X Sentiment Analysis Using CNN

Introduction

Sentiment analysis is a technique used to determine the emotional tone from remarks or comments that users of certain application either X, facebook, instagram or tiktok about a certain topic.

This remarks can have a positive tone, neutral tone and negative tone towards a certain audience.

Business Understanding

Background

X is a popular social media platform that most people use to share their opinions about certain topics, this can either be political, religious or social trends.

These opinions can be positive, negative or neutral towards the topic been addressed. These opinions are mainly in text format.

Problem statement

Due to the growing amount of user-generated content on X, it is becoming more difficult for researchers, corporation to accurately and efficiently gauge public opinion on particular subjects, goods, or occasions. It's challenging to glean useful data from tweets because of their sheer number and informal style, which frequently includes slang, acronyms, and emoticons. This leads to inadequate insights generated by corporations from public opinion to improve certain products or when advertising certain products.

Objective

1. Develop a sentiment analysis model that uses natural preprocessing language(nlp) to preprocess and clean the tweets, and make it in a more structured format for sentiment analysis.
2. Use the sentiment analysis model that can accurately classify tweets into positive, negative and neutral sentiment categories.
3. Evaluate Performance: Measure the model's accuracy, precision, recall, and F1-score on a labeled dataset, and iteratively improve based on evaluation results.

Conclusion

Although emojis, acronyms, and slang are common on Twitter, the informal tone of the network makes it difficult to draw meaningful conclusions from user-generated content. While sophisticated NLP models and neural network approaches, handle the complexity of sentiment grouping, preprocessing is essential to cleanse this noisy data.

Data Understanding

Import Libraries

```
import pandas as pd
import numpy as np
import nltk
import re
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from collections import Counter
import matplotlib.pyplot as plt
import seaborn as sns
```

```
!pip install datasets
```

```
Requirement already satisfied: datasets in c:\users\user\anaconda3\envs\learn-env\lib\si
Requirement already satisfied: filelock in c:\users\user\anaconda3\envs\learn-env\lib\si
Requirement already satisfied: numpy>=1.17 in c:\users\user\anaconda3\envs\learn-env\lib
Requirement already satisfied: pyarrow>=15.0.0 in c:\users\user\anaconda3\envs\learn-env
Requirement already satisfied: dill<0.3.9,>=0.3.0 in c:\users\user\anaconda3\envs\learn-
Requirement already satisfied: pandas in c:\users\user\anaconda3\envs\learn-env\lib\site
Requirement already satisfied: requests>=2.32.2 in c:\users\user\anaconda3\envs\learn-en
Requirement already satisfied: tqdm>=4.66.3 in c:\users\user\anaconda3\envs\learn-env\li
Requirement already satisfied: xxhash in c:\users\user\anaconda3\envs\learn-env\lib\site
Requirement already satisfied: multiprocess in c:\users\user\anaconda3\envs\learn-env\li
Requirement already satisfied: fsspec<=2024.6.1,>=2023.1.0 in c:\users\user\anaconda3\en
Requirement already satisfied: aiohttp in c:\users\user\anaconda3\envs\learn-env\lib\sit
Requirement already satisfied: huggingface-hub>=0.22.0 in c:\users\user\anaconda3\envs\l
Requirement already satisfied: packaging in c:\users\user\anaconda3\envs\learn-env\lib\s
Requirement already satisfied: pyyaml>=5.1 in c:\users\user\anaconda3\envs\learn-env\lib
Requirement already satisfied: attrs>=17.3.0 in c:\users\user\anaconda3\envs\learn-env\l
Requirement already satisfied: chardet<4.0,>=2.0 in c:\users\user\anaconda3\envs\learn-e
Requirement already satisfied: multidict<5.0,>=4.5 in c:\users\user\anaconda3\envs\learn
Requirement already satisfied: async-timeout<4.0,>=3.0 in c:\users\user\anaconda3\envs\l
Requirement already satisfied: yarl<1.6.0,>=1.0 in c:\users\user\anaconda3\envs\learn-en
Requirement already satisfied: typing-extensions>=3.7.4.3 in c:\users\user\anaconda3\env
```

```
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\user\anaconda3\envs\
Requirement already satisfied: idna<4,>=2.5 in c:\users\user\anaconda3\envs\learn-env\li
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\users\user\anaconda3\envs\learn-
Requirement already satisfied: certifi>=2017.4.17 in c:\users\user\anaconda3\envs\learn-
Requirement already satisfied: colorama in c:\users\user\anaconda3\envs\learn-env\lib\si
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\user\anaconda3\envs\le
Requirement already satisfied: pytz>=2017.2 in c:\users\user\anaconda3\envs\learn-env\li
Requirement already satisfied: six>=1.5 in c:\users\user\anaconda3\envs\learn-env\lib\si
```

Loading the data

```
from datasets import load_dataset

ds = load_dataset("mteb/tweet_sentiment_extraction")
```

```
dataset = load_dataset("mteb/tweet_sentiment_extraction")
```

```
dataset
```

```
DatasetDict({
    train: Dataset({
        features: ['id', 'text', 'label', 'label_text'],
        num_rows: 27481
    })
    test: Dataset({
        features: ['id', 'text', 'label', 'label_text'],
        num_rows: 3534
    })
})
```

```
train_data = dataset['train']
# Convert the dataset to a DataFrame
train_df = pd.DataFrame(train_data)

train_df.head()
```

	id	text	label	label_text
0	cb774db0d1	I`d have responded, if I were going	1	neutral
1	549e992a42	Sooo SAD I will miss you here in San Diego!!!	0	negative
2	088c60f138	my boss is bullying me...	0	negative
3	9642c003ef	what interview! leave me alone	0	negative
4	358bd9e861	Sons of ****, why couldn`t they put them on t...	0	negative

```
# checking the columns
train_df.columns
```

```
Index(['id', 'text', 'label', 'label_text'], dtype='object')
```

```
# size of the dataframe
train_df.shape
```

```
(27481, 4)
```

```
# preview a text
train_df['text'][1500]
```

```
'This wind is crampin` my style. I have a section of my yard that won`t get any water.
I`d move the sprinkler, but it`s surrounded by mud.'
```

```
# value counts of the sentiments
train_df['label_text'].value_counts()
```

```
neutral     11118
positive     8582
negative     7781
Name: label_text, dtype: int64
```

```
# summary information
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27481 entries, 0 to 27480
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          27481 non-null  object
 1   text        27481 non-null  object
 2   label       27481 non-null  int64 
 3   label_text  27481 non-null  object
dtypes: int64(1), object(3)
memory usage: 858.9+ KB
```

Handling Missing Values

We want to ensure there are no missing tweets or sentiment labels in the dataset before preprocessing.

```
# Checking for missing values
missing_values = train_df.isnull().sum()
if missing_values.sum() == 0:
```

```
    print('There are no missing values')
else:
    print('Check for the missing values')
```

```
There are no missing values
```

Class Distribution

A bar plot showing the distribution of classes (negative, neutral, positive) can give us insight into whether our dataset is balanced or imbalanced.

```
# Plot class distribution
sns.countplot(x='label_text', data=train_df)
plt.title('Distribution of Sentiment Classes')
plt.show()
```

It shows that the neutral class is the most common sentiment in our dataset, followed by negative and positive sentiments.

Data Preparation

Text Preprocessing

```
# Download stopwords
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
```

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

```
# display stopwords
print(stop_words)
```

```
{'once', 'those', 'not', 'both', 'into', 'up', 'it', 'against', 'which', "mightn't", 'sh
```

```
def preprocess_text(text) -> str:
  """
  Function to clean and preprocess the text
  """
  contractions_dict = {
        "shouldve": "should have",
        "wouldve": "would have",
        "couldve": "could have",
        "mightve": "might have",
        "mustve": "must have",
        "dont": "do not",
        "doesnt": "does not",
        "didnt": "did not",
        "cant": "cannot",
        "couldnt": "could not",
        "wont": "will not",
        "wouldnt": "would not",
        "isnt": "is not",
        "arent": "are not",
        "wasnt": "was not",
        "werent": "were not",
        "havent": "have not",
        "hasnt": "has not",
        "hadnt": "had not",
        "neednt": "need not",
        "shant": "shall not",
        "shouldnt": "should not",
        "mustnt": "must not",
```

```
        "youre": "you are",
        "theyre": "they are",
        "its": "it is",
        "were": "we are",
        "hes": "he is",
        "shes": "she is",
        "id": "i would"
    }

  for contraction, expanded in contractions_dict.items():
      text = text.replace(contraction, expanded)

  # lower case
  text = text.lower()
  # remove html tags
  text = re.sub(r'<.*?>', '', text)
  # remove non-alphabetical
  text = re.sub(r'[^a-z\s]', '', text)
  # remove stop words
  text = ' '.join([word for word in text.split() if word not in stop_words])
  # remove mentions
  text = re.sub(r'@\w+', '', text)
  # remove html links
  text = re.sub(r'http\S+|www.\S+', '', text)
  # replace elongated words (e.g., "sooooo" -> "so")
  text = re.sub(r'\b(\w*?)([aeiou])\2{2,}(\w*?)\b', r'\1\2\3', text)  # Improved regex for v
  # remove possessives (e.g., "ann's" -> "ann")
  text = re.sub(r"\b(\w+)'s\b", r'\1', text)

  return text
```

```
# apply to the text column
train_df['text'] = train_df['text'].apply(preprocess_text)
```

```
# preview a text after preprocessing
train_df['text'][1500]
```

```
'wind crampin style section yard wont get water id move sprinkler surrounded mud'
```

```
train_df.shape
```

```
(27481, 4)
```

Tokenization and Padding

```
# tokenize the 'text' column
tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(train_df['text'])
word_index = tokenizer.word_index
print(f'Vocabulary size: {len(word_index)}')
```

```
Vocabulary size: 26002
```

```
# Convert texts to sequences
X = tokenizer.texts_to_sequences(train_df['text'])
```

```
# before padding - train data
np.shape(X)
```

```
(27481,)
```

```
# Defining a max length for truncating the sequences.
max_len = 500
X = pad_sequences(X, maxlen=max_len)
```

```
# after padding - train data
np.shape(X)
```

```
(27481, 500)
```

```
# Extract the target labels (sentiment) from the 'label' column in the dataset
# This will be used as the dependent variable.
y = train_df['label'].values
```

```
np.shape(y)
```

```
(27481,)
```

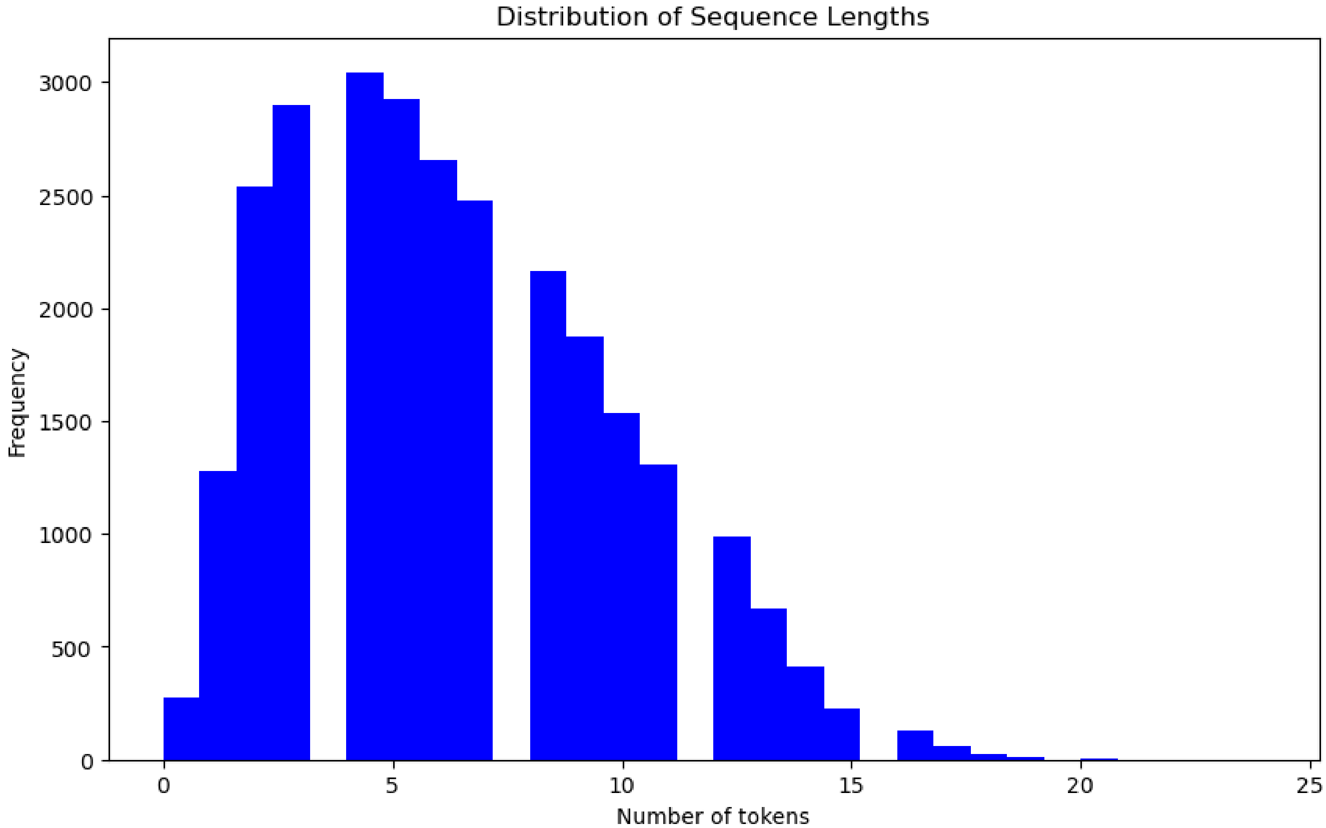
Distribution of Sequence Lengths

After padding, we check the distribution of the lengths of sequences (the number of tokens per sample).This helps ensure that our padding or truncation strategy is appropriate.

```
# Get the length of each sequence (before padding)
seq_lengths = [len(seq) for seq in tokenizer.texts_to_sequences(train_df['text'])]

# Plot distribution of sequence lengths
plt.figure(figsize=(10,6))
plt.hist(seq_lengths, bins=30, color='blue')
```

```
plt.title('Distribution of Sequence Lengths')
plt.xlabel('Number of tokens')
plt.ylabel('Frequency')
plt.show()
```



The distribution plot of sequence lengths shows that the majority of text samples have between 2 and 10 tokens, with a peak around 4-6 tokens. The distribution tail suggests that some samples have longer sequences, though fewer of them exceed 15 tokens.

Loading the test data

```
test_data = dataset['test']
# Convert the dataset to a DataFrame
test_df = pd.DataFrame(test_data)

test_df.head()
```

	id	text	label	label_text
0	f87dea47db	Last session of the day http://twitpic.com/67ezh	1	neutral
1	96d74cb729	Shanghai is also really exciting (precisely -...	2	positive
2	eee518ae67	Recession hit Veronique Branquinho, she has to...	0	negative
3	01082688c6	happy bday!	2	positive
4	33987a8ee5	http://twitpic.com/4w75p - I like it!!	2	positive

```
#checking the columns
test_df.columns
```

```
Index(['id', 'text', 'label', 'label_text'], dtype='object')
```

```
# size of the dataframe
test_df.shape
```

```
(3534, 4)
```

```
# preview a text
test_df['text'][1600]
```

```
'At anthony`s for prom.'
```

```
# value counts of the sentiments
test_df['label_text'].value_counts()
```

```
neutral     1430
positive    1103
negative    1001
Name: label_text, dtype: int64
```

```
# summary information
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3534 entries, 0 to 3533
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          3534 non-null   object
 1   text        3534 non-null   object
 2   label       3534 non-null   int64 
 3   label_text  3534 non-null   object
dtypes: int64(1), object(3)
memory usage: 110.6+ KB
```

Handling Missing Values

We want to ensure there are no missing tweets or sentiment labels in the dataset before preprocessing.

```
# Checking for missing values
missing_values1 = test_df.isnull().sum()
if missing_values1.sum() == 0:
    print('There are no missing values')
else:
    print('Check for the missing values')
```

```
There are no missing values
```

Class Distribution test data

A bar plot showing the distribution of classes (negative, neutral, positive) can give us insight into whether our dataset is balanced or imbalanced.

```
# Plot class distribution
sns.countplot(x='label_text', data=test_df)
plt.title('Distribution of Sentiment Classes')
plt.show()
```

It shows that the neutral class is the most common sentiment in our dataset, followed by negative and positive sentiments.

Data Preparation

Text Preprocessing

```
# apply to the test text column
test_df['text'] = test_df['text'].apply(preprocess_text)
```

```
# preview a text after preprocessing
test_df['text'][1700]
```

```
'so hungry right shouldve eaten wedding'
```

Tokenization and Padding

Test data should be treated as unseen data in the model.

For our test data, we avoid fitting it to the tokenizer to prevent overfitting and data leakage

```
# Convert texts to sequences
X_test = tokenizer.texts_to_sequences(test_df['text'])
```

```
# before padding - test data
np.shape(X_test)
```

```
(3534,)
```

```
# Defining a max length for truncating the sequences.
max_len = 500
X_test = pad_sequences(X_test, maxlen=max_len)
```

```
# after padding - test data
np.shape(X_test)
```

```
(3534, 500)
```

```
# Extract the target labels (sentiment) from the 'label' column in the dataset
# This will be used as the dependent variable.
y_test = test_df['label'].values
```

```
y_test.shape
```

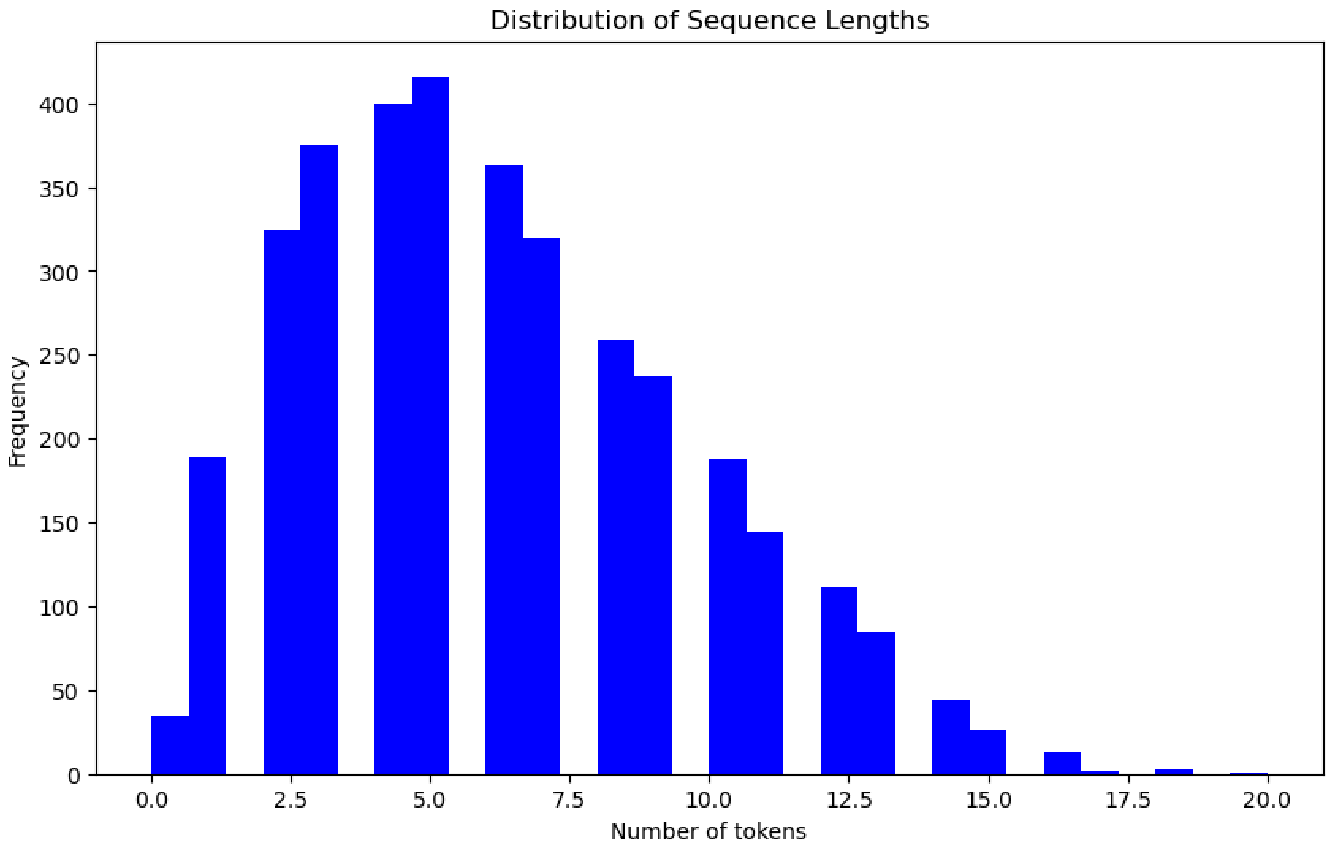
```
(3534,)
```

Distribution of Sequence Lengths

After padding, we check the distribution of the lengths of sequences (the number of tokens per sample).This helps ensure that our padding or truncation strategy is appropriate.

```
# Get the length of each sequence (before padding)
seq_lengths = [len(seq) for seq in tokenizer.texts_to_sequences(test_df['text'])]

# Plot distribution of sequence lengths
plt.figure(figsize=(10,6))
plt.hist(seq_lengths, bins=30, color='blue')
plt.title('Distribution of Sequence Lengths')
plt.xlabel('Number of tokens')
plt.ylabel('Frequency')
plt.show()
```



The distribution plot of sequence lengths shows that the majority of text samples have between 2 and 10 tokens, with a peak around 4-6 tokens. The distribution tail suggests that some samples have longer sequences, though fewer of them exceed 15 tokens.

CNN Base Model

```
# Libraries for modelling
from tensorflow.keras.models import Sequential
from keras.optimizers import Adam
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Embedding, Dropout
```

```
model = Sequential()
```

```
# embedding layer to learn word embeddings
model.add(Embedding(input_dim=5001, output_dim=128, input_length=max_len))
```

```
# 1D convolutional layer
model.add(Conv1D(filters=128, kernel_size=3, activation='relu'))

# GlobalMaxPooling to reduce dimensionality
model.add(GlobalMaxPooling1D())

# fully connected layers
model.add(Dense(10, activation='relu'))
model.add(Dense(3, activation='softmax'))  # output layer for multiple classification

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

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 500, 128)          640128
_________________________________________________________________
conv1d (Conv1D)              (None, 498, 128)          49280
_________________________________________________________________
global_max_pooling1d (Global (None, 128)               0
_________________________________________________________________
dense (Dense)                (None, 10)                1290
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 33
=================================================================
Total params: 690,731
Trainable params: 690,731
Non-trainable params: 0
_________________________________________________________________
```

```
# fitting our data to the model
model_one_history = model.fit(X, y, epochs=5, batch_size=64, validation_data=(X_test, y_test
```

```
Epoch 1/5
430/430 [==============================] - 108s 251ms/step - loss: 0.1705 - accuracy: 0.
Epoch 2/5
430/430 [==============================] - 105s 245ms/step - loss: 0.1198 - accuracy: 0.
Epoch 3/5
430/430 [==============================] - 105s 245ms/step - loss: 0.0909 - accuracy: 0.
Epoch 4/5
430/430 [==============================] - 110s 256ms/step - loss: 0.0707 - accuracy: 0.
Epoch 5/5
430/430 [==============================] - 113s 264ms/step - loss: 0.0605 - accuracy: 0.
```

Evaluating the Model

```
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Test Loss: {loss:.4f}')
print(f'Test Accuracy: {accuracy * 100:.2f}%')
```

```
111/111 [==============================] - 4s 32ms/step - loss: 1.5941 - accuracy: 0.674
Test Loss: 1.5941
Test Accuracy: 67.43%
```

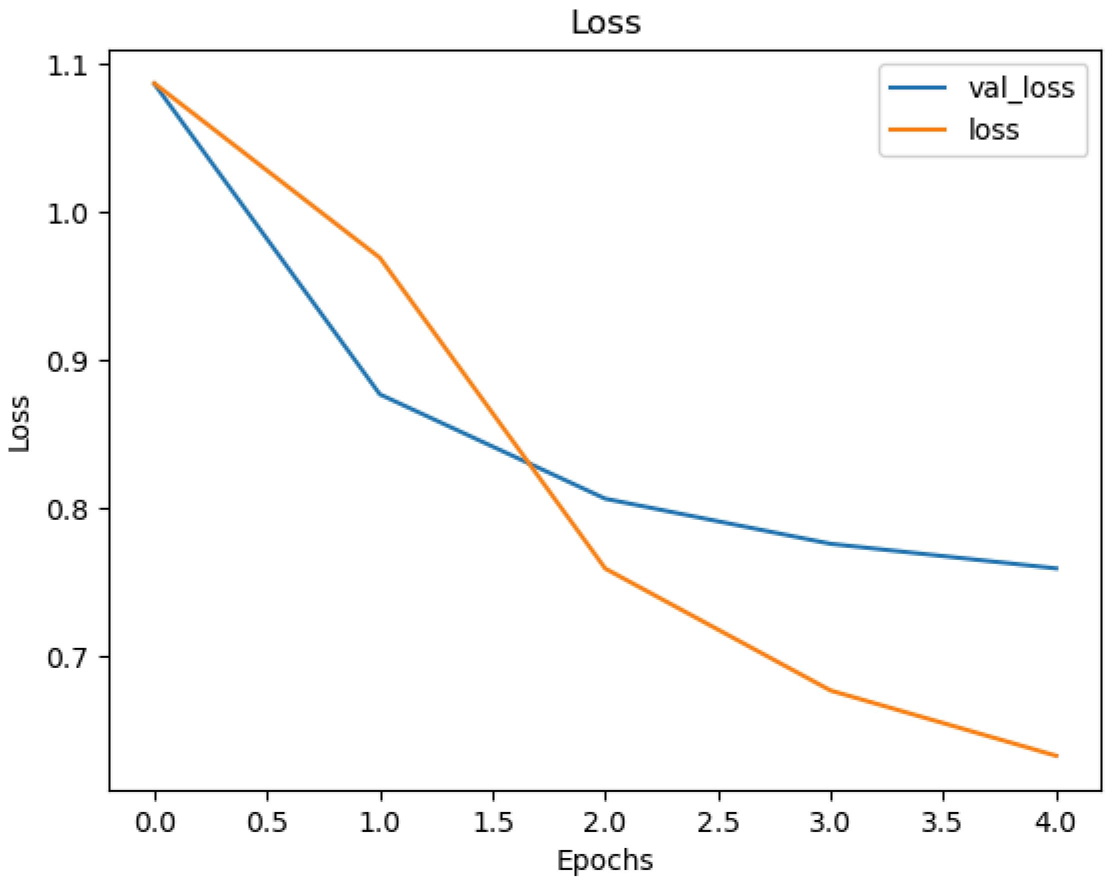
Visualizing loss and accuracy with comparison with validation accuracy and loss

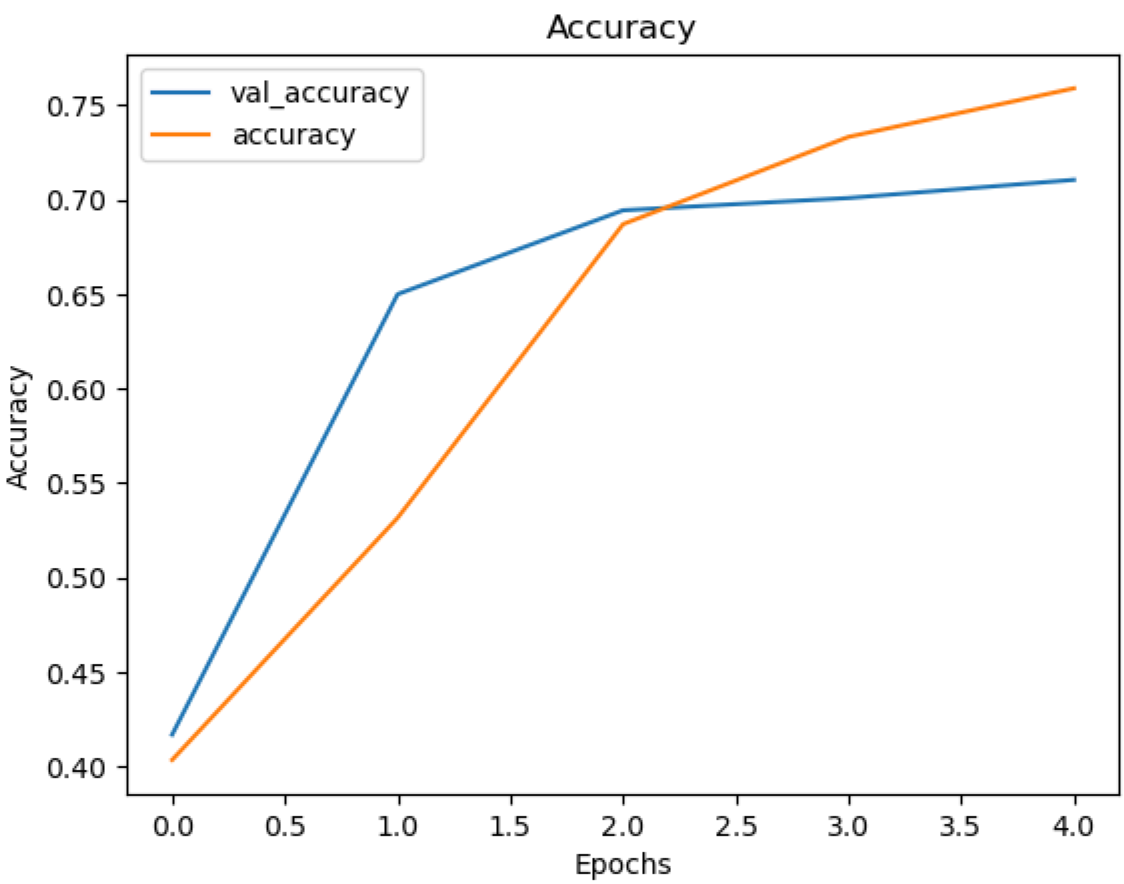
```
# create a function to handle our viz
def visualize_training_results(results):
    history = results.history
    plt.figure()
    plt.plot(history['val_loss'])
    plt.plot(history['loss'])
    plt.legend(['val_loss', 'loss'])
    plt.title('Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.show()

    plt.figure()
    plt.plot(history['val_accuracy'])
    plt.plot(history['accuracy'])
    plt.legend(['val_accuracy', 'accuracy'])
    plt.title('Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.show()
```

CNN Base Model Visualization

```
# plot the cnn base model -> Loss and Accuracy
visualize_training_results(model_one_history)
```


Loss
val_loss
loss
1.1
1.0
0.9
0.8
0.7
Loss
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epochs


Accuracy
val_accuracy
accuracy
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
Accuracy
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epochs

Model 2

```
second_model = Sequential()

# embedding layer to learn word embeddings
second_model.add(Embedding(input_dim=5001, output_dim=128, input_length=max_len))

#convolutional layer
second_model.add(Conv1D(filters=64, kernel_size=3, activation='relu'))

# Max Pooling Layer
second_model.add(MaxPooling1D(pool_size=4))

# Flatten Output
second_model.add(Flatten())

# Fully Connected Layer
second_model.add(Dense(128, activation='relu'))

#Regularization
second_model.add(Dropout(0.35))

# Output Layer
second_model.add(Dense(3, activation='softmax'))

# Compiling the second_model
second_model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['acc
```

```
second_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
embedding_2 (Embedding)     (None, 500, 128)          640128
_________________________________________________________________
conv1d_3 (Conv1D)           (None, 498, 64)           24640
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 124, 64)          0
_________________________________________________________________
flatten_2 (Flatten)         (None, 7936)              0
_________________________________________________________________
dense_6 (Dense)             (None, 128)               1015936
_________________________________________________________________
dropout_2 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_7 (Dense)             (None, 3)                 387
=================================================================
Total params: 1,681,091
Trainable params: 1,681,091
```

```
Non-trainable params: 0
_________________________________________________________________
```

```
# fitting our data to the second model
model_two_history = second_model.fit(X, y, epochs=5, batch_size=64, validation_data=(X_test,
```

```
Epoch 1/5
430/430 [==============================] - 84s 195ms/step - loss: 0.4273 - accuracy: 0.8
Epoch 2/5
430/430 [==============================] - 85s 199ms/step - loss: 0.3595 - accuracy: 0.8
Epoch 3/5
430/430 [==============================] - 92s 215ms/step - loss: 0.3197 - accuracy: 0.8
Epoch 4/5
430/430 [==============================] - 80s 187ms/step - loss: 0.2958 - accuracy: 0.8
Epoch 5/5
430/430 [==============================] - 82s 190ms/step - loss: 0.2794 - accuracy: 0.8
```

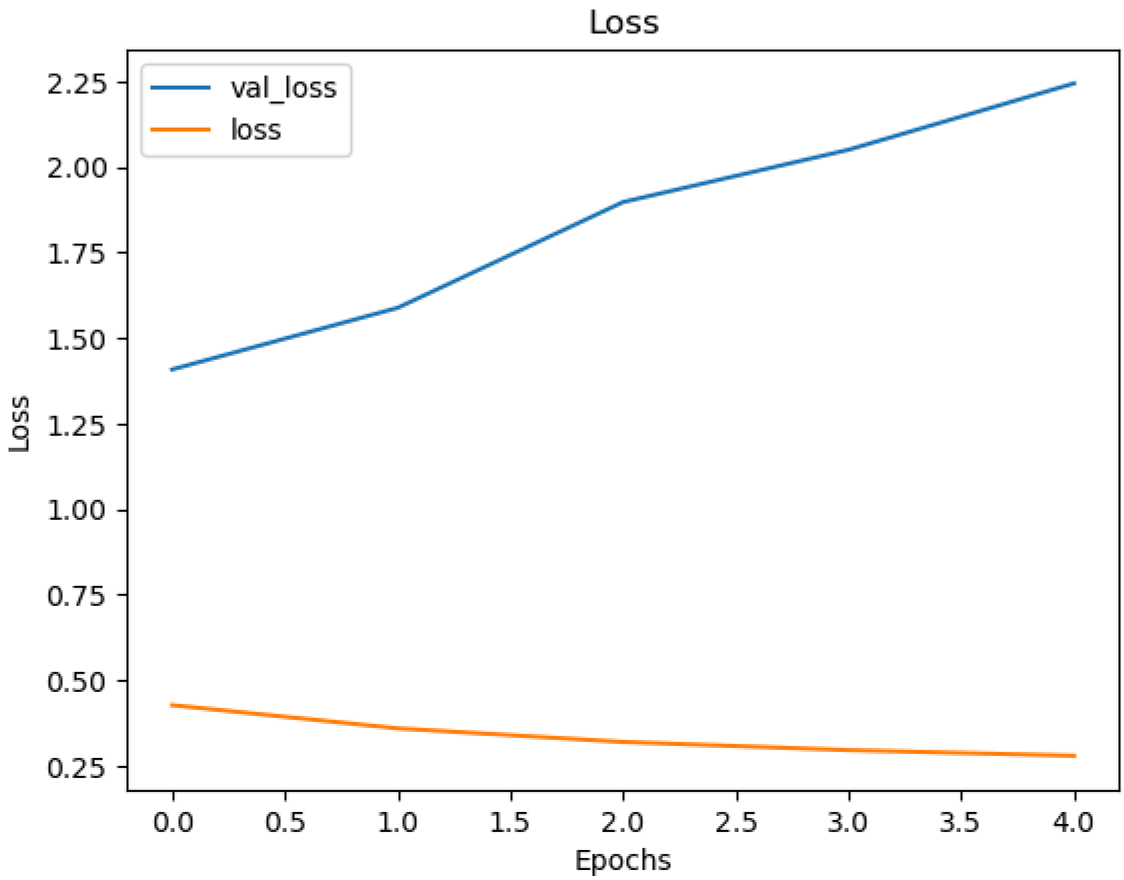
Evaluating the Model

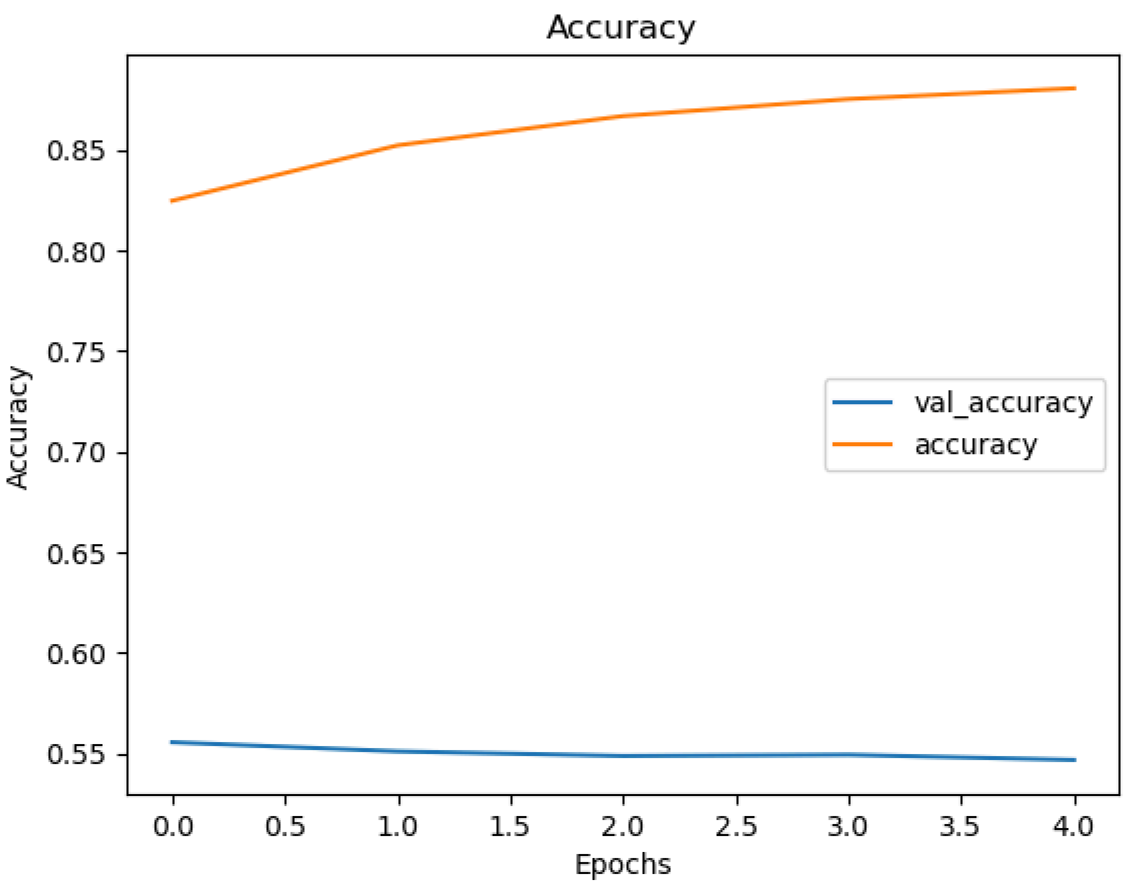
```
loss, accuracy = second_model.evaluate(X_test, y_test)
print(f'Test Loss: {loss:.4f}')
print(f'Test Accuracy: {accuracy * 100:.2f}%')
```

```
111/111 [==============================] - 3s 24ms/step - loss: 2.2444 - accuracy: 0.546
Test Loss: 2.2444
Test Accuracy: 54.67%
```

Second Model Visualization

```
# plot the second model -> Loss and Accuracy
visualize_training_results(model_two_history)
```


Loss
val_loss
loss
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
Loss
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epochs


Accuracy
0.85
0.80
0.75
0.70
0.65
0.60
0.55
Accuracy
val_accuracy
accuracy
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epochs

Model 3

```
# Create the model
third_model = Sequential()
# Embedding layer to learn word embeddings
third_model.add(Embedding(input_dim=5001, output_dim=128, input_length=max_len))

# 1D convolutional layer
third_model.add(Conv1D(filters=128, kernel_size=3, activation='relu'))
third_model.add(Dropout(0.5))  # Dropout layer to prevent overfitting

# Bidirectional LSTM for capturing sequence context
third_model.add(Bidirectional(LSTM(64, return_sequences=True)))
third_model.add(Dropout(0.5))

# GlobalMaxPooling to reduce dimensionality
third_model.add(GlobalMaxPooling1D())

# Fully connected layers
third_model.add(Dense(64, activation='relu'))
third_model.add(Dropout(0.5))  # Dropout for further regularization
third_model.add(Dense(3, activation='softmax'))  # Output layer for multi-class classificati

# Compile the model with sparse categorical crossentropy
third_model.compile(loss='sparse_categorical_crossentropy', optimizer=Adam(learning_rate=0.0
```

```
third_model.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
embedding_3 (Embedding)	(None, 500, 128)	640128
conv1d_4 (Conv1D)	(None, 498, 128)	49280
dropout_3 (Dropout)	(None, 498, 128)	0
bidirectional (Bidirectional	(None, 498, 128)	98816
dropout_4 (Dropout)	(None, 498, 128)	0
global_max_pooling1d_1 (Glob	(None, 128)	0
dense_8 (Dense)	(None, 64)	8256
dropout_5 (Dropout)	(None, 64)	0
dense_9 (Dense)	(None, 3)	195

Total params: 796,675

```
Trainable params: 796,675
Non-trainable params: 0
_________________________________________________________________
```

```
# fitting our data to the third model
history = third_model.fit(X, y, epochs=5, batch_size=64, validation_data=(X_test, y_test))
```

```
Epoch 1/5
430/430 [==============================] - 906s 2s/step - loss: 1.0872 - accuracy: 0.403
Epoch 2/5
430/430 [==============================] - 747s 2s/step - loss: 0.9695 - accuracy: 0.531
Epoch 3/5
430/430 [==============================] - 795s 2s/step - loss: 0.7595 - accuracy: 0.687
Epoch 4/5
430/430 [==============================] - 715s 2s/step - loss: 0.6771 - accuracy: 0.733
Epoch 5/5
430/430 [==============================] - 733s 2s/step - loss: 0.6330 - accuracy: 0.759
```

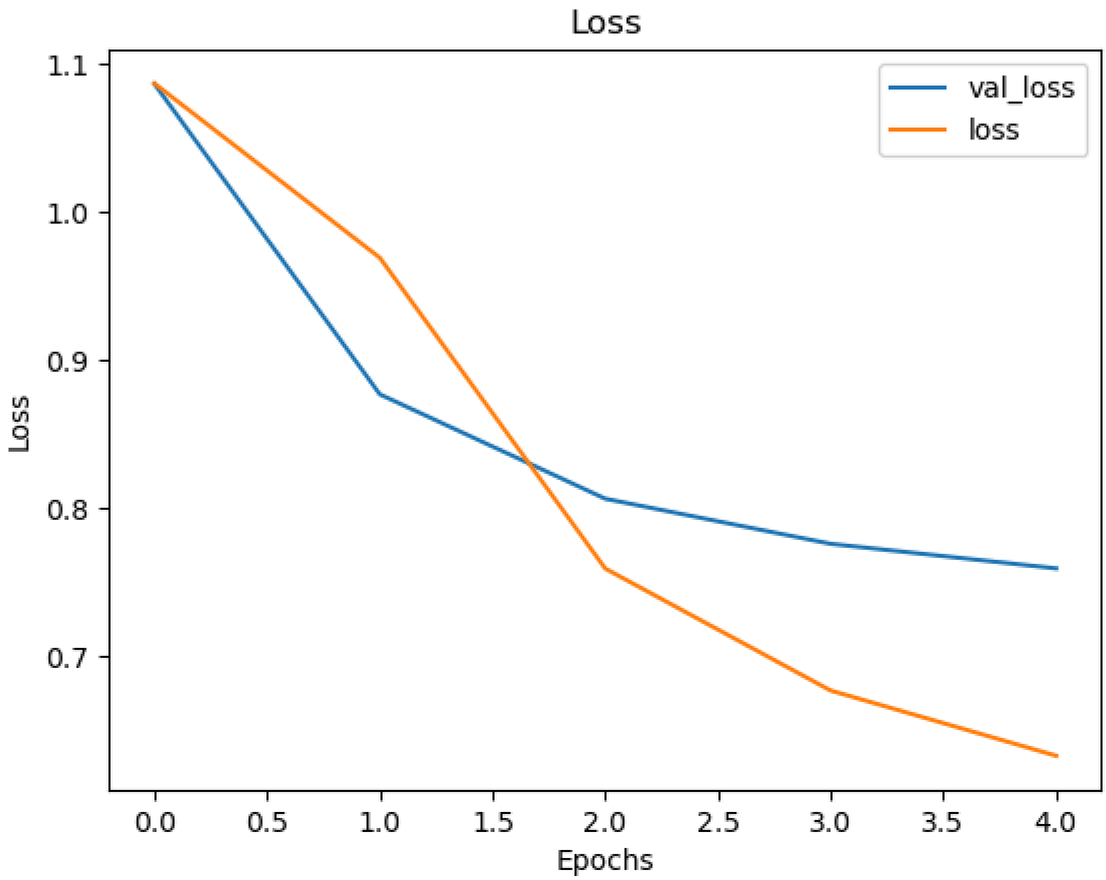
Evaluating the Model

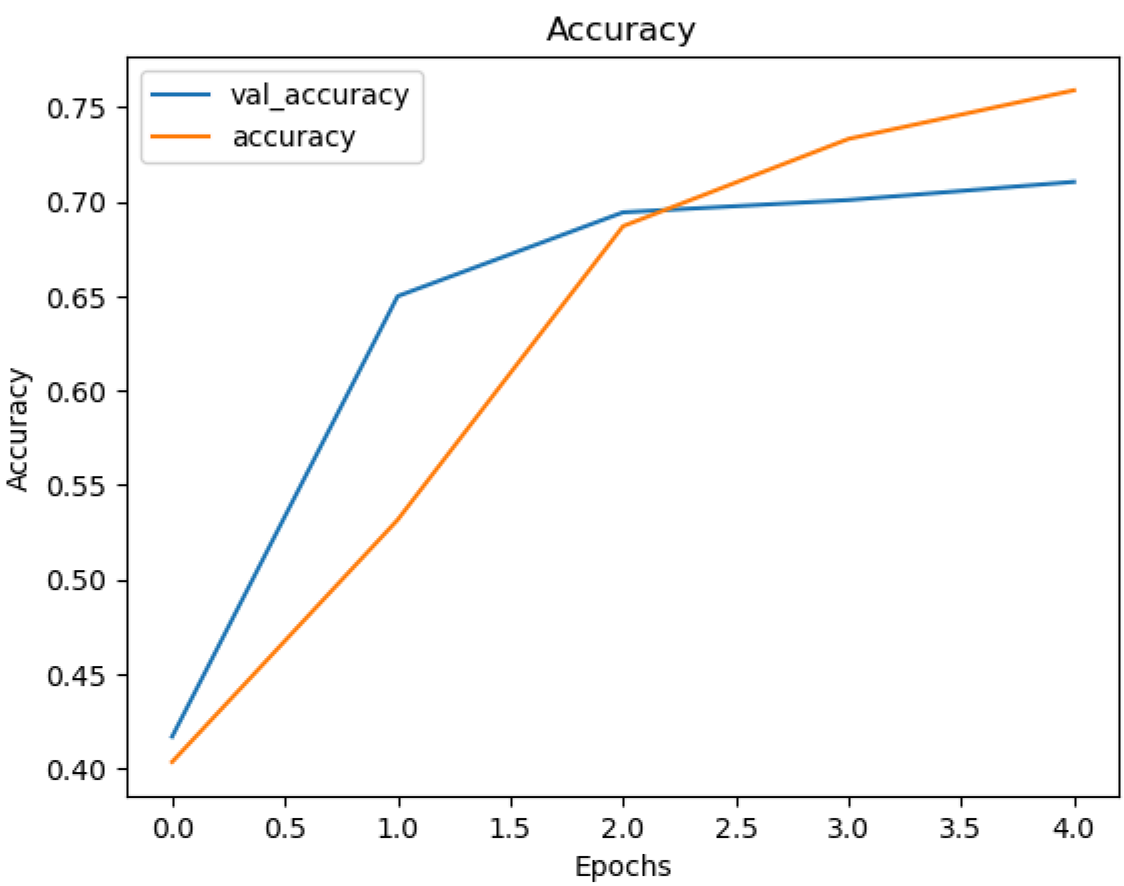
```
loss, accuracy = third_model.evaluate(X_test, y_test)
print(f'Test Loss: {loss:.4f}')
print(f'Test Accuracy: {accuracy * 100:.2f}%')
```

```
111/111 [==============================] - 16s 146ms/step - loss: 0.7596 - accuracy: 0.7
Test Loss: 0.7596
Test Accuracy: 71.05%
```

Third Model Visualization

```
# plot the third model -> Loss and Accuracy
visualize_training_results(history)
```





The best Model

Model 3(third_model) is the best performing model among the three models build.

It proves its top perfomance by having a low Test Loss(0.7596) and a high Test Accuracy(71.05%) overall.