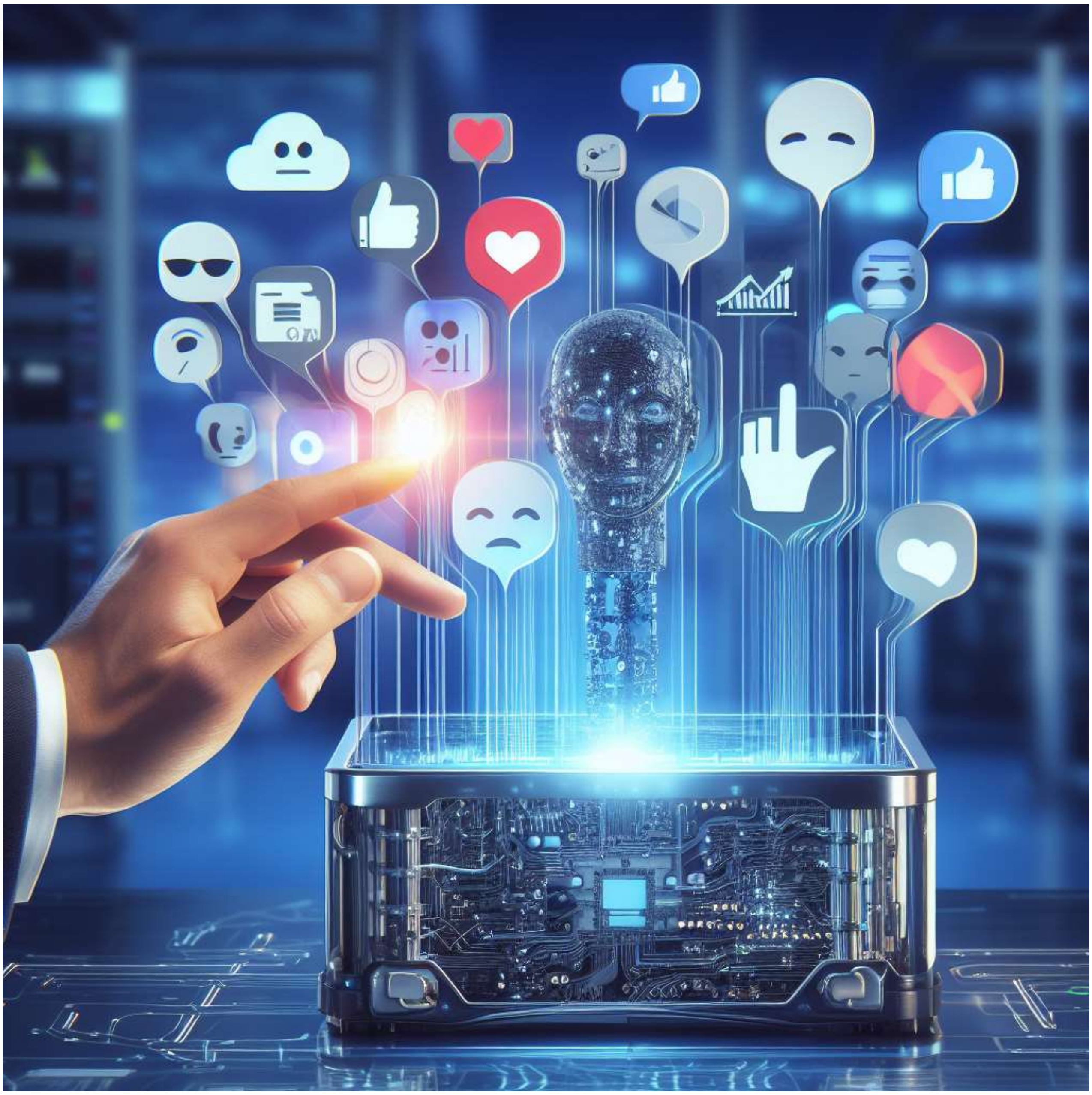

A guide to sentimental analysis using machine learning and deep learning and large language models

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Inspired from: ***Yussria Ahmed***

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About the author

The author, with a robust background spanning nearly seven years in the construction industry, brings a unique blend of expertise and academic achievement to the table. Holding a bachelor's degree in construction and engineering management, he has laid a solid foundation in the technical aspects of the industry. Further elevating his qualifications, the author pursued and attained a Master of Science degree in Commercial Management and Quantity Surveying, a discipline that marries the technicalities of construction with the nuances of business management. Complementing their construction-centric education, the author also delved into the realm of data analytics, acquiring a degree that marks a significant pivot in their career trajectory. This educational journey is crowned by their chartered status from two prestigious institutions: the Royal Institution of Chartered Surveyor and the British Computer Society, reflecting a rare confluence of construction expertise and computational acumen.

In recent years, the author has shifted their focus towards the data world, dedicating the past three years to working intensively in this domain. Their interest particularly lies in the deployment of Artificial Intelligence (AI) and Machine Learning (ML) within the construction industry, a sector ripe for digital transformation. Recognizing the potential of AI and ML to revolutionize traditional practices, the author has been at the forefront of integrating these technologies into construction processes, aiming to enhance efficiency, accuracy, and overall project management.

One of the author's notable contributions is the development of a series of chatbots using open-source large language models. These chatbots represent a significant innovation, leveraging the power of AI to streamline communication, automate routine tasks, and provide intelligent assistance in various construction-related scenarios. The author's work in this area not only showcases their technical prowess but also their commitment to driving the construction industry forward through the adoption of cutting-edge technologies. Their unique blend of construction knowledge, data analytics expertise, and passion for AI and ML positions them as a visionary figure, poised to make a lasting impact on the industry.

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Disclaimer

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Executive Summary

The proposed innovation leverages advanced machine learning (ML), deep learning (DL), and large language models for sentiment analysis in text data, offering a transformative tool for organizations. By analysing customer feedback, and internal communications, this technology provides critical insights into market trends, customer preferences, and employee morale. Its application spans from enhancing market segmentation and strategic planning to improving employee engagement and customer satisfaction. This approach empowers management with data-driven decision-making capabilities, enabling proactive responses to market shifts and internal challenges. As a result, organizations can not only align their strategies more effectively with customer needs and employee well-being but also gain a competitive edge in the market.

Acknowledgement

The preparation of this work has started in December 2022 where I started with understanding how smaller versions of large language models could be utilized to decipher the sentiment in a given text. I had early trials for Vader Sentiment, Text Blob and Roberta LLM which achieved a fair accuracy.

I have seen a post in the following link : https://www.linkedin.com/feed/update/urn:li:activity:7140847736299364354?updateEntityUrn=urn%3Ali%3Afs_updateV2%3A%28urn%3Ali%3Aactivity%3A7140847736299364354%2CFEED_DETAIL%2CEMPTY%2CDEFAULT%2Cfalse%29 provided by **Yussria Ahmed** (https://www.linkedin.com/in/yusria-ahmed-3b3628284/) where she shared a very valuable piece of work about how to use machine learning to detect the sentiments in a certain text.

I drafted my code utilizing the piece of code provided by **Yussria** and I added on top of it some extra models and more explanation within the code. The full code is provided at the bottom of this report in Appendix 1.

Innovation Idea

Objective

The primary goal of this innovation is to utilize cutting-edge ML, DL, and language models to analyse sentiments expressed in various text sources, such as customer feedback, employee reviews, and internal communication. This analysis aims to assist top management in better understanding market trends, customer preferences, employee satisfaction, and overall organizational health.

Technology Overview

<u>Machine Learning Models:</u> These models are adept at classifying text into sentiment categories (positive, negative, neutral) based on historical data. They can process large volumes of data efficiently, providing quick and reliable sentiment analysis.

Deep Learning Models: Utilizing neural networks, these models excel in understanding the nuances of human language, capturing the context and subtleties often missed by traditional ML models. They are particularly effective in processing unstructured text data from various sources.

Small and Large Language Models: Leveraging models like GPT (Generative Pre-trained Transformer), we can analyse text with a deep understanding of language semantics. These models can interpret complex text and provide more accurate sentiment analysis, even with limited data.

Applications

There are multiple applications for the developed innovation idea as shown below:

- Market Segmentation: By analysing customer feedback and social media sentiment, organizations can identify market trends, customer preferences, and areas for product improvement.
- Employee Engagement: Sentiment analysis of employee feedback and communication channels helps in understanding employee morale, identifying areas of concern, and improving workplace culture.
- Strategic Planning: Insights from sentiment analysis can inform strategic decisions, helping leaders align their strategies with customer needs and employee well-being.

Benefits

Undoubtedly, this sentimental analysis code and tool comes with a bag of benefits as shown below.

- Data-Driven Decisions: Empowers management to make informed decisions based on quantifiable sentiment data.
- Proactive Response: Enables organizations to proactively address market shifts and internal challenges.
- Enhanced Customer Experience: Helps in tailoring products and services to meet customer expectations, thereby improving satisfaction and loyalty.
- Improved Employee Satisfaction: Contributes to a positive work environment by addressing employee concerns and fostering a culture of listening.

Structure

The pilot created in this report relies on having sentiment related data represented in a simple table composed of 2 columns: Sentences & Sentiment. The sentences represent a wide variety of feedback information obtained from different clients about different projects. The “Sentiment” column contains values of “Positive”, “Negative” or “Neutral”. The sentiment classification was carried out initially manually by employees. This data represents a rich source of training models to provide accurate classification for future data.

The dataset is then embedded withing a number of models depending on their architecture and the end product is to predict the sentiment within a given text as well as measuring the accuracy of the models to determine which is the best model in this use case.

**Disclaimer: I am going to share the full code within this report in appendix 1 without the dataset. The code could be altered to suit the needs in other datasets.*

Requirements

The code provided is written in Python programming language and using a Jupyter notebook. Jupyter notebooks are available through Anaconda which could be downloaded through this link (https://www.anaconda.com/). You have to have a python version >3.7 installed on your machine with pip enabled. You can download python from the following link (https://www.python.org/downloads/).

Some libraries are important in order to get the code presented in appendix 1 working perfectly. You could install the libraries through a python environment under terminal or a conda environment. The list is not exhaustive and could include other unmentioned packages:

- Pandas
- Numpy
- Nltk
- Scikit-sklearn
- Vadersentiment
- Textblob
- Transformers
- Scipy
- Matplotlib
- Tensorflow
- Xgboost
- Wordcloud
- Matplotlib

Models Overview

For the purpose of this task, I used 8 Models to compare the results between them as explained below.

- **VADER Sentiment**: VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool specifically attuned to sentiments expressed in social media. It is known for its simplicity and ability to understand the context of text, including the polarity (positive/negative) and intensity of emotions.
- **RoBERTa**: RoBERTa (Robustly Optimized BERT Approach) is a deep learning model built on BERT's (Bidirectional Encoder Representations from Transformers) architecture. It is optimized for more robust performance and is particularly effective in natural language understanding tasks, outperforming BERT in several benchmarks.
- **TextBlob:** TextBlob is a Python library for processing textual data. It provides simple APIs for common natural language processing (NLP) tasks, including sentiment analysis, part-of-speech tagging, noun phrase extraction, and translation, making it highly accessible for beginners in NLP.
- **Logistic Regression:** Logistic Regression is a statistical model used for binary classification tasks. It predicts the probability of a binary outcome based on one or more independent variables, making it useful for scenarios where the output is dichotomous, such as spam detection or sentiment analysis.

- **Multinomial NB:** Multinomial Naive Bayes is a variant of the Naive Bayes classifier that is particularly suited for classification with discrete features (e.g., word counts for text classification). It is widely used in NLP for tasks like document classification due to its simplicity and efficiency.
- **SVM:** Support Vector Machine (SVM) is a powerful and versatile supervised machine learning model used for classification and regression. In text classification, it finds the best hyperplane that separates different classes in the feature space, often performing well with high-dimensional data.
- **XGBoost Classifier:** XGBoost (Extreme Gradient Boosting) Classifier is an efficient and scalable implementation of gradient boosting framework. It is known for its performance and speed, often winning machine learning competitions. XGBoost is particularly effective for structured data classification tasks.
- **Long Short Term Memory (LSTM):** LSTM is a type of Recurrent Neural Network (RNN) architecture used in deep learning. It is designed to recognize patterns in sequences of data, such as time series or textual data, and is capable of learning long-term dependencies, making it effective for tasks like language modeling and text generation.

Implementation Steps

In this section I am going to explain the steps that I followed to tackle the sentiment analysis using the models explained in the previous section. The full code is provided in Appendix 1 at the end of this report.

1. **Vader Sentiment:**
    a. Importing the necessary libraries; pandas ,numpy and vadersentiment.
    b. Loading the sentiment data from the csv file
    c. Converting the csv file into a pandas dataframe.
    d. Use the polarity score function within vader sentiment library to give every row within the dataframe a score between -1 &1.
    e. Initiating a rule that rows with a score above 0.2 represent positive sentiments, rows with a score between 0.2 & -0.8 represent neutral sentiments and those rows with a score below -0.8 represent negative sentiments.
    f. Using the previous step to calculate the degree of coincidence between vader sentiment model and the original dataset.
2. **TextBlob:**
    a. Importing the necessary libraries; pandas ,numpy and textblob.
    b. Loading the sentiment data from the csv file
    c. Converting the csv file into a pandas dataframe.
    d. Use the polarity and subjectivity score function within text blob library to give every row within the dataframe a score between -1 &1.
    e. Initiating a rule that rows with a score above 0.2 represent positive sentiments, rows with a score between 0.2 & -0.8 represent neutral sentiments and those rows with a score below -0.8 represent negative sentiments.
    f. Using the previous step to calculate the degree of coincidence between text blob model and the original dataset.
3. **Roberta:**
    a. Importing the necessary libraries; pandas ,numpy and transformers.

b. Loading the sentiment data from the csv file
c. Converting the csv file into a pandas dataframe.
d. Loading the large language model and the tokenizer.
e. Looping through every row in the dataframe to create encondings, store them in a vector and then use the softmax function to convert the vector values into probabilities and scores.
f. For every row, I have taken the highest probability of positive, negative and neutral to determine the dominant sentiment for every row.
g. Using the previous step to calculate the degree of coincidence between text blob model and the original dataset.

Concerning the **Logistic Regression, Multinomial Naïve Bayes, Support Vector Machine and Extreme Gradient Boosting** models, they all share the same pre-processing work as shown below.

a. Importing necessary libraries: sklearn, numpy, pandas, nltk, tensorflow, re, wordcloud and keras.
b. Loading the sentiment data from the csv file
c. Converting the csv file into a pandas dataframe.
d. Splitting the created dataframe into training and testing data.
e. Loading stopwords and making sure to remove them as well as undesired characters and irrelevant letters the training and testing datasets.
f. Applying stemming to the training and testing datasets to return the words to their original roots (e.g. running → run)
g. Using the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization technique on text data. It's a common approach in natural language processing (NLP) to convert text data into a numerical format that machine learning algorithms can understand.
h. Create numeric labels for the text sentiments in both the training and testing datasets.

The post-processing work for the **Logistic Regression, Multinomial Naïve Bayes, Support Vector Machine and Extreme Gradient Boosting models** is shown below

4. **Extreme Gradient Boosting:**
   a. Initialize the model.
   b. Train the classifier on the TF-IDF training features and encoded labels.
   c. Predict the encoded labels for the TF-IDF validation features.
   d. Decode the predicted labels back to the original class labels.
   e. Display additional classification metrics.
5. **Logistic Regression:**
   a. Initialize the model with its parameters.
   b. Train the model.
   c. Fit the model on a bag of words taking into account the TF-IDF training features and encoded labels.
   d. Calculate the accuracy and printing it.
   e. Print the confusion matrix.
6. **SGD Linear Classifier:**
   a. Initialize the model with its parameters.

b. Train the model.
c. Fit the model on a bag of words taking into account the TF-IDF training features and encoded labels.
d. Calculate the accuracy and printing it.
e. Print the confusion matrix.

7. **Multinomial Naïve Bayes Classifier:**
   a. Initialize the model with its parameters.
   b. Train the model.
   c. Fit the model on a bag of words taking into account the TF-IDF training features and encoded labels.
   d. Calculate the accuracy and printing it.
   e. Print the confusion matrix.

Deploying the **Long Short-Term Memory** using deep learning follows the following steps:

a. Importing necessary libraries: sklearn, numpy, pandas, nltk, tensorflow, re, wordcloud and keras.
b. Loading the sentiment data from the csv file
c. Converting the csv file into a pandas dataframe.
d. Pre-processing the sentence text by removing any undesired characters.
e. Tokenizing sentences, applying padding, labelling the encoder and then splitting the data into train and test sets.
f. Building a sequential model, assigning layers and training it on the dataset.
g. Calculating the accuracy of the learning and testing processes and plotting the results.

Results and next steps

Having applied the full code on the available dataset, I came by the following results shown in the graph below.

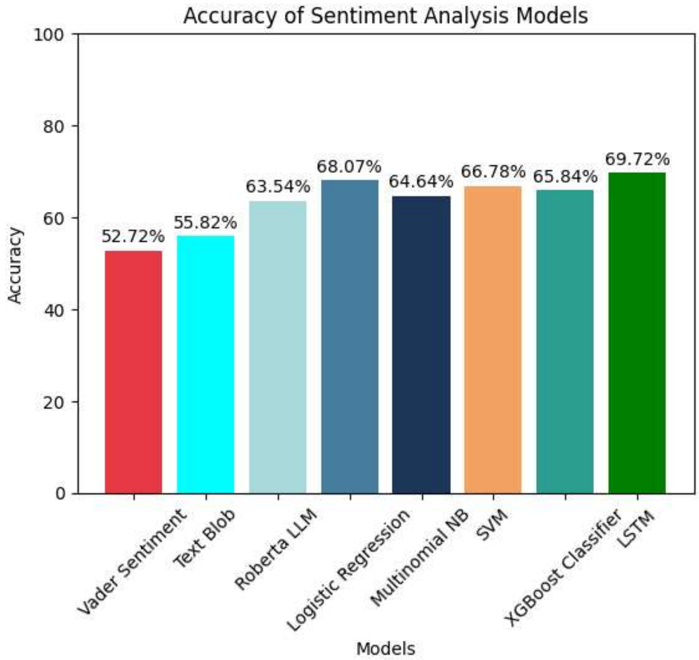


Figure 1: Accuracy of models in detecting the sentiment within text

In this case scenario, the Long Short-Term Memory model relying on deep learning was the clear winner with an accuracy approaching 70% followed the small large language model Roberta with an accuracy of circa 68%.

It is clear from the graph that all the models used except for vader sentiment and text blob are within the 63%+ accuracy range. It is worth noting that I have tried using the application of both the pre-processing function and the stemming function and it gave worse accuracies. I would also like to note that the accuracy of the LSTM was achieved by having 2 epochs only. Bizzarely, the LSTM accuracy decreased after 10 epochs which could tell that I did not have the best dataset to deal with in the first place. For the purpose of this project, I would not suggest using the automated way of getting the sentiment analysis as the accuracy is below 85%.

I would note that the accuracy of the modelling would be enhanced by reviewing the training dataset and making sure that it contains correct English language as much as possible and also the sentiment classification within the training dataset has to make sense.

I think the next steps is to compare the performance of available open source models such as Mistral, Falcon, Llama and other against the paid Large Language models such as GPT-4 and Gemini. The comparison also against the models contained within this report is going to be interesting.

Finally, I would suggest that the reader apply the code with due care and take his/her time to digest the datasets available and decipher the results thoroughly before choosing a specific model.

Appendix 1 – Sentimental Analysis code using different models

Using Vader Sentiment

In [1]:

```
#importing the important modules
import re
import nltk
import pandas as pd
import numpy as np
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
sentiment = SentimentIntensityAnalyzer()

#reading the CSV file containing the feedback and creating a dataframe

Feedback=pd.read_csv(r'D:\Documents\Dossiers du travail\Technical Excellence\Sentimental Analysis\data.csv')
df=pd.DataFrame(Feedback)
vader_sentiment=pd.DataFrame()

# #Creating a function to pre-process the sentence text

# def preprocess_text(text):
#     text = re.sub(r'\$\w*', '', text)
#     text = re.sub(r'^RT[\s]+', '', text)
#     text = re.sub(r'https?://[^\s\n\r]+', '', text)
#     text = re.sub(r'#', '', text)
#     text = re.sub(r'http\S+', '', text)
#     text = re.sub(r'[^a-zA-Z\s]', '', text)
#     return text

# df['Sentence']=df['Sentence'].apply(preprocess_text)

# #Creating a stemming function to return the words to their original roots.
# def simple_stemmer(text):
#  ps=nltk.porter.PorterStemmer()
#  text= ' '.join([ps.stem(word) for word in text.split()])
#  return text

# df['Sentence']=df['Sentence'].apply(simple_stemmer)


#Determining the sentiment in every line in the dataframe

for i in df['Sentence']:
    sent_text=sentiment.polarity_scores(i)
    vader_sentiment=vader_sentiment._append(sent_text,ignore_index=True)

#Adjusting the columns within the generated dataframe to showcase the original sentiment and the generated sentiments
vader_sentiment['Sentence'],vader_sentiment['Original Sentiment'],vader_sentiment['Vader Sentiment Score']=df['Sentence'],df['Sentiment'],vader_sentiment['compound']
vader_sentiment['Vader Sentiment']=vader_sentiment['compound'].apply(lambda x: 'positive' if x >0.2 else('neutral' if x<=0.2 and x>-0.8 else 'negative'))
vader_sentiment['Common Sentiments']=np.where(vader_sentiment['Original Sentiment']==vader_sentiment['Vader Sentiment'],'coincident','incoincident')
vader_sentiment=vader_sentiment.iloc[:,4:]

#Determination the accuracy percentage of Vader sentiment
coincident_count=(vader_sentiment['Common Sentiments']=='coincident').sum()
total_no_rows=len(vader_sentiment)
vader_sentiment_accuracy=(coincident_count/total_no_rows)*100
print(f'Vader Sentiment Model Accuracy = {vader_sentiment_accuracy:.2f}%')


vader_sentiment.head(10)
```

```
Vader Sentiment Model Accuracy = 52.72%
```

Out[1]:

	Sentence	Original Sentiment	Vader Sentiment Score	Vader Sentiment	Common Sentiments
0	The GeoSolutions technology will leverage Bene...	positive	0.5423	positive	coincident
1	$ESIonlows$,1.50 to $2.50 BK a real po... $down$	negative	-0.2023	neutral	incoincident
2	For the last quarter of 2010 , Componenta 's n...	positive	0.1531	neutral	incoincident
3	According to the Finnish-Russian Chamber of Co...	neutral	0.0000	neutral	coincident
4	The Swedish buyout firm has sold its remaining...	neutral	0.0000	neutral	coincident
5	$SPY wouldn't be surprised to see a green close	positive	-0.1695	neutral	incoincident
6	Shell's $70 Billion BG Deal Meets Shareholder ...	negative	-0.2500	neutral	incoincident
7	SSH COMMUNICATIONS SECURITY CORP STOCK EXCHANG...	negative	0.2103	positive	incoincident
8	Kone 's net sales rose by some 14 % year-on-ye...	positive	0.0000	neutral	incoincident
9	The Stockmann department store will have a tot...	neutral	0.0000	neutral	coincident

Using TextBlob for sentiment analysis

In [2]:

```
#importing the important modules

import pandas as pd
import numpy as np
from textblob import TextBlob

#reading the CSV file containing the feedback and creating a dataframe

Feedback=pd.read_csv(r'D:\Documents\Dossiers du travail\Technical Excellence\Sentimental
Analysis\data.csv')
df=pd.DataFrame(Feedback)
text_blob=pd.DataFrame(dict(Polarity=[],Subjectivity=[]),dtype=float)

# #Creating a function to pre-process the sentence text

# def preprocess_text(text):
#     text = re.sub(r'\$\w*', '', text)
#     text = re.sub(r'^RT[\s]+', '', text)
#     text = re.sub(r'https?://[^\s\n\r]+', '', text)
#     text = re.sub(r'#', '', text)
#     text = re.sub(r'http\S+', '', text)
#     text = re.sub(r'[^a-zA-Z\s]', '', text)
#     return text

# df['Sentence']=df['Sentence'].apply(preprocess_text)

# # #Creating a stemming function to return the words to their original roots.
# # def simple_stemmer(text):
# #  ps=nltk.porter.PorterStemmer()
# #  text= ' '.join([ps.stem(word) for word in text.split()])
# #  return text

# # df['Sentence']=df['Sentence'].apply(simple_stemmer)

#Determining the sentiment in every line in the dataframe

for i in df['Sentence']:
    polarity_text=TextBlob(i).sentiment.polarity
    subjectivity_text=TextBlob(i).sentiment.subjectivity
    text_blob=text_blob._append(dict(Polarity=polarity_text,Subjectivity=subjectivity_tex
t),ignore_index=True)
```

```python
 #Adjusting the columns within the generated dataframe to showcase the original sentiment and the generated sentiments
text_blob['Sentence'],text_blob['Original Sentiment'],text_blob['Text Blob Score']=df['Sentence'],df['Sentiment'],text_blob['Polarity']
text_blob['Text Blob Sentiment']=text_blob['Polarity'].apply(lambda x: 'positive' if x > 0.2 else('neutral' if x<=0.2 and x>-0.8 else 'negative'))
text_blob['Common Sentiments']=np.where(text_blob['Original Sentiment']==text_blob['Text Blob Sentiment'],'coincident','incoincident')
text_blob=text_blob.iloc[:,2:]

#Determination the accuracy percentage of Text Blob
coincident_count=(text_blob['Common Sentiments']=='coincident').sum()
total_no_rows=len(text_blob)
text_blob_accuracy=(coincident_count/total_no_rows)*100
print(f'Text Blob Model Accuracy = {text_blob_accuracy:.2f}%')

text_blob.head(10)
```

```
Text Blob Model Accuracy = 55.82%
```

Out[2]:

	Sentence	Original Sentiment	Text Blob Score	Text Blob Sentiment	Common Sentiments
0	The GeoSolutions technology will leverage Bene...	positive	0.209091	positive	coincident
1	*ESIonlows*,1.50 to $2.50 BK a real po... *down*	negative	0.022222	neutral	incoincident
2	For the last quarter of 2010 , Componenta 's n...	positive	0.000000	neutral	incoincident
3	According to the Finnish-Russian Chamber of Co...	neutral	0.062500	neutral	coincident
4	The Swedish buyout firm has sold its remaining...	neutral	-0.100000	neutral	coincident
5	$SPY wouldn't be surprised to see a green close	positive	-0.050000	neutral	incoincident
6	Shell's $70 Billion BG Deal Meets Shareholder ...	negative	0.000000	neutral	incoincident
7	SSH COMMUNICATIONS SECURITY CORP STOCK EXCHANG...	negative	0.350000	positive	incoincident
8	Kone 's net sales rose by some 14 % year-on-ye...	positive	0.283333	positive	coincident
9	The Stockmann department store will have a tot...	neutral	0.000000	neutral	coincident

Using Roberta LLM for Sentiment Analysis

In [3]:

```python
import pandas as pd
import numpy as np
from transformers import AutoTokenizer, AutoModelForSequenceClassification
from scipy.special import softmax


#reading the CSV file containing the feedback and creating a dataframe

Feedback=pd.read_csv(r'D:\Documents\Dossiers du travail\Technical Excellence\Sentimental Analysis\data.csv')
df=pd.DataFrame(Feedback)

# Load model and tokenizer

roberta="cardiffnlp/twitter-roberta-base-sentiment"
model = AutoModelForSequenceClassification.from_pretrained(roberta)
Tokenizer= AutoTokenizer.from_pretrained(roberta)
Roberta_Scores=pd.DataFrame(dict(negative=[],neutral=[],positive=[]),dtype=float)

#For loop for Sentiment Analysis for every row in the dataset

for sentence in df['Sentence']:
```

```
    Encoded_feedback=Tokenizer(sentence,return_tensors='pt')
    Output=model(Encoded_feedback['input_ids'],Encoded_feedback['attention_mask'])
    scores=Output[0][0].detach().numpy()
    scores=softmax(scores)
    Roberta_Scores=Roberta_Scores._append(dict(Negative=scores[0],Neutral=scores[1],Posi
tive=scores[2]),ignore_index=True)

#Adjustment of the columns of the generated dataframe to include the original sentences a
nd their corresponding sentiments
Roberta_Scores['Roberta Sentiment']=Roberta_Scores.idxmax(axis=1)
Roberta_Scores['Sentence'],Roberta_Scores['Original Sentiment']=df['Sentence'],df['Senti
ment']
Roberta_Scores['Common Sentiments']=np.where(Roberta_Scores['Original Sentiment']==Rober
ta_Scores['Roberta Sentiment'].str.lower(),'coincident','incoincident')
Roberta_Scores=Roberta_Scores.iloc[:,3:]

#Determination the accuracy percentage of Roberta LLM
coincident_count=(Roberta_Scores['Common Sentiments']=='coincident').sum()
total_no_rows=len(Roberta_Scores)
Roberta_accuracy=(coincident_count/total_no_rows)*100
print(f'Roberta Model Accuracy = {Roberta_accuracy:.2f}%')

Roberta_Scores.head(10)
```

```
c:\Users\Mo_As\AppData\Local\Programs\Python\Python39\lib\site-packages\tqdm\auto.py:21:
TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See https://ipywi
dgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

```
Roberta Model Accuracy = 63.54%
```

Out[3]:

	Negative	Neutral	Positive	Roberta Sentiment	Sentence	Original Sentiment	Common Sentiments
0	0.004404	0.349696	0.645900	Positive	The GeoSolutions technology will leverage Bene...	positive	coincident
1	0.143034	0.810581	0.046385	Neutral	*ESIonlows*, 1.50 to $2.50 BK a real po... *down*	negative	incoincident
2	0.151266	0.711914	0.136821	Neutral	For the last quarter of 2010 , Componenta 's n...	positive	incoincident
3	0.114385	0.822406	0.063209	Neutral	According to the Finnish-Russian Chamber of Co...	neutral	coincident
4	0.073200	0.902309	0.024490	Neutral	The Swedish buyout firm has sold its remaining...	neutral	coincident
5	0.029851	0.509396	0.460752	Neutral	$SPY wouldn't be surprised to see a green close	positive	incoincident
6	0.080382	0.888695	0.030923	Neutral	Shell's $70 Billion BG Deal Meets Shareholder ...	negative	incoincident
7	0.167845	0.744486	0.087670	Neutral	SSH COMMUNICATIONS SECURITY CORP STOCK EXCHANG...	negative	incoincident
8	0.002929	0.509826	0.487246	Neutral	Kone 's net sales rose by some 14 % year-on-ye...	positive	incoincident
9	0.018258	0.853465	0.128277	Neutral	The Stockmann department store will have a tot...	neutral	coincident

Sentiment Analysis using Machine Learning Models

In [4]:

```
#Importing the required packages and libraries

import pandas as pd
import matplotlib.pyplot as plt
import nltk
```

```python
from nltk.tokenize.toktok import ToktokTokenizer
from wordcloud import WordCloud, STOPWORDS
import re
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
import xgboost as xgb
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.preprocessing import LabelBinarizer
import numpy as np
from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Embedding, Dropout, SpatialDropout1D
from keras.layers import LSTM
from sklearn.feature_extraction.text import CountVectorizer
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
```

```
WARNING:tensorflow:From c:\Users\Mo_As\AppData\Local\Programs\Python\Python39\lib\site-pa
ckages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is depre
cated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

In [5]:

```python
#Loading the raw data and splitting into training and testing data

Feedback=pd.read_csv(r'D:\Documents\Dossiers du travail\Technical Excellence\Sentimental
Analysis\data.csv')
df=pd.DataFrame(Feedback)
train_data=pd.DataFrame()
test_data=pd.DataFrame()
train_data=df.iloc[:round(0.8*len(df)),:]
test_data=df.iloc[round(0.8*len(df)):len(df),:]
```

In [6]:

```python
#Exploring both the training and testing data as well as profiling the sentiments in both
datasets.
print(train_data.head())
print(test_data.head())
print('\nTrain Data shape is:'+ str(train_data.shape))
print('\nTest Data shape is:'+ str(test_data.shape))
print('\n The train data profile is :\n'+str(train_data['Sentiment'].value_counts()))
print('\n The train data profile is :\n'+str(test_data['Sentiment'].value_counts()))
```

```
                                            Sentence Sentiment
0  The GeoSolutions technology will leverage Bene...  positive
1  $ESI on lows, down $1.50 to $2.50 BK a real po...  negative
2  For the last quarter of 2010 , Componenta 's n...  positive
3  According to the Finnish-Russian Chamber of Co...   neutral
4  The Swedish buyout firm has sold its remaining...   neutral
                                               Sentence Sentiment
4674  Both companies will keep their commercial inde...   neutral
4675  Scanfil expects net sales in 2008 to remain at...   neutral
4676  The inaugural speech will be given by Hannu Ky...   neutral
4677  It now owns 80,565 shares in Amer Sports Corpo...   neutral
4678  Peer Peugeot fell 0.81 pct as its sales rose o...  negative

Train Data shape is:(4674, 2)

Test Data shape is:(1168, 2)

 The train data profile is :
Sentiment
neutral     2517
positive    1482
```

```
negative     675
Name: count, dtype: int64

 The train data profile is :
Sentiment
neutral     613
positive    370
negative    185
Name: count, dtype: int64
```

In [7]:

```
#Natural Language Processing important wording download and tokenization
nltk.download('stopwords')

#Text Tokenization
tokenizer=ToktokTokenizer()

#Setting English stopwords
stopword_list=nltk.corpus.stopwords.words('english')

#Create a function to cleanse the sentences within both the train and test data
def preprocess_text(text):
    text = re.sub(r'\$\w*', '', text)
    text = re.sub(r'^RT[\s]+', '', text)
    text = re.sub(r'https?://[^\s\n\r]+', '', text)
    text = re.sub(r'#', '', text)
    text = re.sub(r'http\S+', '', text)
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    return text
train_data['Sentence']=train_data['Sentence'].apply(preprocess_text)
test_data['Sentence']=test_data['Sentence'].apply(preprocess_text)

print(train_data.head())
print(test_data.head())
```

```
                                            Sentence Sentiment
0  The GeoSolutions technology will leverage Bene...  positive
1            on lows down  to  BK a real possibility  negative
2  For the last quarter of   Componenta s net sal...  positive
3  According to the FinnishRussian Chamber of Com...   neutral
4  The Swedish buyout firm has sold its remaining...   neutral
                                               Sentence Sentiment
4674  Both companies will keep their commercial inde...   neutral
4675  Scanfil expects net sales in  to remain at the...   neutral
4676  The inaugural speech will be given by Hannu Ky...   neutral
4677  It now owns  shares in Amer Sports Corporation...   neutral
4678  Peer Peugeot fell  pct as its sales rose only ...  negative
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Mo_As\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
C:\Users\Mo_As\AppData\Local\Temp\ipykernel_2404\395275518.py:19: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  train_data['Sentence']=train_data['Sentence'].apply(preprocess_text)
C:\Users\Mo_As\AppData\Local\Temp\ipykernel_2404\395275518.py:20: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  test_data['Sentence']=test_data['Sentence'].apply(preprocess_text)
```

In [8]:

```
#Undertaking stemming of words by returning them to their original root
```

```
#This is followed by applying this concept to the sentence column in the train and test d
ataframes
#This concept did not work properly in my case as the printed results from this step show
ed gibberish english

def simple_stemmer(text):
 ps=nltk.porter.PorterStemmer()
 text= ' '.join([ps.stem(word) for word in text.split()])
 return text
#Apply function on review column
train_data['Sentence']=train_data['Sentence'].apply(simple_stemmer)
test_data['Sentence']=test_data['Sentence'].apply(simple_stemmer)

print(train_data.head())
print(test_data.head())
```

```
                                            Sentence Sentiment
0  the geosolut technolog will leverag benefon s ...  positive
1                   on low down to bk a real possibl  negative
2  for the last quarter of componenta s net sale ...  positive
3  accord to the finnishrussian chamber of commer...   neutral
4  the swedish buyout firm ha sold it remain perc...   neutral
                                               Sentence Sentiment
4674  both compani will keep their commerci independ...   neutral
4675  scanfil expect net sale in to remain at the level   neutral
4676  the inaugur speech will be given by hannu kyro...   neutral
4677  it now own share in amer sport corpor equal of...   neutral
4678  peer peugeot fell pct as it sale rose onli pct...  negative
```

```
C:\Users\Mo_As\AppData\Local\Temp\ipykernel_2404\52532570.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  train_data['Sentence']=train_data['Sentence'].apply(simple_stemmer)
C:\Users\Mo_As\AppData\Local\Temp\ipykernel_2404\52532570.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  test_data['Sentence']=test_data['Sentence'].apply(simple_stemmer)
```

Loading stopwords and then removing them from the sentences column

In [9]:

```
#Loading and printing stopwords
stop=set(stopwords.words('english'))
print(stop)

#Creating a function to remove the stopwords from the sentence column in both the train a
nd test data frames
def remove_stopwords(text, is_lower_case=False):
    tokens = tokenizer.tokenize(text)
    tokens = [token.strip() for token in tokens]
    if is_lower_case:
        filtered_tokens = [token for token in tokens if token not in stopword_list]
    else:
        filtered_tokens = [token for token in tokens if token.lower() not in stopword_li
st]
    filtered_text = ' '.join(filtered_tokens)
    return filtered_text

train_data['Sentence']=train_data['Sentence'].apply(remove_stopwords)
test_data['Sentence']=test_data['Sentence'].apply(remove_stopwords)

print(train_data.head())
print(test_data.head())
```

```
{'don', "it's", 'at', 'but', 'theirs', 'needn', 'your', 'on', 'to', "won't", 'd', 'are',
```

```
'down', "she's", 'you', 'when', 'i', 'who', 'above', 'were', 'more', 'if', 'been', "aren'
t", 'had', 'from', 'doing', 'during', 'hers', 'other', 'further', 'all', 'we', 'have', "m
ightn't", 'our', 'through', 'did', 'own', 'herself', 'wouldn', 'can', 'where', 'aren', 't
hese', 'too', 'ma', "you'd", 'be', "you'll", 'yourselves', 'its', 'about', 'between', 'it
self', 'has', 'having', 'yourself', 'hadn', 'hasn', 'is', 'very', 'such', 'now', 'for', '
or', 'ours', 'both', 'he', 'no', 'won', 'that', 'y', 'couldn', "needn't", 'what', 'was',
't', 'most', 'just', "shan't", 'haven', 'wasn', 'their', 'than', 'each', 'there', 'under'
, 'mustn', 'didn', 'does', "don't", 'after', "should've", 'ain', 'and', 'themselves', "ha
sn't", 're', "weren't", 'out', 'weren', "you're", 'ourselves', 'as', 'will', 'because', "
you've", 'here', 'o', 'do', "wasn't", 'how', 's', 'in', 'doesn', "doesn't", 'them', 'myse
lf', 'whom', 'an', 'isn', 'it', 'they', 'below', 'same', 'any', 'll', "haven't", 'before'
, 'so', "mustn't", 'which', 'mightn', 'this', 'shouldn', 'again', 'a', 'the', 'with', 'sh
e', 'being', 'why', 'me', 'some', "couldn't", 'not', 'his', 'my', 'am', 'once', 've', 'sh
an', 'her', "isn't", 'over', 'until', "wouldn't", 'only', 'm', 'by', "shouldn't", "that'l
l", "hadn't", 'yours', 'himself', 'nor', 'while', 'then', 'against', "didn't", 'him', 'sh
ould', 'up', 'off', 'those', 'into', 'few', 'of'}
                                            Sentence Sentiment
0  geosolut\ttechnolog\tleverag\tbenefon\tgp\tsol...  positive
1                             low\tbk\treal\tpossibl  negative
2  last\tquarter\tcomponenta\tnet\tsale\tdoubl\te...  positive
3  accord\tfinnishrussian\tchamber\tcommerc\tmajo...   neutral
4  swedish\tbuyout\tfirm\tha\tsold\tremain\tperce...   neutral
                                               Sentence Sentiment
4674  compani\tkeep\tcommerci\tindepend\tcontinu\tma...   neutral
4675          scanfil\texpect\tnet\tsale\tremain\tlevel   neutral
4676  inaugur\tspeech\tgiven\thannu\tkyrolainen\tfin...   neutral
4677  share\tamer\tsport\tcorpor\tequal\tcompani\tsh...   neutral
4678  peer\tpeugeot\tfell\tpct\tsale\trose\tonli\tpc...  negative
```

```
C:\Users\Mo_As\AppData\Local\Temp\ipykernel_2404\3261840839.py:16: SettingWithCopyWarning
:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  train_data['Sentence']=train_data['Sentence'].apply(remove_stopwords)
C:\Users\Mo_As\AppData\Local\Temp\ipykernel_2404\3261840839.py:17: SettingWithCopyWarning
:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  test_data['Sentence']=test_data['Sentence'].apply(remove_stopwords)
```

Term Frequency-Inverse Document Frequency (TF-IDF) vectorization technique

In [10]:

```python
# Using the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization technique on text data.
# It's a common approach in natural language processing (NLP) to convert text data into a numerical format that machine learning algorithms can understand.

tfidf_vectorizer = TfidfVectorizer(max_features=10000)  # You can adjust the 'max_features' parameter based on your dataset and reqirements
#Fit and transform the training and test data
tfidf_train_features = tfidf_vectorizer.fit_transform(train_data['Sentence'])
tfidf_test_features = tfidf_vectorizer.transform(test_data['Sentence'])

#The fitting was done only on the training features because of an error faced.
#When using text data, if the TfidfVectorizer (or any other vectorizer) is fit separately on training and test sets, they might end up having different vocabularies (and hence, different feature sizes).

# Display the shape of the TF-IDF features
print(f"TF-IDF Training Features Shape: {tfidf_train_features.shape}")
print(f"TF-IDF Validation Features Shape: {tfidf_test_features.shape}")
```

```
TF-IDF Training Features Shape: (4674, 6851)
```

```
TF-IDF Validation Features Shape: (1168, 6851)
```

Create text labels

In [11]:

```
#The purpose of this step is to convert categorical text labels into a numeric format.

# Initialize the LabelEncoder -->  LabelEncoder is used to transform non-numerical labels
(as long as they are hashable and comparable) into numerical labels.
label_encoder = LabelEncoder()

# Encode the class labels in both training and validation datasets
train_labels_encoded= label_encoder.fit_transform(train_data['Sentiment'])
test_labels_encoded = label_encoder.transform(test_data['Sentiment'])
print(train_labels_encoded.shape)
print(test_labels_encoded.shape)

unique_values = np.unique(train_labels_encoded)
print(unique_values)
unique_values = np.unique(test_labels_encoded)
print(unique_values)
print(label_encoder.inverse_transform(unique_values))
```

```
(4674,)
(1168,)
[0 1 2]
[0 1 2]
['negative' 'neutral' 'positive']
```

XGBoost classifier

In [12]:

```
# Initialize the XGBoost classifier
xgb_classifier = xgb.XGBClassifier()
# Train the classifier on the TF-IDF training features and encoded labels
xgb_classifier.fit(tfidf_train_features, train_labels_encoded)
# Predict the encoded labels for the TF-IDF validation features
test_predictions_xgb_encoded = xgb_classifier.predict(tfidf_test_features)
# Decode the predicted labels back to the original class labels
test_predictions_xgb = label_encoder.inverse_transform(test_predictions_xgb_encoded)

accuracy_xgb = accuracy_score(test_data['Sentiment'], test_predictions_xgb)*100
print(f"XGBoost Accuracy: {accuracy_xgb:.2f}%")

# Display additional classification metrics for XGBoost
print("XGBoost Confusion Matrix:")
print(confusion_matrix(test_data['Sentiment'], test_predictions_xgb))
print("XGBoost Classification Report:")
print( classification_report(test_data['Sentiment'], test_predictions_xgb))
```

```
XGBoost Accuracy: 65.84%
XGBoost Confusion Matrix:
[[ 36 132  17]
 [ 60 511  42]
 [  7 141 222]]
XGBoost Classification Report:
              precision    recall  f1-score   support

    negative       0.35      0.19      0.25       185
     neutral       0.65      0.83      0.73       613
    positive       0.79      0.60      0.68       370

    accuracy                           0.66      1168
   macro avg       0.60      0.54      0.55      1168
weighted avg       0.65      0.66      0.64      1168
```

Logistic Regression

In [13]:

```
#Using Logistic Regression, training the model on the training data followed by predictin
g for test data.
#The last step is to calculate the accuracy of this model.

#training the model
lr=LogisticRegression(penalty='l2',max_iter=500,C=1,random_state=42)
#Fitting the model for Bag of words
lr.fit(tfidf_train_features, train_labels_encoded)

#Fitting the model for tfidf features
test_predictions_lr_encoded=lr.predict(tfidf_test_features)
test_predictions_lr = label_encoder.inverse_transform(test_predictions_lr_encoded)

#Calculating the accuracy and printing it
accuracy_lr = accuracy_score(test_data['Sentiment'], test_predictions_lr)*100
print(f"Logistic Regression Accuracy: {accuracy_lr:.2f}%")

#Printing Logistic Regression Confusion Matrix
print("Logistic Regression Confusion Matrix:")
print(confusion_matrix(test_data['Sentiment'], test_predictions_lr))
print("Logistic Regression Classification Report:")
print( classification_report(test_data['Sentiment'], test_predictions_lr))
```

```
Logistic Regression Accuracy: 68.07%
Logistic Regression Confusion Matrix:
[[ 29 125  31]
 [ 26 538  49]
 [  5 137 228]]
Logistic Regression Classification Report:
              precision    recall  f1-score   support

    negative       0.48      0.16      0.24       185
     neutral       0.67      0.88      0.76       613
    positive       0.74      0.62      0.67       370

    accuracy                           0.68      1168
   macro avg       0.63      0.55      0.56      1168
weighted avg       0.66      0.68      0.65      1168
```

SGD linear classifier

In [14]:

```
#Using SGD linear classifier, training the model on the training data followed by predict
ing for test data.
#The last step is to calculate the accuracy of this model.

#training the model
svm=SGDClassifier(loss='hinge',max_iter=500,random_state=42)
#Fitting the model for Bag of words
svm.fit(tfidf_train_features, train_labels_encoded)
#Fitting the model for tfidf features
test_predictions_svm_encoded=svm.predict(tfidf_test_features)
test_predictions_svm = label_encoder.inverse_transform(test_predictions_svm_encoded)

#Print the accuracy of the model
accuracy_svm= accuracy_score(test_data['Sentiment'], test_predictions_svm)*100
print(f"SGD Classifier Accuracy: {accuracy_svm:.2f}%")

#Print a detailed report about the model used and the corresponding accuracy and confusio
n matrix
print("SGD Classifier Confusion Matrix:")
print(confusion_matrix(test_data['Sentiment'], test_predictions_svm ))
print("SGD Classifier Classification Report:")
```

```
print( classification_report(test_data['Sentiment'], test_predictions_svm ))
```

```
SGD Classifier Accuracy: 66.78%
SGD Classifier Confusion Matrix:
[[ 54 101  30]
 [ 64 472  77]
 [ 14 102 254]]
SGD Classifier Classification Report:
              precision    recall  f1-score   support

    negative       0.41      0.29      0.34       185
     neutral       0.70      0.77      0.73       613
    positive       0.70      0.69      0.69       370

    accuracy                           0.67      1168
   macro avg       0.60      0.58      0.59      1168
weighted avg       0.65      0.67      0.66      1168
```

Using Multinomial Naive Boyes classifier

In [15]:

```
#Using Multinomial Naive Boyes classifier, training the model on the training data follow
ed by predicting for test data.
#The last step is to calculate the accuracy of this model.

mnb=MultinomialNB()
#fitting the mnb for bag of words
mnb.fit(tfidf_train_features, train_labels_encoded)
#Fitting the model for tfidf features
test_predictions_mnb_encoded=mnb.predict(tfidf_test_features)
test_predictions_mnb = label_encoder.inverse_transform(test_predictions_mnb_encoded)

#Printing the accuracy
accuracy_mnb= accuracy_score(test_data['Sentiment'], test_predictions_mnb)*100
print(f"Multinomial NB Accuracy: {accuracy_mnb:.2f}%")

#Print a detailed report about the model used and the corresponding accuracy and confusio
n matrix
print("Multinomial NB Confusion Matrix:")
print(confusion_matrix(test_data['Sentiment'], test_predictions_mnb))
print("Multinomial NB Classification Report:")
print( classification_report(test_data['Sentiment'], test_predictions_mnb))
```

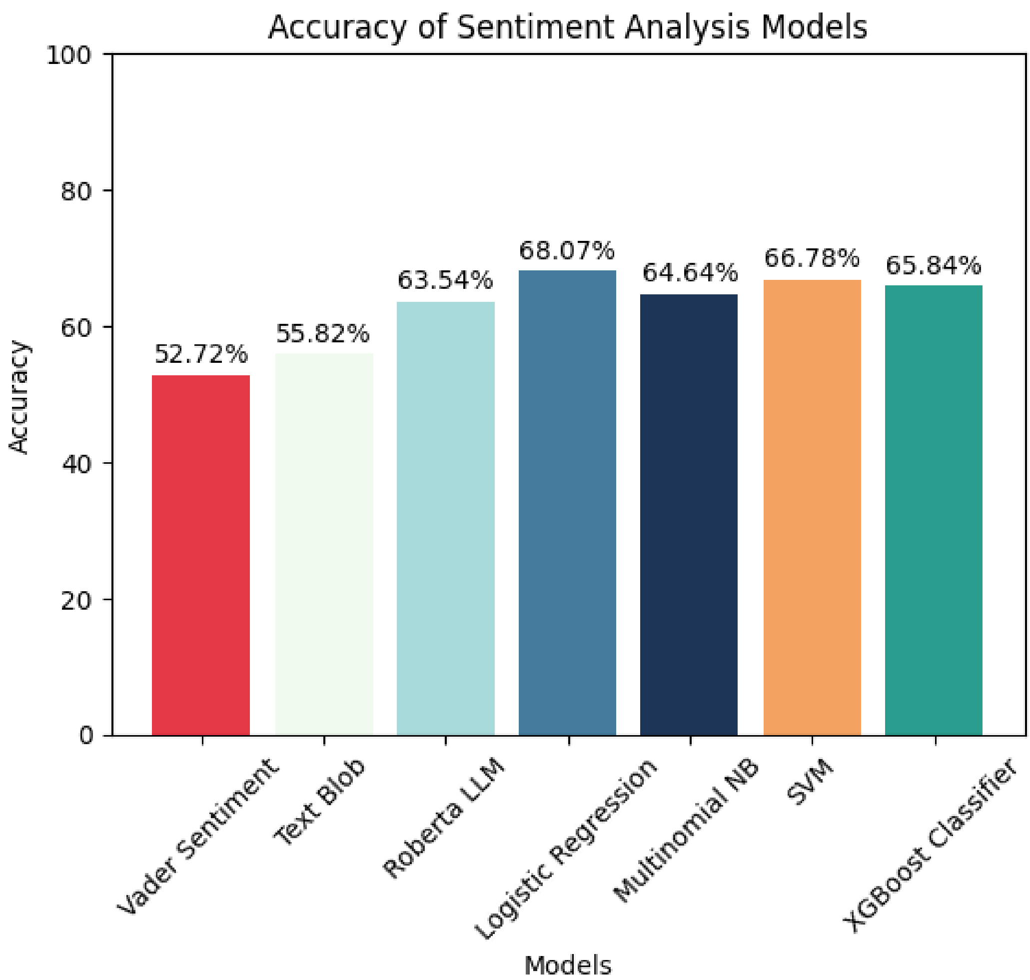
```
Multinomial NB Accuracy: 64.64%
Multinomial NB Confusion Matrix:
[[  6 141  38]
 [  0 587  26]
 [  0 208 162]]
Multinomial NB Classification Report:
              precision    recall  f1-score   support

    negative       1.00      0.03      0.06       185
     neutral       0.63      0.96      0.76       613
    positive       0.72      0.44      0.54       370

    accuracy                           0.65      1168
   macro avg       0.78      0.48      0.45      1168
weighted avg       0.71      0.65      0.58      1168
```

Accuracies Plot

In [16]:

```
#Plotting the accuracies achieved so far for the different models used
models = ['Vader Sentiment','Text Blob','Roberta LLM','Logistic Regression','Multinomial
NB','SVM','XGBoost Classifier']
```

```
accuracies = [vader_sentiment_accuracy,text_blob_accuracy,Roberta_accuracy,accuracy_lr,accuracy_mnb,accuracy_svm,accuracy_xgb]

# Specify a color for each bar
colors=['#E63946', '#F1FAEE','#A8DADC','#457B9D','#1D3557','#F4A261','#2A9D8F']

#Drafting the actual plot
plt.bar(models, accuracies, color=colors)
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Accuracy of Sentiment Analysis Models')
plt.ylim(0, 100)  # Set the y-axis limits to 0 and 100 for accuracy percentage
plt.xticks(rotation=45)  # Rotate x-axis labels if needed

# Annotate each bar with its value
for i, value in enumerate(accuracies):
    plt.text(i, value + 1, f'{value:.2f}%', ha='center', va='bottom')

plt.show()
```



Sentiment Analysis using Deep Learning - Long Short-Term Memory (LSTM)

Data Loading

In [17]:

```
#Loading the raw sentiment data and understanding the dataset profiling

Feedback=pd.read_csv(r'D:\Documents\Dossiers du travail\Technical Excellence\Sentimental Analysis\data.csv')
df=pd.DataFrame(Feedback)
print(df.head())
print(df['Sentiment'].value_counts())
```

```
                                            Sentence Sentiment
```

```
0  The GeoSolutions technology will leverage Bene...  positive
1  $ESI on lows, down $1.50 to $2.50 BK a real po...  negative
2  For the last quarter of 2010 , Componenta 's n...  positive
3  According to the Finnish-Russian Chamber of Co...   neutral
4  The Swedish buyout firm has sold its remaining...   neutral
Sentiment
neutral     3130
positive    1852
negative     860
Name: count, dtype: int64
```

Cleansing sentences data from undesirable characters

In [18]:

```
#Prepare a function to cleanse the sentences out of the undesirable characters and then p
reprocess the sentences for training

def preprocess_text(text):
    # Remove mentions (e.g., @username)
    text = re.sub(r'@\w+', '', text)
    # Remove emojis
    emoji_pattern = re.compile(
        "["
        "\U0001F600-\U0001F64F"  # Emoticons
        "\U0001F300-\U0001F5FF"  # Symbols & pictographs
        "\U0001F680-\U0001F6FF"  # Transport & map symbols
        "\U0001F700-\U0001F77F"  # Alchemical symbols
        "\U0001F780-\U0001F7FF"  # Geometric shapes
        "\U0001F800-\U0001F8FF"  # Miscellaneous Symbols and Arrows
        "\U0001F900-\U0001F9FF"  # Supplemental Symbols and Pictographs
        "\U0001FA00-\U0001FA6F"  # Extended-A
        "\U0001FA70-\U0001FAFF"  # Extended-B
        "\U00002702-\U000027B0"  # Dingbats
        "\U000024C2-\U0001F251"
        "]+"
    )
    text = emoji_pattern.sub(r'', text)
    # Remove other special characters (keep only alphanumeric and spaces)
    text = re.sub(r'[^a-zA-Z0-9\s]', '', text)
    return text.strip()
# Apply the preprocessing function to the 'sentence' column
df['Sentence'] = df['Sentence'].apply(preprocess_text)

#Display the end result of the cleansed text within the sentiment dataframe
df.head()
```

Out[18]:

	Sentence	Sentiment
0	**The GeoSolutions technology will leverage Bene...**	**positive**
1	**ESI on lows down 150 to 250 BK a real possibility**	**negative**
2	**For the last quarter of 2010 Componenta s net...**	**positive**
3	**According to the FinnishRussian Chamber of Com...**	**neutral**
4	**The Swedish buyout firm has sold its remaining...**	**neutral**

In [20]:

```
#The following step is optional and had no impact on my case.
# It tries to split the data by discarding the rows which have a number of words exceedin
g an arbitrary value.
#This can help the deep learning algorithm to understand the data quicker.


#Split the dataframe to include only rows which have 70 words in sentences or less
df = df[df['Sentence'].apply(lambda x: len(x.split()) <= 70)]
# Resetting the index after dropping rows
```

```
df.reset_index(drop=True, inplace=True)
df
```

Out[20]:

	Sentence	Sentiment
0	The GeoSolutions technology will leverage Bene...	positive
1	ESI on lows down 150 to 250 BK a real possibility	negative
2	For the last quarter of 2010 Componenta s net...	positive
3	According to the FinnishRussian Chamber of Com...	neutral
4	The Swedish buyout firm has sold its remaining...	neutral
...	...	...
5837	RISING costs have forced packaging producer Hu...	negative
5838	Nordic Walking was first used as a summer trai...	neutral
5839	According shipping company Viking Line the EU...	neutral
5840	In the building and home improvement trade sa...	neutral
5841	HELSINKI AFX KCI Konecranes said it has won a...	positive

5842 rows × 2 columns

Tokenizing sentences, applying padding, lablling the encoder and then splitting the data into train and test sets

In [23]:

```
# Tokenizing the sentences column within the dataframe
tokenizer= Tokenizer()
Sentences= df['Sentence'].tolist()
tokenizer.fit_on_texts(Sentences)
sequences= tokenizer.texts_to_sequences(Sentences)
print('The max length in Sentences is:',max([len(x) for x in sequences]))
print('The Unique word in the Sentences are:',len(tokenizer.word_index))

# Undertaking the padding process to make sure that the arrays generated after tokenizati
on of words are always going to have the same length.
input_pad_sequences=pad_sequences(sequences,maxlen=70,padding='pre')
X=input_pad_sequences
y=df['Sentiment']

# label encoder
le= LabelEncoder()
y= le.fit_transform(y)
y= to_categorical(y)

# train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
The max length in Sentences is: 52
The Unique word in the Sentences are: 12650
(4673, 70)
(1169, 70)
(4673, 3)
(1169, 3)
```

Building a sequential model, assigning layers and training it on the dataset.

In [39]:

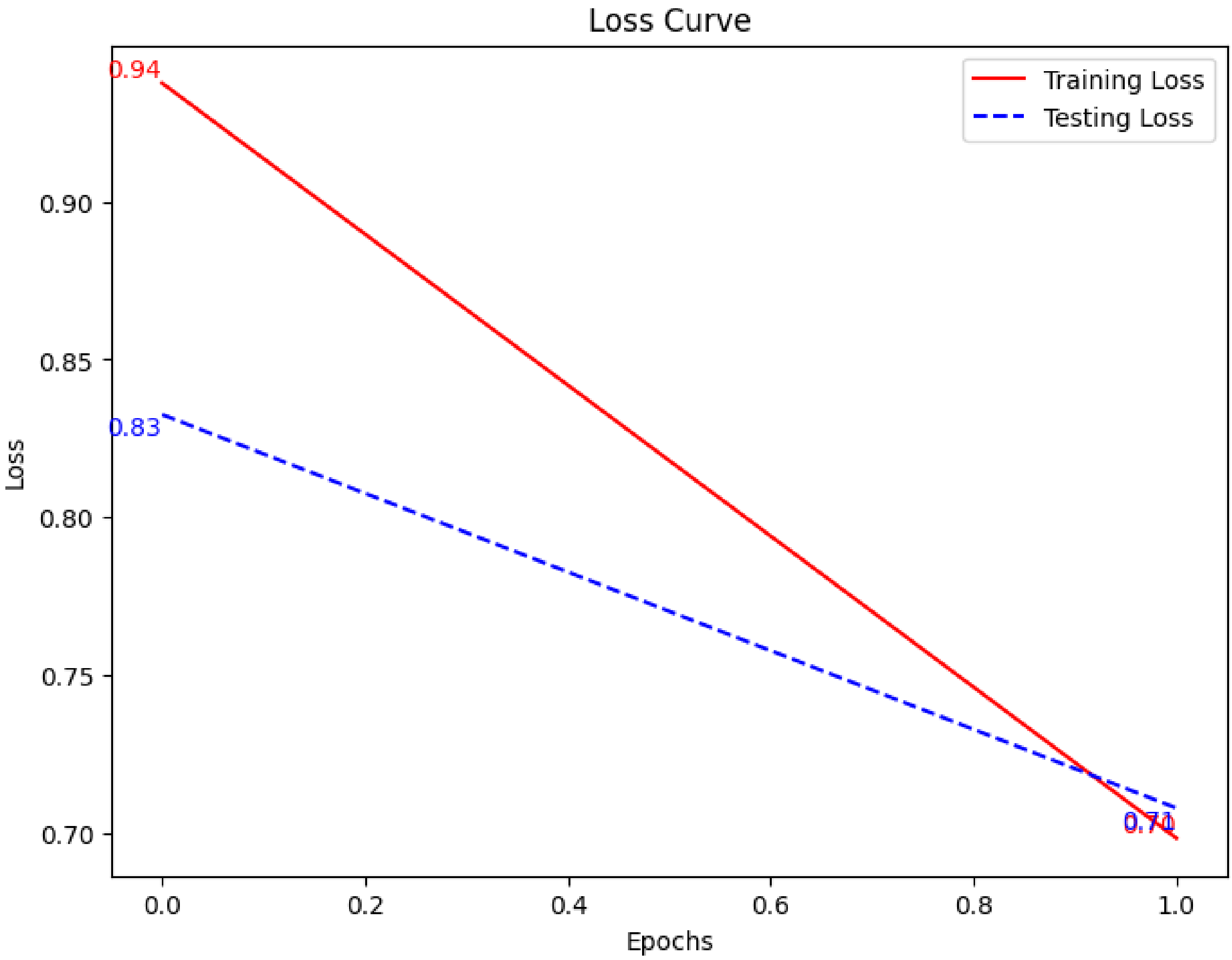
```
#Importing an initializer  for initializing weights in a neural network
```

```
from keras.initializers import glorot_normal

#Initializing a sequential model which has stacks of layers. Every layer has exactly one
input tensor and one output tensor
model = Sequential()

#Embedding to convert words in vectors of fixed size(second argument) taking into account
a vocabulary of a certain size(first argument)
model.add(Embedding(40758,200,input_length=70,embeddings_initializer=glorot_normal()))

# Adds LSTM (Long Short-Term Memory) layers to the model. LSTM layers are a type of recur
rent neural network (RNN) layer that are good at capturing long-term dependencies in sequ
ence data.
# Return_sequences=True means the output for each timestep is returned (necessary for sta
cking LSTM layers).
# Dropout=0.6 is used for regularization to prevent overfitting by ignoring randomly sele
cted neurons during training.
model.add(LSTM(100,return_sequences=True,dropout=0.6))
model.add(LSTM(100,return_sequences=True,dropout=0.6))
model.add(LSTM(100,return_sequences=True,dropout=0.6))
model.add(LSTM(100))

#Adding a Dropout layer that randomly sets a fraction (0.5) of input units to 0 at each u
pdate during training, which also helps in preventing overfitting.
model.add(Dropout(0.5))

# Adding a Dense layer (fully connected layer) with 3 units and a softmax activation fun
ction.
# This is typically used as the output layer for multi-class classification problems
model.add(Dense(3,activation='softmax'))

# Compiles the model with the Adam optimizer and categorical crossentropy loss function,
which is appropriate for multi-class classification problems.
# The model will use accuracy as the metric for evaluation.
model.compile(optimizer= 'adam',loss= 'categorical_crossentropy',metrics=['accuracy'])

# Model Training by splitting the data into test and train
history =model.fit(X_train, y_train,epochs=2,batch_size=32,validation_data=(X_test,y_tes
t))
```

```
Epoch 1/2
147/147 [==============================] - 17s 94ms/step - loss: 0.9376 - accuracy: 0.574
8 - val_loss: 0.8325 - val_accuracy: 0.6672
Epoch 2/2
147/147 [==============================] - 13s 88ms/step - loss: 0.6982 - accuracy: 0.716
5 - val_loss: 0.7078 - val_accuracy: 0.6972
```

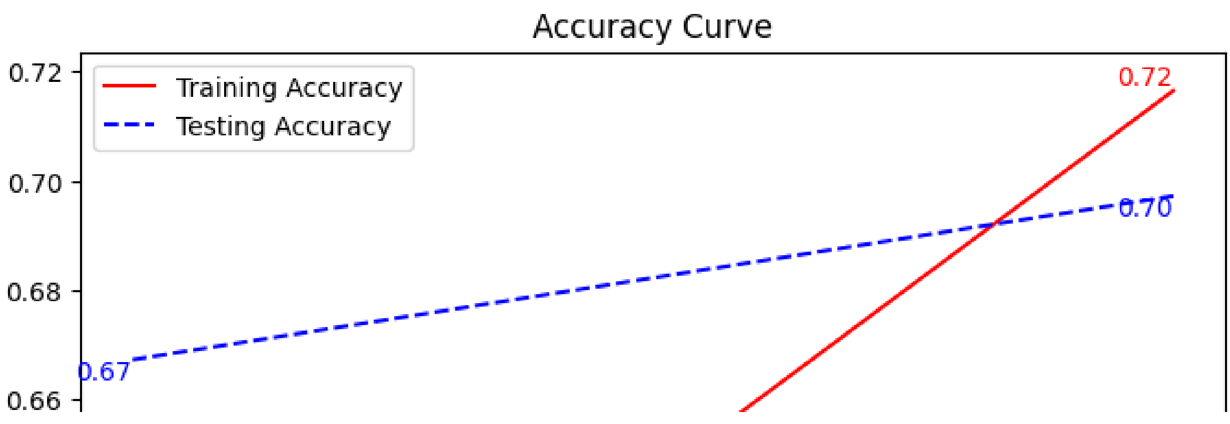
In [43]:

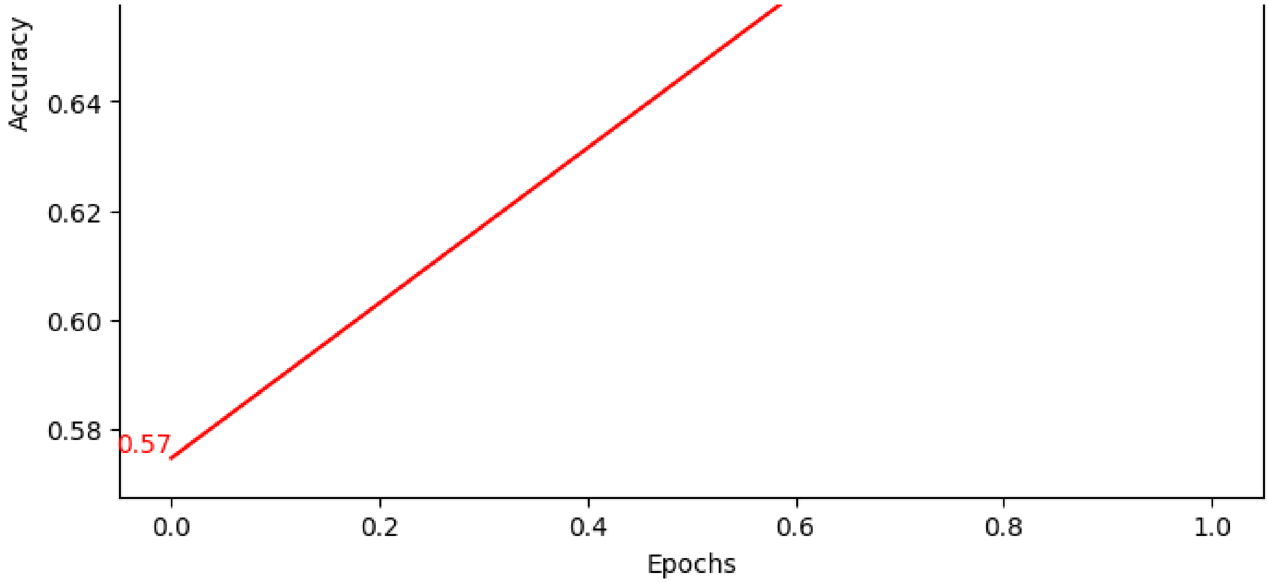
```
# Plotting the Loss Curves of the above learning process
plt.figure(figsize=(8,6))

#Plotting training loss
plt.plot(history.history['loss'],color='red')

#Plotting validation loss
plt.plot(history.history['val_loss'],ls='--',color='blue')

# Add data labels
for i, (loss, val_loss) in enumerate(zip(history.history['loss'], history.history['val_l
oss'])):
    # # Annotate certain points, e.g., last point
    # if i == len(history.history['loss']) - 1:
    plt.text(i, loss, f'{loss:.2f}', ha='right', va='bottom', color='red')
    plt.text(i, val_loss, f'{val_loss:.2f}', ha='right', va='top', color='blue')

plt.legend(['Training Loss','Testing Loss'])
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss Curve')
plt.show()
```



In [42]:

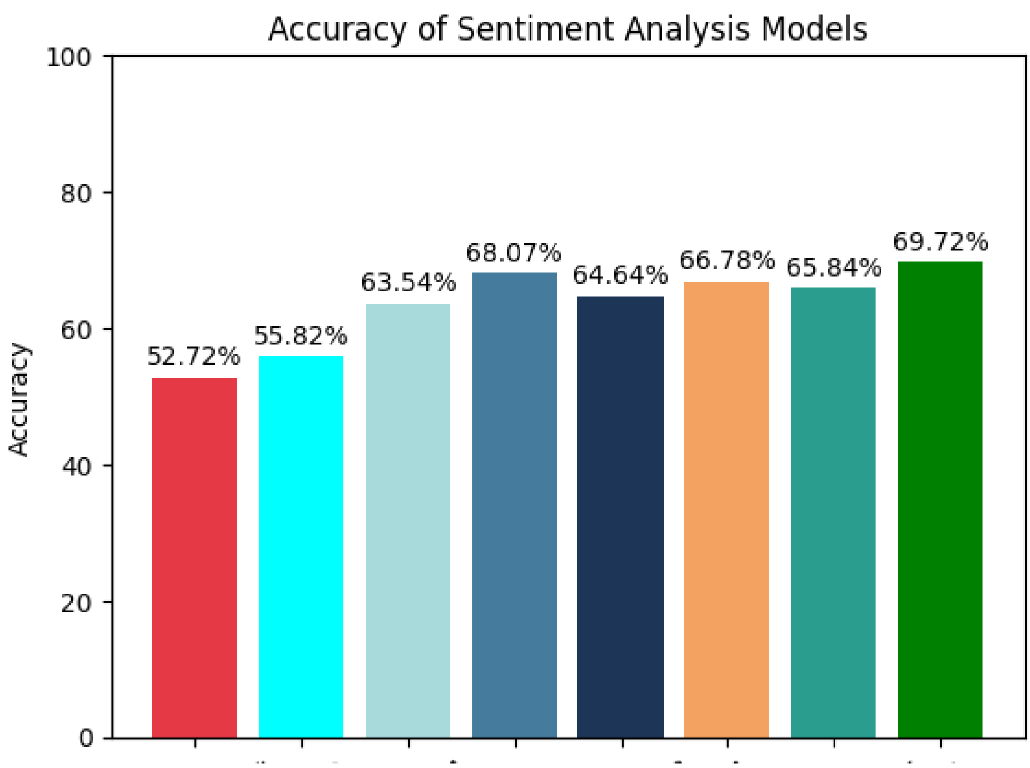
```
#Plotting the accuracy curves of the above learning process
plt.figure(figsize=(8,6))

#Plotting Training accuracy
plt.plot(history.history['accuracy'],color='red')

#Plotting Testing accuracy
plt.plot(history.history['val_accuracy'],ls='--',color='blue')

# Add data labels
for i, (acc, val_acc) in enumerate(zip(history.history['accuracy'], history.history['val
_accuracy'])):
    # # Annotate certain points, e.g., last point
    # if i == len(history.history['accuracy']) - 1:
    plt.text(i, acc, f'{acc:.2f}', ha='right', va='bottom', color='red')
    plt.text(i, val_acc, f'{val_acc:.2f}', ha='right', va='top', color='blue')

plt.legend(['Training Accuracy','Testing Accuracy'])
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Accuracy Curve')
plt.show()
```

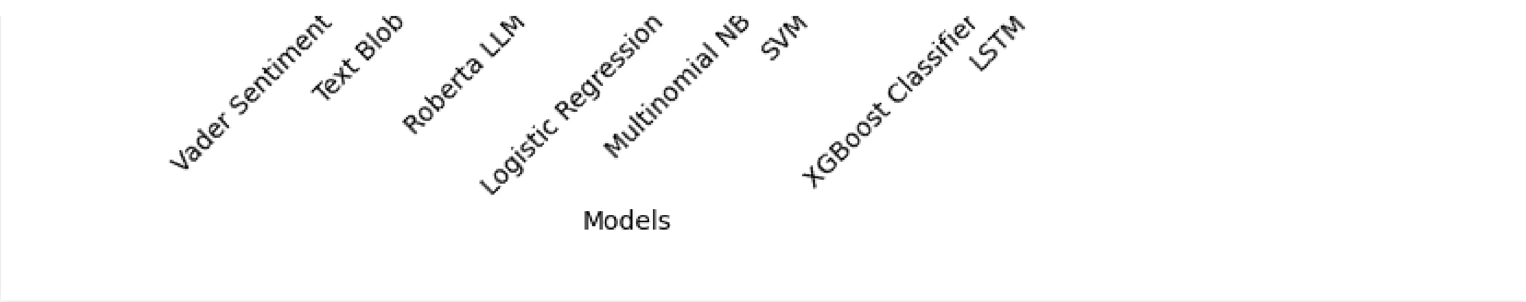




In [51]:

```
#Plotting the accuracies achieved so far for the different models used
models = ['Vader Sentiment','Text Blob','Roberta LLM','Logistic Regression','Multinomial NB','SVM','XGBoost Classifier','LSTM']
LSTM_accuracy=history.history['val_accuracy'][-1]*100
accuracies = [vader_sentiment_accuracy,text_blob_accuracy,Roberta_accuracy,accuracy_lr,accuracy_mnb,accuracy_svm,accuracy_xgb,LSTM_accuracy]


# Specify a color for each bar
colors=['#E63946', 'aqua','#A8DADC','#457B9D','#1D3557','#F4A261','#2A9D8F','green']

#Drafting the actual plot
plt.bar(models, accuracies, color=colors)
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Accuracy of Sentiment Analysis Models')
plt.ylim(0, 100)  # Set the y-axis limits to 0 and 100 for accuracy percentage
plt.xticks(rotation=45)  # Rotate x-axis labels if needed

# Annotate each bar with its value
for i, value in enumerate(accuracies):
    plt.text(i, value + 1, f'{value:.2f}%', ha='center', va='bottom')

plt.show()
```




Vader Sentiment
Text Blob
Roberta LLM
Logistic Regression
Multinomial NB
SVM
XGBoost Classifier
LSTM
Models