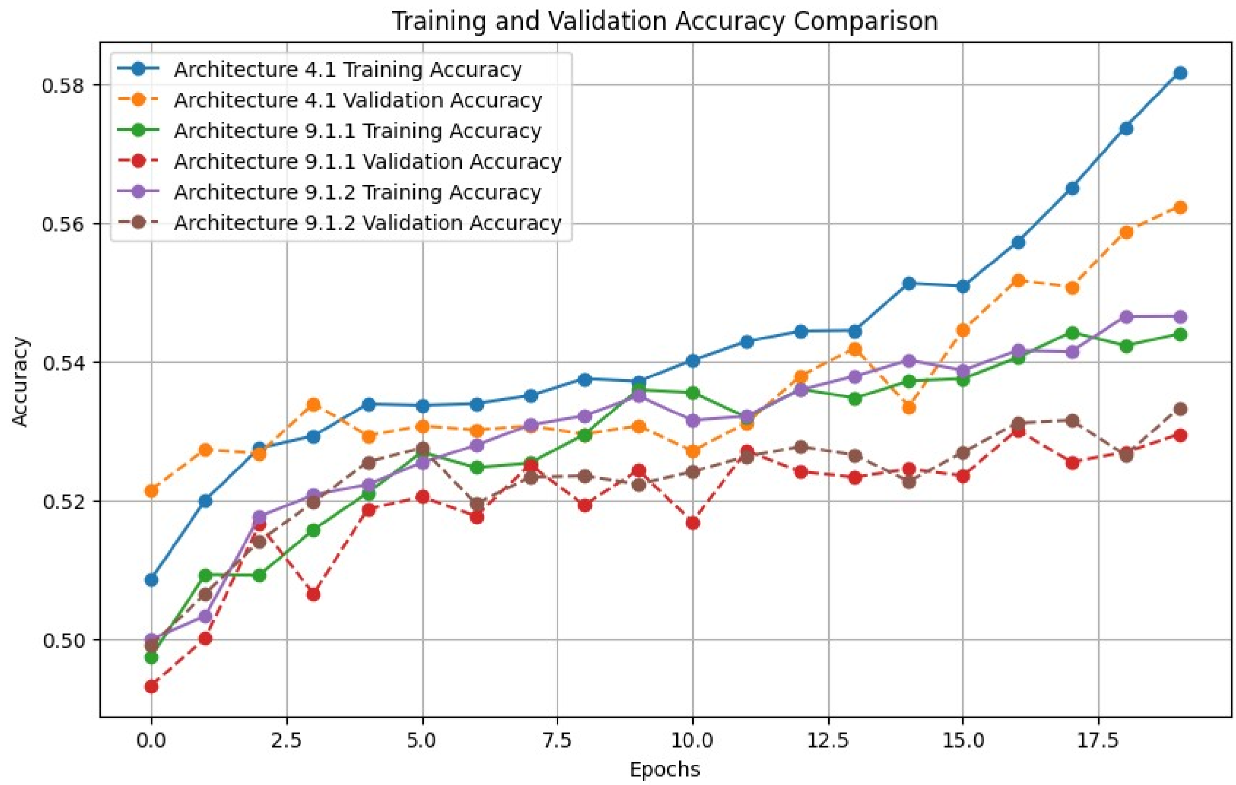
```
Epoch 1/20
313/313 [==============================] - 4s 10ms/step - loss: 0.6937
- accuracy: 0.5001 - val_loss: 0.6935 - val_accuracy: 0.4992
Epoch 2/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6933
- accuracy: 0.5034 - val_loss: 0.6933 - val_accuracy: 0.5066
Epoch 3/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6927
- accuracy: 0.5178 - val_loss: 0.6931 - val_accuracy: 0.5142
Epoch 4/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6926
- accuracy: 0.5209 - val_loss: 0.6930 - val_accuracy: 0.5198
Epoch 5/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6923
- accuracy: 0.5224 - val_loss: 0.6928 - val_accuracy: 0.5256
Epoch 6/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6920
- accuracy: 0.5255 - val_loss: 0.6926 - val_accuracy: 0.5276
Epoch 7/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6915
- accuracy: 0.5280 - val_loss: 0.6925 - val_accuracy: 0.5196
Epoch 8/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6914
- accuracy: 0.5309 - val_loss: 0.6924 - val_accuracy: 0.5234
Epoch 9/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6907
- accuracy: 0.5322 - val_loss: 0.6923 - val_accuracy: 0.5236
Epoch 10/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6907
- accuracy: 0.5351 - val_loss: 0.6923 - val_accuracy: 0.5224
Epoch 11/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6905
- accuracy: 0.5316 - val_loss: 0.6922 - val_accuracy: 0.5242
Epoch 12/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6903
- accuracy: 0.5322 - val_loss: 0.6921 - val_accuracy: 0.5264
Epoch 13/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6899
- accuracy: 0.5360 - val_loss: 0.6920 - val_accuracy: 0.5278
Epoch 14/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6899
- accuracy: 0.5379 - val_loss: 0.6919 - val_accuracy: 0.5266
Epoch 15/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6893
- accuracy: 0.5403 - val_loss: 0.6919 - val_accuracy: 0.5228
Epoch 16/20
313/313 [==============================] - 3s 9ms/step - loss: 0.6895
- accuracy: 0.5388 - val_loss: 0.6916 - val_accuracy: 0.5270
Epoch 17/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6888
```

```
- accuracy: 0.5416 - val_loss: 0.6914 - val_accuracy: 0.5312
Epoch 18/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6888
- accuracy: 0.5415 - val_loss: 0.6912 - val_accuracy: 0.5316
Epoch 19/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6882
- accuracy: 0.5465 - val_loss: 0.6911 - val_accuracy: 0.5266
Epoch 20/20
313/313 [==============================] - 3s 10ms/step - loss: 0.6878
- accuracy: 0.5466 - val_loss: 0.6907 - val_accuracy: 0.5334
```

9.2 The comparison of the training and validation accuracy of the three (4.1, 9.1.1 and 9.1.2)

```
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Architecture 4.1 Training
Accuracy', linestyle='-', marker='o')
plt.plot(history.history['val_accuracy'], label='Architecture 4.1
Validation Accuracy', linestyle='--', marker='o')
plt.plot(history3.history['accuracy'], label='Architecture 9.1.1
Training Accuracy', linestyle='-', marker='o')
plt.plot(history3.history['val_accuracy'], label='Architecture 9.1.1
Validation Accuracy', linestyle='--', marker='o')
plt.plot(history4.history['accuracy'], label='Architecture 9.1.2
Training Accuracy', linestyle='-', marker='o')
plt.plot(history4.history['val_accuracy'], label='Architecture 9.1.2
Validation Accuracy', linestyle='--', marker='o')

plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy Comparison')
plt.legend()
plt.grid(True)
plt.show()
```



10. Optimisers

An optimizer is an algorithm or function that adapts the neural network's attributes, like learning rate and weights. Hence, it assists in improving the accuracy and reduces the total loss. But it is a daunting task to choose the appropriate weights for the model.

10.1.1 Modify the code written in section 5.2

1. RMSProp (Root Mean Square Propagation):

RMSprop addresses the slow convergence issue of Adagrad by using a moving average of squared gradients.It adapts the learning rates per parameter based on the recent gradient history.

```
model5 = tf.keras.Sequential([
    Embedding(input_dim=max_words, output_dim=16,
input_length=max_sequence_length),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1, activation='sigmoid')
])

model5.compile(optimizer='rmsprop', loss='binary_crossentropy',
metrics=['accuracy'])
```

```
history5=model5.fit(X_train,y_train,validation_data=(X_val, y_val),
epochs=epochs,batch_size=batch_size)
```

```
Epoch 1/20
313/313 [==============================] - 4s 11ms/step - loss: 0.4885
- accuracy: 0.7513 - val_loss: 0.3150 - val_accuracy: 0.8666
Epoch 2/20
313/313 [==============================] - 4s 11ms/step - loss: 0.2401
- accuracy: 0.9064 - val_loss: 0.2797 - val_accuracy: 0.8850
Epoch 3/20
313/313 [==============================] - 3s 11ms/step - loss: 0.1494
- accuracy: 0.9459 - val_loss: 0.3070 - val_accuracy: 0.8764
Epoch 4/20
313/313 [==============================] - 3s 11ms/step - loss: 0.0748
- accuracy: 0.9760 - val_loss: 0.3643 - val_accuracy: 0.8706
Epoch 5/20
313/313 [==============================] - 3s 11ms/step - loss: 0.0288
- accuracy: 0.9921 - val_loss: 0.4387 - val_accuracy: 0.8656
Epoch 6/20
313/313 [==============================] - 3s 10ms/step - loss: 0.0096
- accuracy: 0.9980 - val_loss: 0.5198 - val_accuracy: 0.8614
Epoch 7/20
313/313 [==============================] - 3s 11ms/step - loss: 0.0037
- accuracy: 0.9992 - val_loss: 0.6101 - val_accuracy: 0.8554
Epoch 8/20
313/313 [==============================] - 3s 11ms/step - loss: 0.0012
- accuracy: 0.9998 - val_loss: 0.6485 - val_accuracy: 0.8556
Epoch 9/20
313/313 [==============================] - 4s 11ms/step - loss:
7.9441e-04 - accuracy: 0.9998 - val_loss: 0.6622 - val_accuracy:
0.8616
Epoch 10/20
313/313 [==============================] - 3s 11ms/step - loss:
3.3248e-04 - accuracy: 0.9999 - val_loss: 0.6890 - val_accuracy:
0.8590
Epoch 11/20
313/313 [==============================] - 3s 11ms/step - loss:
1.8585e-04 - accuracy: 1.0000 - val_loss: 0.7101 - val_accuracy:
0.8608
Epoch 12/20
313/313 [==============================] - 3s 11ms/step - loss:
9.3928e-05 - accuracy: 1.0000 - val_loss: 0.7186 - val_accuracy:
0.8604
Epoch 13/20
313/313 [==============================] - 3s 11ms/step - loss:
7.9582e-05 - accuracy: 1.0000 - val_loss: 0.7347 - val_accuracy:
0.8608
Epoch 14/20
313/313 [==============================] - 3s 11ms/step - loss:
5.7678e-05 - accuracy: 1.0000 - val_loss: 0.7478 - val_accuracy:
```

```
0.8596
Epoch 15/20
313/313 [==============================] - 4s 12ms/step - loss:
4.6822e-05 - accuracy: 1.0000 - val_loss: 0.7544 - val_accuracy:
0.8608
Epoch 16/20
313/313 [==============================] - 4s 12ms/step - loss:
3.9995e-05 - accuracy: 1.0000 - val_loss: 0.7614 - val_accuracy:
0.8596
Epoch 17/20
313/313 [==============================] - 4s 12ms/step - loss:
3.5337e-05 - accuracy: 1.0000 - val_loss: 0.7688 - val_accuracy:
0.8596
Epoch 18/20
313/313 [==============================] - 4s 12ms/step - loss:
3.1753e-05 - accuracy: 1.0000 - val_loss: 0.7756 - val_accuracy:
0.8576
Epoch 19/20
313/313 [==============================] - 4s 12ms/step - loss:
2.9744e-05 - accuracy: 1.0000 - val_loss: 0.7981 - val_accuracy:
0.8596
Epoch 20/20
313/313 [==============================] - 4s 13ms/step - loss:
2.5272e-05 - accuracy: 1.0000 - val_loss: 0.7866 - val_accuracy:
0.8586
```

10.1.2 Modify the code written in section 5.2

1. Adam(Adaptive Moment Estimation):

Adam combines the advantages of momentum and RMSprop.It uses both moving averages of past gradients and squared gradients to adaptively adjust the learning rates for each parameter.Adam is one of the most popular and widely used optimizers due to its robustness and effectiveness.

```
model6 = tf.keras.Sequential([
    Embedding(input_dim=max_words, output_dim=16,
input_length=max_sequence_length),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1, activation='sigmoid')
])

model6.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

history6=model6.fit(X_train,y_train,validation_data=(X_val, y_val),
epochs=epochs,batch_size=batch_size)
```

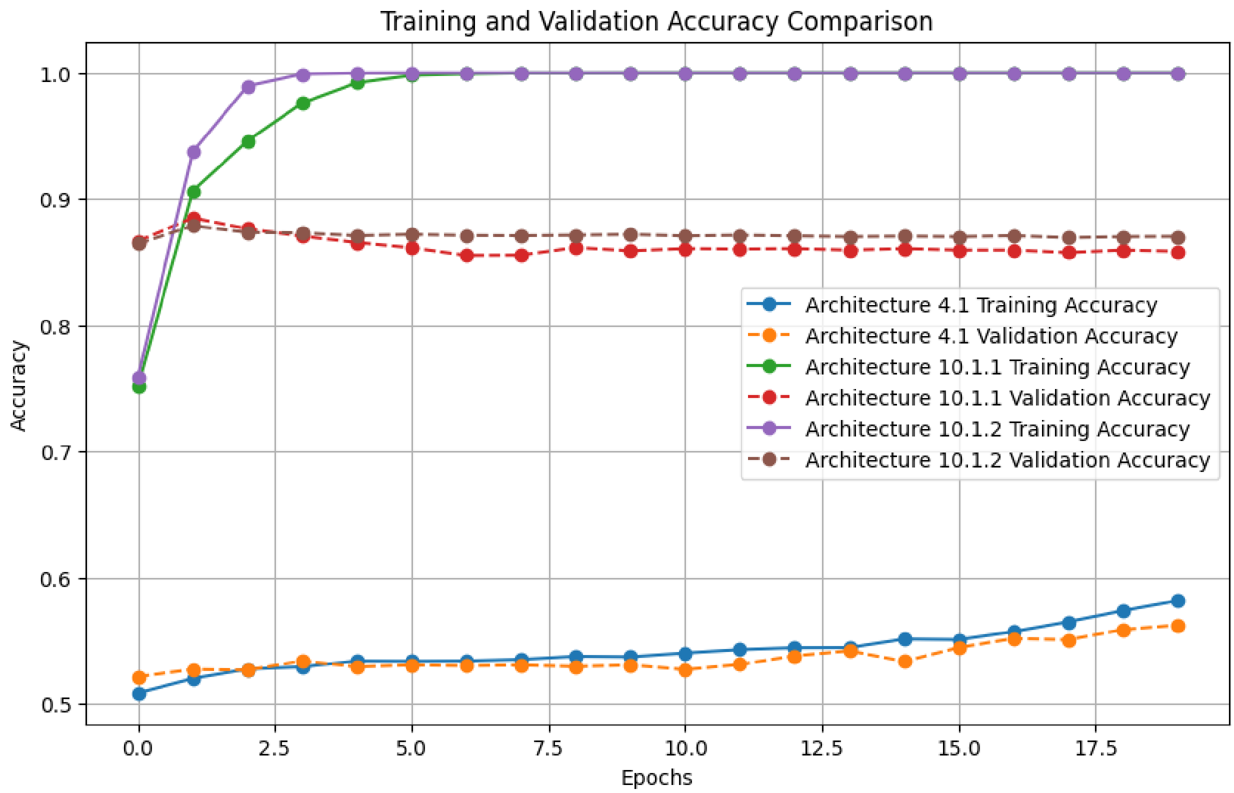
```
Epoch 1/20
313/313 [==============================] - 5s 14ms/step - loss: 0.4599
- accuracy: 0.7588 - val_loss: 0.3111 - val_accuracy: 0.8646
Epoch 2/20
313/313 [==============================] - 4s 12ms/step - loss: 0.1712
- accuracy: 0.9372 - val_loss: 0.3029 - val_accuracy: 0.8788
Epoch 3/20
313/313 [==============================] - 4s 14ms/step - loss: 0.0473
- accuracy: 0.9894 - val_loss: 0.3850 - val_accuracy: 0.8736
Epoch 4/20
313/313 [==============================] - 4s 14ms/step - loss: 0.0101
- accuracy: 0.9991 - val_loss: 0.4400 - val_accuracy: 0.8732
Epoch 5/20
313/313 [==============================] - 5s 16ms/step - loss: 0.0025
- accuracy: 0.9998 - val_loss: 0.4818 - val_accuracy: 0.8710
Epoch 6/20
313/313 [==============================] - 4s 13ms/step - loss: 0.0011
- accuracy: 1.0000 - val_loss: 0.5155 - val_accuracy: 0.8720
Epoch 7/20
313/313 [==============================] - 4s 12ms/step - loss:
6.5157e-04 - accuracy: 1.0000 - val_loss: 0.5385 - val_accuracy:
0.8712
Epoch 8/20
313/313 [==============================] - 4s 12ms/step - loss:
4.3343e-04 - accuracy: 1.0000 - val_loss: 0.5606 - val_accuracy:
0.8710
Epoch 9/20
313/313 [==============================] - 4s 11ms/step - loss:
3.0380e-04 - accuracy: 1.0000 - val_loss: 0.5793 - val_accuracy:
0.8714
Epoch 10/20
313/313 [==============================] - 4s 14ms/step - loss:
2.2084e-04 - accuracy: 1.0000 - val_loss: 0.5960 - val_accuracy:
0.8720
Epoch 11/20
313/313 [==============================] - 4s 13ms/step - loss:
1.6723e-04 - accuracy: 1.0000 - val_loss: 0.6124 - val_accuracy:
0.8708
Epoch 12/20
313/313 [==============================] - 3s 11ms/step - loss:
1.2645e-04 - accuracy: 1.0000 - val_loss: 0.6264 - val_accuracy:
0.8714
Epoch 13/20
313/313 [==============================] - 4s 12ms/step - loss:
9.8893e-05 - accuracy: 1.0000 - val_loss: 0.6408 - val_accuracy:
0.8708
Epoch 14/20
313/313 [==============================] - 3s 11ms/step - loss:
7.7497e-05 - accuracy: 1.0000 - val_loss: 0.6548 - val_accuracy:
0.8702
```

```
Epoch 15/20
313/313 [==============================] - 4s 12ms/step - loss:
6.1828e-05 - accuracy: 1.0000 - val_loss: 0.6673 - val_accuracy:
0.8706
Epoch 16/20
313/313 [==============================] - 4s 12ms/step - loss:
4.9713e-05 - accuracy: 1.0000 - val_loss: 0.6806 - val_accuracy:
0.8702
Epoch 17/20
313/313 [==============================] - 3s 11ms/step - loss:
4.0006e-05 - accuracy: 1.0000 - val_loss: 0.6929 - val_accuracy:
0.8710
Epoch 18/20
313/313 [==============================] - 4s 11ms/step - loss:
3.2410e-05 - accuracy: 1.0000 - val_loss: 0.7063 - val_accuracy:
0.8694
Epoch 19/20
313/313 [==============================] - 4s 12ms/step - loss:
2.6212e-05 - accuracy: 1.0000 - val_loss: 0.7178 - val_accuracy:
0.8702
Epoch 20/20
313/313 [==============================] - 3s 11ms/step - loss:
2.1611e-05 - accuracy: 1.0000 - val_loss: 0.7291 - val_accuracy:
0.8704
```

10.2 The comparison of the training and validation accuracy of the three (5.2, 10.1.1 and 10.1.2)

```
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Architecture 4.1 Training
Accuracy', linestyle='-', marker='o')
plt.plot(history.history['val_accuracy'], label='Architecture 4.1
Validation Accuracy', linestyle='--', marker='o')
plt.plot(history5.history['accuracy'], label='Architecture 10.1.1
Training Accuracy', linestyle='-', marker='o')
plt.plot(history5.history['val_accuracy'], label='Architecture 10.1.1
Validation Accuracy', linestyle='--', marker='o')
plt.plot(history6.history['accuracy'], label='Architecture 10.1.2
Training Accuracy', linestyle='-', marker='o')
plt.plot(history6.history['val_accuracy'], label='Architecture 10.1.2
Validation Accuracy', linestyle='--', marker='o')

plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy Comparison')
plt.legend()
plt.grid(True)
plt.show()
```



11. Conclusion

By comparing all the models trained I came to the cconlusion that the model used in the section 10.1 with the Adam has the high accuracy in the valdation. Thus, I conclude by saying that following can improve our validation score.

Model: The model in 4.1 without adding any layer has high validation accuracy so we can use the same model.

Architecture: The model in 4.1 without adding any layer has high validation accuracy so we can use the same model.

optimizer: Adam has high validation accuracy then rmsprop. so we can use Adam as optimzer.

Regularization: Use initial model without any dropout layer becase it has high validation accuracy.