Chapter 4: Exploratory Data Analysis/Initial Results

4.1 Introduction

In chapter-4, the exploratory data analysis (EDA) and initial results will be the main focus of the study. It is divided into three main parts: 4.2 Visualisations and descriptive statistics for data exploration, 4.3 Feature engineering, 4.4 Expected results. Section 4.2.1 using different visualization methods, the study will uncover the patterns, trends, and potential correlations between news sentiment and stock price changes in the Malaysian market. For section 4.2.2, by analyzing metrics like mean, median, standard deviation, and frequency counts, the research will provide a comprehensive understanding of the sentiment distribution and characteristics within the dataset. Section 4.3 using techniques like text preprocessing, categorical feature encoding, and the incorporation of relevant stock market features to transform the raw data into a format that suitable for the subsequent predictive modeling. In section 4.4, preliminary insights generated from the exploratory data analysis that affects stock price changes, guiding the direction and focus for more advanced modeling and evaluation.

4.2 Visualisations and descriptive statistics for data exploration

Visualizations and descriptive statistics play a crucial role in exploring and understanding the data (Qin et al., 2020). The duo will be employed in this research for effective presentation and analysis of results.

4.2.1 Visualisation tools

For this study, the first step will examine the distribution of sentiment scores using histograms. These visualizations will provide insights into the central tendency, spread, and skewness of the sentiment scores derived from both machine-learning models and lexicon-based approaches. Histograms will be used to visualize the frequency of different sentiment scores, which will allow how sentiments are distributed across the articles to be seen. Box plots will be used in this exploration to highlight the median, quartiles, and potential outliers, thus offering a clear view of the variability and central tendencies of the sentiment scores. Such visual tools, according to Ortis, et al. (2021) are essential in understanding whether the sentiment distribution is balanced or biased towards positive, negative, or neutral sentiments.

Time series analysis is another powerful approach this research will explored. Line plots of sentiment scores over time can reveal trends, patterns, and anomalies in the data, which can then be correlated with stock price movements. By resampling the data on a monthly or weekly basis, the study can observe how average sentiment scores evolve and identify periods of significant sentiment shifts. Additionally, scatter plots and heatmaps will be used for correlation analysis. Scatter plots can visually demonstrate the relationship between sentiment scores and stock prices, potentially uncovering trends or patterns that indicate a correlation between media sentiment and market behaviour. Heatmaps of correlation matrices can concisely present the direction of relationships between multiple variables (sentiment scores and various stock market indicators) and their strength. These visualizations, combined with rolling mean and standard deviation plots, will help in identifying trends and volatility in sentiment over time, providing a dynamic view of how sentiment interacts with stock market movements.

4.2.2 Descriptive statistics

Descriptive statistics complement visualization tools by providing a numerical summary of the data (Narechania, et al., 2020). Metrics such as mean, median, standard deviation, and variance offer a quantitative understanding of the central tendency and dispersion of sentiment scores which will be used in this research. Frequency counts of sentiment categories (positive, negative, neutral) add another layer of analysis that will help to quantify the overall sentiment landscape of the news articles. By combining these descriptive statistics with visual tools, the research will comprehensively explore the sentiment data, uncovering patterns and insights that inform the relationship between media sentiment and stock price movements. This integrated approach of visualization and descriptive statistics will not only enhance the understanding of the dataset but also provides a solid foundation for further predictive modelling and analysis in the context of financial markets.

4.3 Feature engineering

Feature engineering is the process that extracts and creates new variables (features) from raw data that can help improve the performance of machine learning models by using domain knowledge (Verdonck et al., 2021). It involves selecting, modifying, and transforming data to enhance the predictive power of models. Effective feature engineering, according to Fan et al. (2019), can lead to better model accuracy and insights, as it allows the model to focus on the most relevant aspects of the data. In the context of this research, feature engineering is crucial to transform raw text data from news articles into meaningful features that can be used to predict stock price movements. In this research, feature engineering will be applied in the following:

- **Text Preprocessing**: This involves **tokenization** which has to do with breaking down the article content into separate words or tokens; **stop words removal** (remove the common words that do not have important meaning), and **stemming and lemmatization** (reducing words to their root forms to ensure consistency e.g. "running" to "run").
- **Sentiment Scores**: This involves **overall sentiment score** (using NLP models to assign a sentiment score to each article, indicating whether the sentiment is positive, neutral, or negative, and **lexicon-based sentiment score** (calculating sentiment based on predefined lexicons to provide an alternative measure of sentiment).
- **Textual Features**: This involves **the term frequency-inverse document frequency (TF-IDF),** i. e. Measuring the importance of words in an article relative to a corpus of articles, helping to highlight unique and significant terms, and **N-grams (e**xtracting contiguous sequences of n words e.g., bigrams, trigrams, to capture context and common phrases).
- **Temporal Features**: This has to do with **publication date and time** (incorporating the date and time when the article was published to analyse temporal patterns and their impact on stock prices) and **lag features** (i.e. creating lagged versions of sentiment scores to capture delayed effects of news sentiment on stock prices, e.g., sentiment score from the previous day or week).
- **Categorical Features**: Such features include **source and author** (encoding the source and author of the article to account for potential biases or credibility variations).
- **Stock Market Features**: This includes **previous day's stock price** (including the stock price from the previous trading day to account for existing market trends) and trading **volume** (incorporating trading volume to understand market activity and sentiment impact).

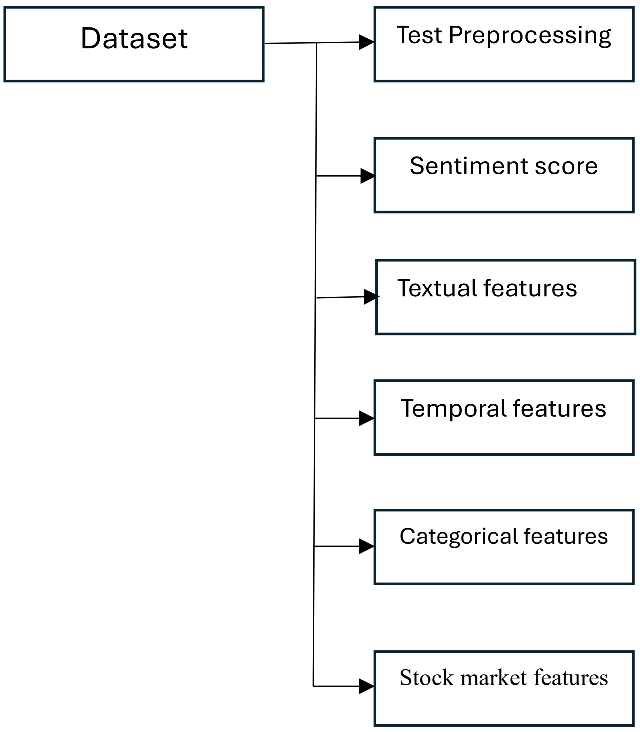


Figure 4.1: Feature engineering applications on the datasets

4.4 Expected Results

S/No	Research objectives	Expected results
1	To analyze the nuanced impact of specific sentiments expressed in financial news headlines on stock price movements within the Malaysian stock market context.	• Detailed Sentiment Categories: Identification and classification of specific sentiments (optimism, pessimism, fear, confidence) expressed in financial news headlines. • Impact on Stock Price Movements: Quantitative analysis showing how these specific sentiments impact stock price movements. For example, headlines that expressed strong confidence might correlate with an increase in stock prices,

S/No	Research objectives	Expected results
		while negative headlines might lead to a decrease. • Sector-Specific Impact: Insights to check how different sectors (technology, finance, consumer goods) are affected by various sentiment types, separately. Certain sectors may react more strongly to specific sentiments than others. • Sentiment Intensity: Analysis to check how the intensity of sentiment (strongly positive/negative vs. mildly positive/negative) affects the magnitude of stock price movements.
2	The aim is to recognize and assess the main obstacles in accurately forecasting stock prices in the Malaysian market through sentiment analysis methods, and improve advanced models such as LSTM networks to boost prediction accuracy by tackling these obstacles.	• Performance Metrics: Compare the performance metrics (precision, accuracy, F1-score, recall, etc.) for traditional sentiment analysis techniques and advanced machine learning models in predicting stock price movements. • Model Effectiveness: Findings that indicate which models (e.g., Naive Bayes, Lexicon-based, LSTM networks) are more effective in capturing the sentiment from news headlines and predicting stock price movements.

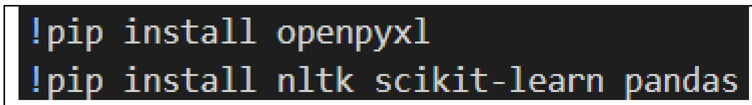
S/No	Research objectives	Expected results
		• Feature Importance: Insights into which features (specific words, phrases, or sentiment scores) are most predictive of stock price movements for each model. • Time Sensitivity: Evaluation of how different models can handle the temporal aspect of news sentiment and stock price prediction. Possibly showing that LSTM networks can account for sequential data and outperform the traditional methods.
3	To analyze the effects of various sentiment analysis algorithms, like Hybrid Naive Bayes and Opinion Lexicon-based methods, on forecasting stock price changes in Malaysia, and enhancing these algorithms to enhance prediction accuracy.	• Temporal Patterns: Identification of temporal patterns showing the correlation of sentiment data from news headlines with historical stock price movements. For example, a lagged effect where sentiment influences stock prices after a certain time delay. • Causality and Correlation: Analysis of causality and correlation between sentiment changes and stock price movements over different time frames (either immediate, short-term, or long-term). • Volatility Analysis: Insights to check sentiment-driven news impacts stock price volatility over

S/No	Research objectives	Expected results
		time. Periods of high sentiment activity might correspond with higher volatility. • Event-Based Analysis: Case studies of significant events (e.g., earnings announcements, political changes) and their temporal impact on stock prices, revealing specific patterns during these events. • Historical Trends: Uncovering long-term trends where certain types of sentiment consistently lead or lag behind stock price movements, providing a historical perspective on sentiment's influence on the market.

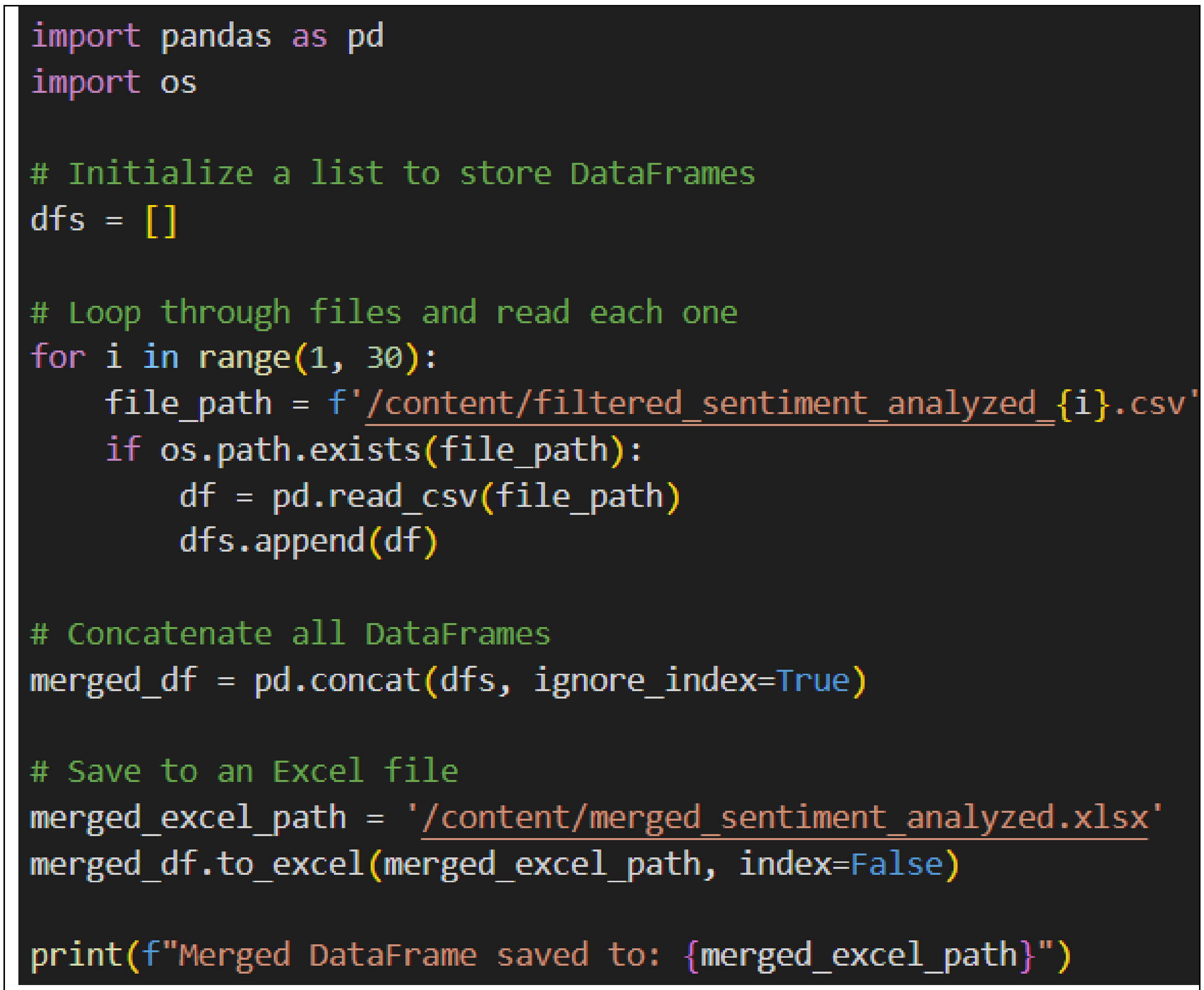
Table 4.1: Research objectives and expected results

4.4.1 Machine Learning (Initial Result)

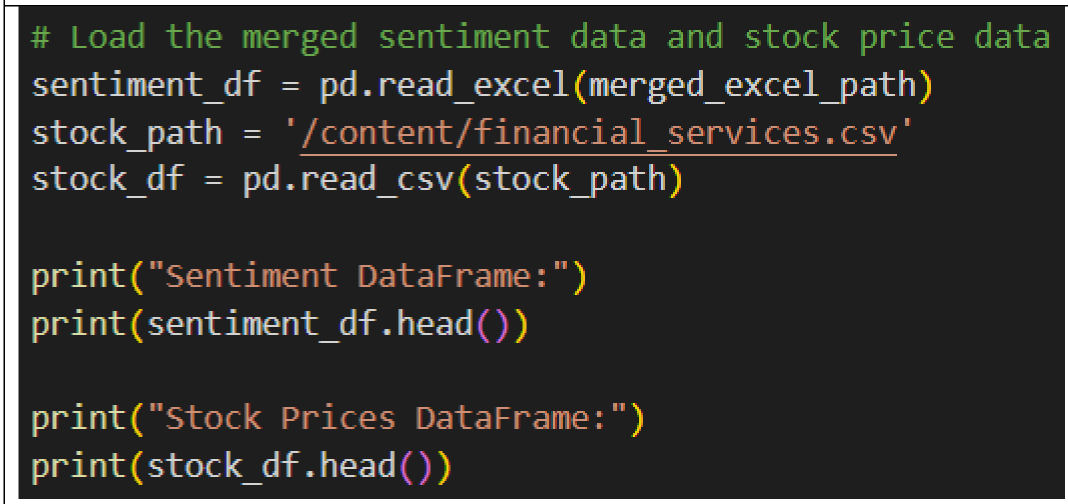
The process and steps to get initial result of machine learning by using Scikit-learn (sklearn) at Colab as shown at below:



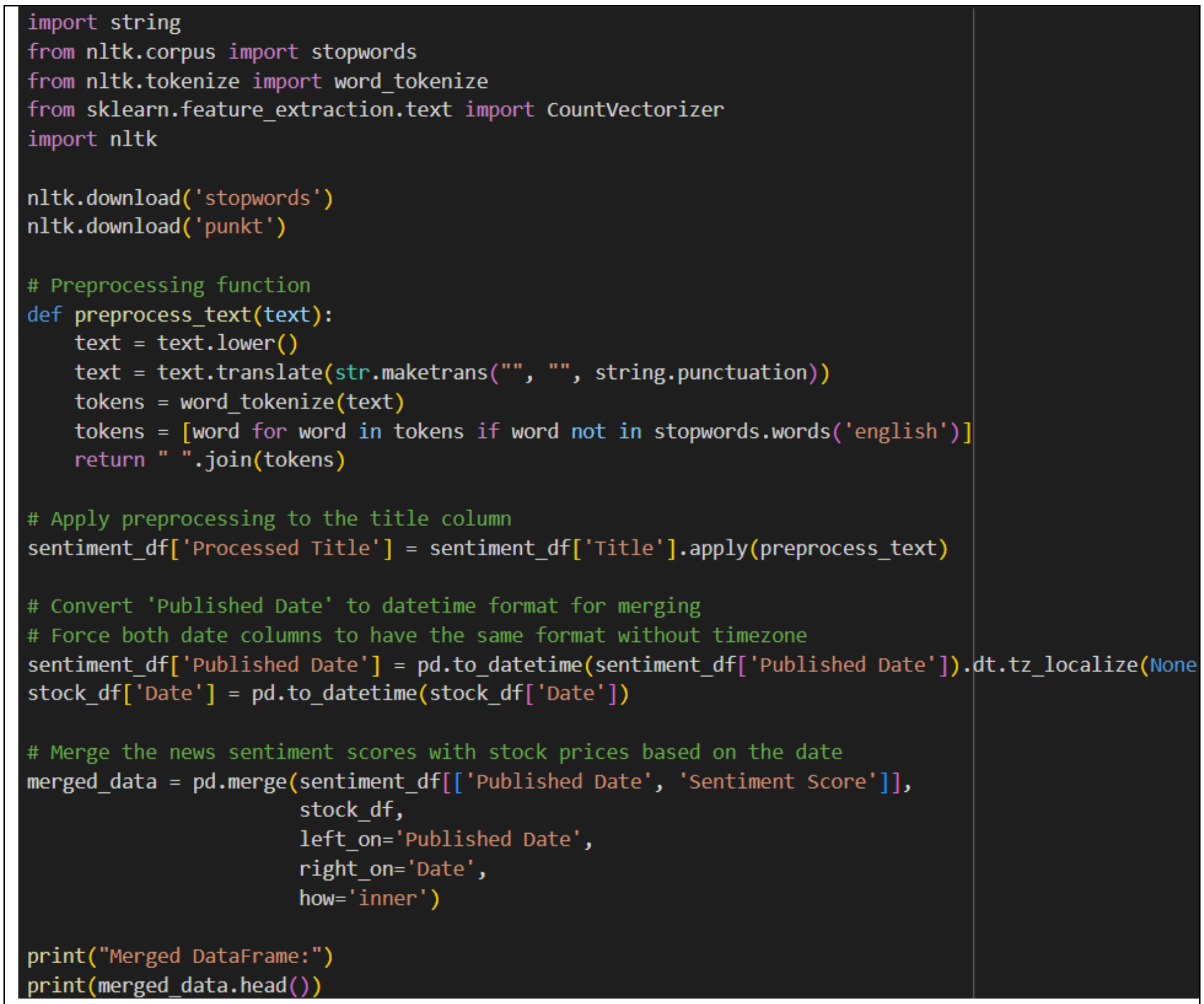
```
!pip install openpyxl
!pip install nltk scikit-learn pandas
```



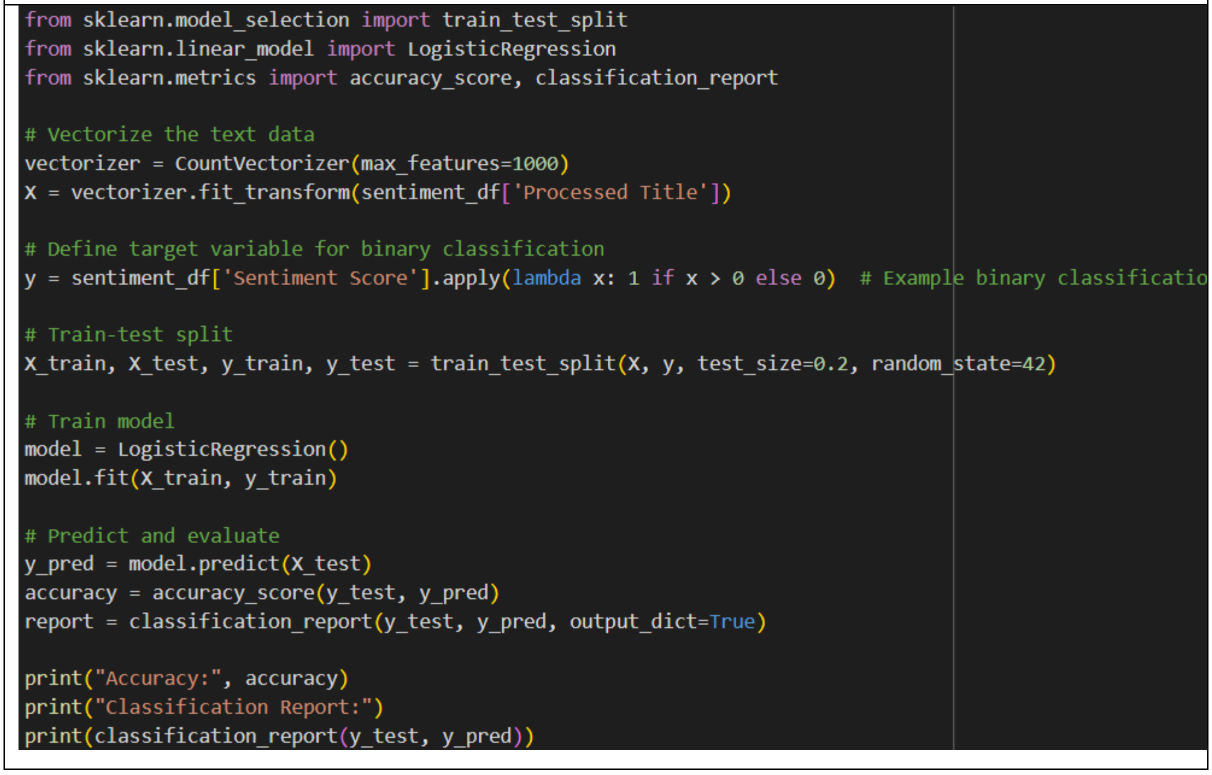
```python
import pandas as pd
import os

# Initialize a list to store DataFrames
dfs = []

# Loop through files and read each one
for i in range(1, 30):
    file_path = f'/content/filtered_sentiment_analyzed_{i}.csv'
    if os.path.exists(file_path):
        df = pd.read_csv(file_path)
        dfs.append(df)

# Concatenate all DataFrames
merged_df = pd.concat(dfs, ignore_index=True)

# Save to an Excel file
merged_excel_path = '/content/merged_sentiment_analyzed.xlsx'
merged_df.to_excel(merged_excel_path, index=False)

print(f"Merged DataFrame saved to: {merged_excel_path}")
```



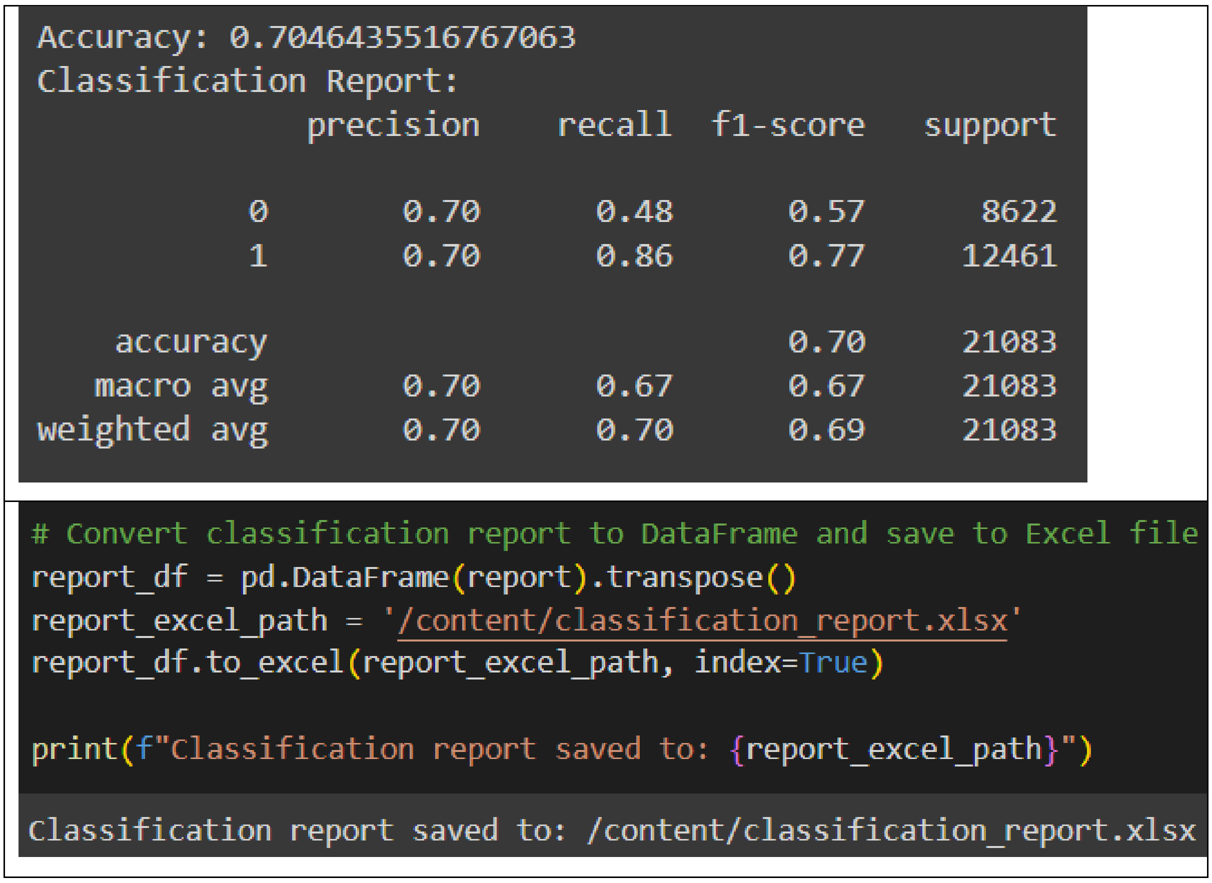
```python
# Load the merged sentiment data and stock price data
sentiment_df = pd.read_excel(merged_excel_path)
stock_path = '/content/financial_services.csv'
stock_df = pd.read_csv(stock_path)

print("Sentiment DataFrame:")
print(sentiment_df.head())

print("Stock Prices DataFrame:")
print(stock_df.head())
```



```
import string
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import CountVectorizer
import nltk

nltk.download('stopwords')
nltk.download('punkt')

# Preprocessing function
def preprocess_text(text):
    text = text.lower()
    text = text.translate(str.maketrans("", "", string.punctuation))
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stopwords.words('english')]
    return " ".join(tokens)

# Apply preprocessing to the title column
sentiment_df['Processed Title'] = sentiment_df['Title'].apply(preprocess_text)

# Convert 'Published Date' to datetime format for merging
# Force both date columns to have the same format without timezone
sentiment_df['Published Date'] = pd.to_datetime(sentiment_df['Published Date']).dt.tz_localize(None
stock_df['Date'] = pd.to_datetime(stock_df['Date'])

# Merge the news sentiment scores with stock prices based on the date
merged_data = pd.merge(sentiment_df[['Published Date', 'Sentiment Score']],
                       stock_df,
                       left_on='Published Date',
                       right_on='Date',
                       how='inner')

print("Merged DataFrame:")
print(merged_data.head())
```



```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Vectorize the text data
vectorizer = CountVectorizer(max_features=1000)
X = vectorizer.fit_transform(sentiment_df['Processed Title'])

# Define target variable for binary classification
y = sentiment_df['Sentiment Score'].apply(lambda x: 1 if x > 0 else 0)  # Example binary classificatio

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred, output_dict=True)

print("Accuracy:", accuracy)
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

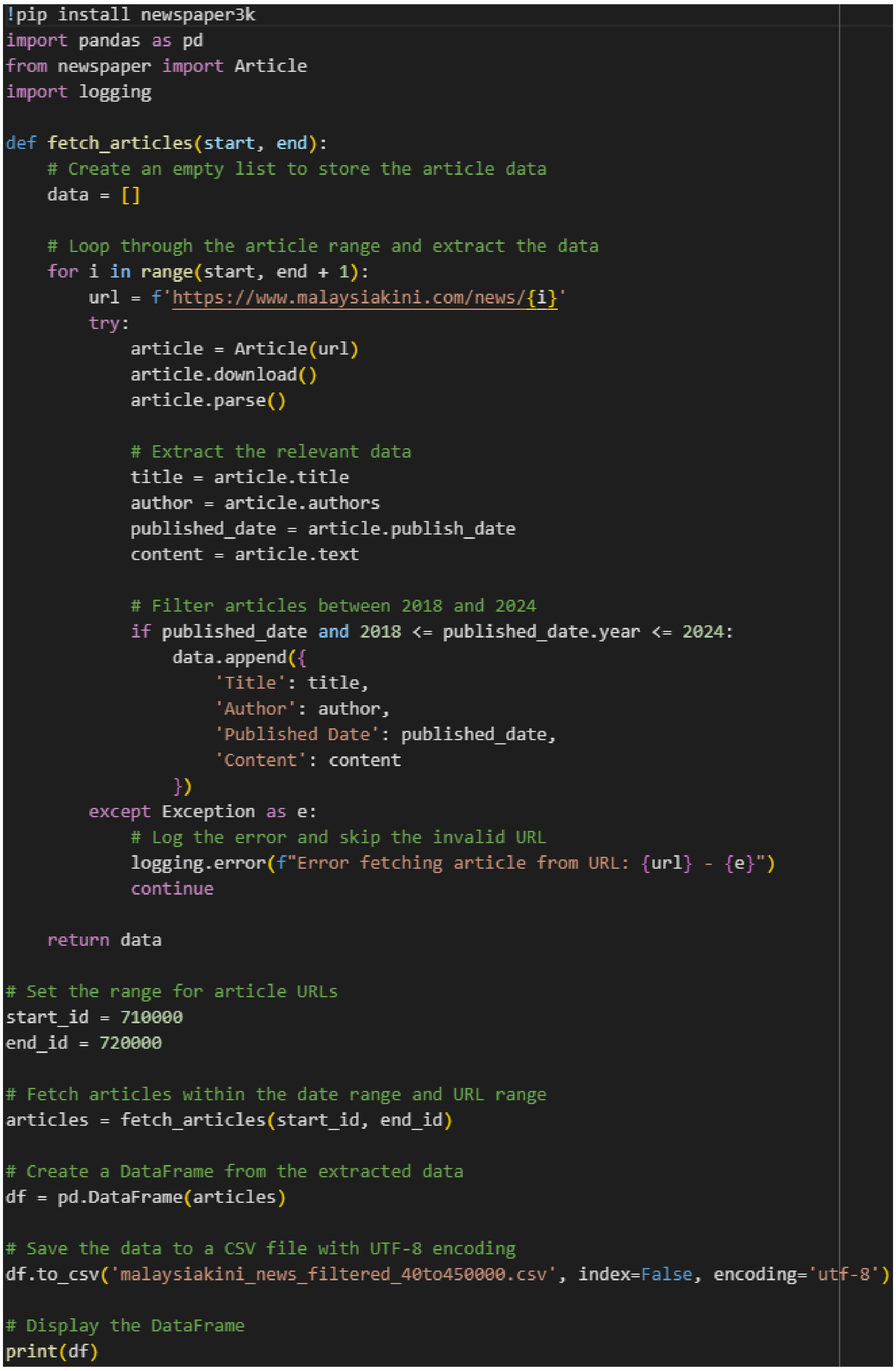


```
Accuracy: 0.7046435516767063
Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.48      0.57      8622
           1       0.70      0.86      0.77     12461

    accuracy                           0.70     21083
   macro avg       0.70      0.67      0.67     21083
weighted avg       0.70      0.70      0.69     21083
```

```
# Convert classification report to DataFrame and save to Excel file
report_df = pd.DataFrame(report).transpose()
report_excel_path = '/content/classification_report.xlsx'
report_df.to_excel(report_excel_path, index=True)

print(f"Classification report saved to: {report_excel_path}")
```

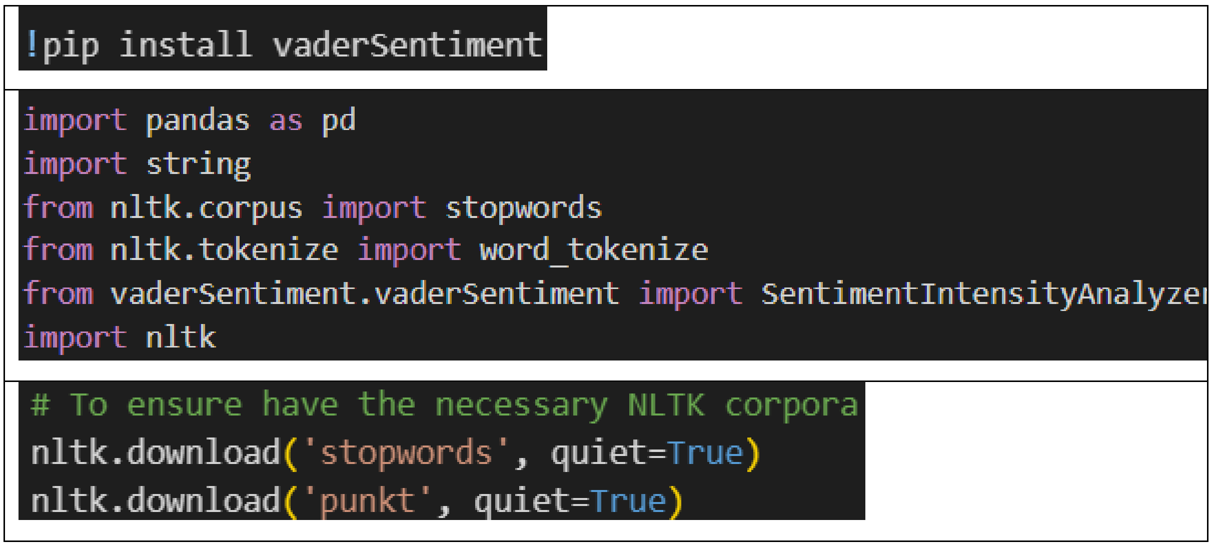
```
Classification report saved to: /content/classification_report.xlsx
```

Figure 4.2: Initial result of machine learning by Scikit-learn



```python
!pip install newspaper3k
import pandas as pd
from newspaper import Article
import logging

def fetch_articles(start, end):
    # Create an empty list to store the article data
    data = []

    # Loop through the article range and extract the data
    for i in range(start, end + 1):
        url = f'https://www.malaysiakini.com/news/{i}'
        try:
            article = Article(url)
            article.download()
            article.parse()

            # Extract the relevant data
            title = article.title
            author = article.authors
            published_date = article.publish_date
            content = article.text

            # Filter articles between 2018 and 2024
            if published_date and 2018 <= published_date.year <= 2024:
                data.append({
                    'Title': title,
                    'Author': author,
                    'Published Date': published_date,
                    'Content': content
                })
        except Exception as e:
            # Log the error and skip the invalid URL
            logging.error(f"Error fetching article from URL: {url} - {e}")
            continue

    return data

# Set the range for article URLs
start_id = 710000
end_id = 720000

# Fetch articles within the date range and URL range
articles = fetch_articles(start_id, end_id)

# Create a DataFrame from the extracted data
df = pd.DataFrame(articles)

# Save the data to a CSV file with UTF-8 encoding
df.to_csv('malaysiakini_news_filtered_40to450000.csv', index=False, encoding='utf-8')

# Display the DataFrame
print(df)
```

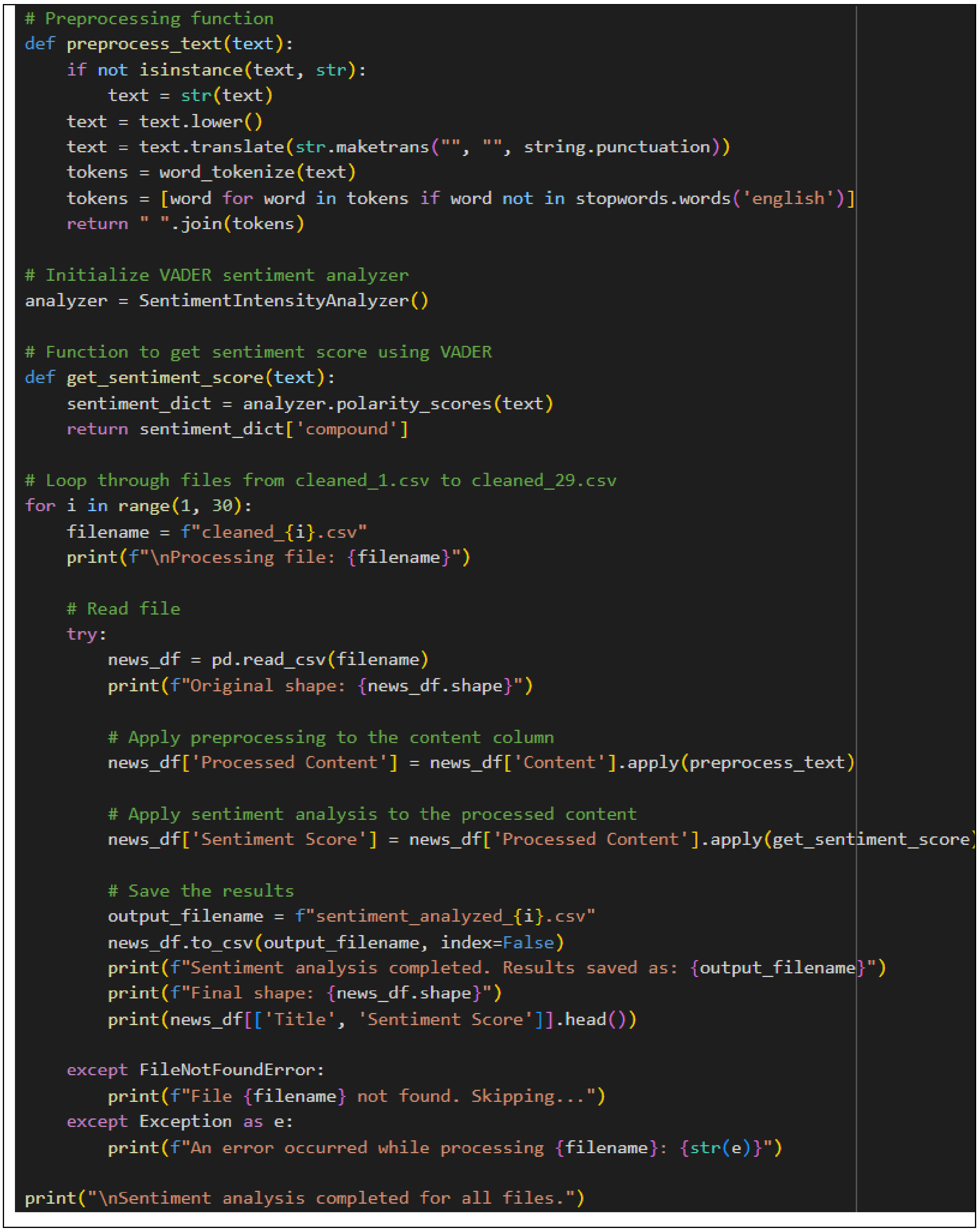
Figure 4.3: Coding for Data Collection of News title



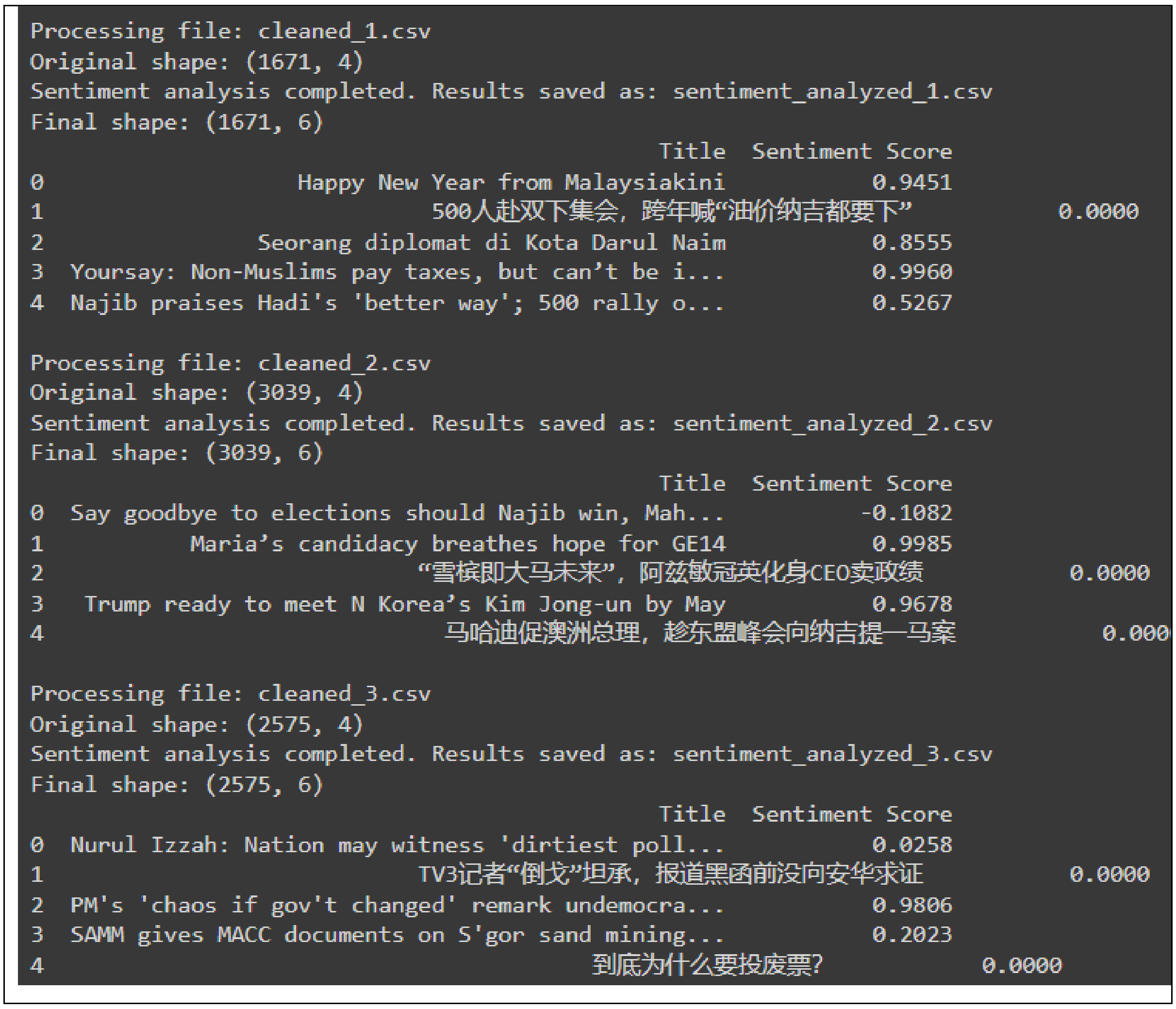
```
!pip install vaderSentiment
```

```
import pandas as pd
import string
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import nltk
```

```
# To ensure have the necessary NLTK corpora
nltk.download('stopwords', quiet=True)
nltk.download('punkt', quiet=True)
```



```python
# Preprocessing function
def preprocess_text(text):
    if not isinstance(text, str):
        text = str(text)
    text = text.lower()
    text = text.translate(str.maketrans("", "", string.punctuation))
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stopwords.words('english')]
    return " ".join(tokens)

# Initialize VADER sentiment analyzer
analyzer = SentimentIntensityAnalyzer()

# Function to get sentiment score using VADER
def get_sentiment_score(text):
    sentiment_dict = analyzer.polarity_scores(text)
    return sentiment_dict['compound']

# Loop through files from cleaned_1.csv to cleaned_29.csv
for i in range(1, 30):
    filename = f"cleaned_{i}.csv"
    print(f"\nProcessing file: {filename}")

    # Read file
    try:
        news_df = pd.read_csv(filename)
        print(f"Original shape: {news_df.shape}")

        # Apply preprocessing to the content column
        news_df['Processed Content'] = news_df['Content'].apply(preprocess_text)

        # Apply sentiment analysis to the processed content
        news_df['Sentiment Score'] = news_df['Processed Content'].apply(get_sentiment_score)

        # Save the results
        output_filename = f"sentiment_analyzed_{i}.csv"
        news_df.to_csv(output_filename, index=False)
        print(f"Sentiment analysis completed. Results saved as: {output_filename}")
        print(f"Final shape: {news_df.shape}")
        print(news_df[['Title', 'Sentiment Score']].head())

    except FileNotFoundError:
        print(f"File {filename} not found. Skipping...")
    except Exception as e:
        print(f"An error occurred while processing {filename}: {str(e)}")

print("\nSentiment analysis completed for all files.")
```



```
Processing file: cleaned_1.csv
Original shape: (1671, 4)
Sentiment analysis completed. Results saved as: sentiment_analyzed_1.csv
Final shape: (1671, 6)
                                               Title  Sentiment Score
0                    Happy New Year from Malaysiakini           0.9451
1                              500人赴双下集会，跨年喊“油价纳吉都要下”           0.0000
2                 Seorang diplomat di Kota Darul Naim           0.8555
3  Yoursay: Non-Muslims pay taxes, but can’t be i...           0.9960
4  Najib praises Hadi's 'better way'; 500 rally o...           0.5267

Processing file: cleaned_2.csv
Original shape: (3039, 4)
Sentiment analysis completed. Results saved as: sentiment_analyzed_2.csv
Final shape: (3039, 6)
                                               Title  Sentiment Score
0  Say goodbye to elections should Najib win, Mah...          -0.1082
1           Maria’s candidacy breathes hope for GE14           0.9985
2                             “雪槟即大马未来”，阿兹敏冠英化身CEO卖政绩           0.0000
3   Trump ready to meet N Korea’s Kim Jong-un by May           0.9678
4                               马哈迪促澳洲总理，趁东盟峰会向纳吉提一马案           0.000

Processing file: cleaned_3.csv
Original shape: (2575, 4)
Sentiment analysis completed. Results saved as: sentiment_analyzed_3.csv
Final shape: (2575, 6)
                                               Title  Sentiment Score
0  Nurul Izzah: Nation may witness 'dirtiest poll...           0.0258
1                             TV3记者“倒戈”坦承，报道黑函前没向安华求证           0.0000
2  PM's 'chaos if gov't changed' remark undemocra...           0.9806
3  SAMM gives MACC documents on S'gor sand mining...           0.2023
4                                        到底为什么要投废票?           0.0000
```

Figure 4.4: Coding to get sentiment score