DETECTING NEWS BIAS IN THE EMERGING MARKETS USING THE TRANSFORMER MODEL

by

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Declaration of authorship

I Gift Mahlatse Mphahlele declare that Detecting News Bias in Emerging Markets Using the Transformer model hereby submitted to the University of Limpopo, for the degree of Masters of Science in e-science has not previously been submitted by me for a degree at this or any other university; that it is my work in design and in execution, and that all material contained herein has been duly acknowledged.

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Dedication

This research is dedicated to my mother and sisters, Violet Kholofelo Mphahlele, Nthabiseng Beauty Mphahlele, and Liezel Nkadimeng for their endless support, care, and encouragement throughout my studies, without them I honestly do not think I would have completed the study.

Abstract

The news readers from western countries are exposed to news reports from the global news media outlets that focus fundamentally on the conflicts happening in third-world countries such as those in South Africa and Nigeria. Many financial institutions from western countries provide financial opportunities to emerging markets in Africa. For this purpose, an important source of information used by those institutions is the global media outlets reporting the financial news. Therefore, there is a need to assess the credibility of global news outlets in covering financial news for African countries. This study focuses on detecting financial news bias in the emerging markets countries such as South Africa and Nigeria using a transformer model called BERT. The transformer model for sentiment classification was developed using the pre-trained model to achieve this goal. The financial news titles from the local and global news media outlets about South Africa and Nigeria were downloaded from the online news database called Global Database of Events, Language, and Tone project, and they were injected into the BERT model to compute the sentiment scores and labels for each news title. The pretrained BERT model achieved a good accuracy of 89.76% after being fine-tuned with a sample of 5000 movie review dataset. We found that both the local and global news media outlets report more positive financial news than negative news for both countries based on the results from the sentiment scores and labels. To assess news bias between the local and global news media outlets for South Africa and Nigeria, the average monthly sentiment scores were compared with the average monthly exchange rates for each country to determine the correlation between them and test if that correlation is significant or not. It was found that only the Nigerian global news coverage correlates with the exchange rates. Therefore, it was concluded that there is no evidence to suggest that the global news media outlets are biased in reporting the financial news in emerging markets countries since it was seen that the sentiment scores from the local news outlets for both countries do not correlate with their respective exchanges rates. It is evident that the transformer model can be used to accurately compute the sentiment in the financial news articles for the purpose of detecting news bias.

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Chapter 1: Introduction

1.1 Problem statement

There are different kind of news as such sport, entertainment, political, science, lifestyle, and financial news, to name a few. Financial news are news articles that focus on covering the financial sector such as asset management, banking investment, regulation around salaries, fintech, employment trends, and trading and regulation. Financial news articles continue to play a significant role in the distribution of financial information across the globe, more especially to investors in South Africa (Modise,2019). Nowadays media outlets report more negative news such as killings, corruption, and theft, while positive nation-building stories receive less attention (Doddi et al., 2014 and Seroka et al., 2019). This could influence people to see their surroundings through a negative eye. Not only do people draw influence from the news content but financial news can also be used to predict the behaviour of the exchange rates (Jin et al., 2013). Bias in the news occurs when media outlets, news producers, or journalists display unfairness in the selection of stories and events as well as the way they are reported.

News readers from western countries are exposed to news reports that focus fundamentally on the conflicts happening in third-world countries such as African countries (Riffe and Shaw, 1982). Many financial institutions from western countries provide financing opportunities to emerging markets in Africa and an important source of information used by those institutions is the global news outlets for current and future investment opportunities to be able to assess the risk of investing. Business Map online for the South African Foreign Direct Investment (FDI) indicate that the united state investments continue to outperform those of any country in the world, they have invested more than 17 billion rands since the year 1994 (Heese, 2010). The global news coverage in certain countries is usually politically driven, and one-sided, and there are situations where the sentiment of the news is negative, but the markets suggest otherwise, as indicated by exchange rates that the sentiment might be positive (Jacobs et al., 2021). Sentiment in the news involves identifying the options and attitude that is covered in the content and can be classified as negative, positive, or neutral.

This phenomenon of misinformation in financial news through reporting of more negative could prohibit the emerging markets in Africa since the investors who are responsible for the economic growth will probably not provide investments because the financial news articles suggest that the country is not performing well economically (Niessner and So, 2017). Most studies used classification techniques or methods such as Naïve Bayes, Support Vector Machine, and maximum entropy to detect news bias by classifying news according to their sentiment such as labelling news titles to be neutral, positive, or negative. But these classical machine learning techniques underperformed when doing the sentiment analysis task with an accuracy ranging from 65% to 77% (Kaya et al., 2012; Pang et al., 2002). Bhowmick and Jana (2021) used the two class transformer-based model to do a sentiment analysis for the Bengali Language, and the models yielded an outstanding maximum accuracy of approximately 95%. The two fine-tuned transformer pretrained models, BERT and XLM -RoBERTa were investigated for their usefulness in performing sentiment analysis. Hence this study intends to use one of the two pretrained binary class classification model call BERT to further apply sentiment analysis to the financial news articles, but in this study the pretrained model will be used in English written news articles rather than Bengali language, therefore we will be using English dataset to fine tune the model so that the model could understand English written articles. This BERT pretrained model will allow us to analyse the polarity of large number articles faster and accurately. BERT pretrained model introduces the attention mechanism layer which helps the model to output accurate results than all the classification techniques used to do sentiment analysis in the past. This model is chosen due to its ability to easily switch from one language to another and good accuracy for doing two class sentiment analysis.

1.2 Rationale

Technology has opened a new window of information sharing. Therefore, publishing of news articles has become easier and faster with the help of blogs, micro-blogging websites, and social media outlets, moving away from the traditional methods of printing news articles to online publishing. Therefore, a large news data is created in a short period of time, which makes the manual assessment of the content or sentiment expressed in the news a challenging task. Hence more sophisticated techniques are required to perform news content assessment automatically and efficiently (Samuels and Mcgonical, 2017).

Due to the goals of news organizations and their sponsors to provide people with information to enable them to make better and informed decisions about the lives, governments, communities, business, and societies, the news media outlets are not guaranteed to be free from bias in attempt to influence people's perspectives (Budak et al., 2016). News bias can also be seen through the selective publishing of news content (Gangula et al., 2019). The most favoured way to weigh media bias is to have automated or human-coded assessment of the sentiment in the news through the sentiment analysis process. Human-coded assessment of the sentiment can be any machine learning or deep learning algorithm that is trained to classify sentiment based on the word, sentence or document is applied on. The accuracy of this technique depends on the algorithm and the training dataset used. Sentiment analysis can be defined as a recent area of study that uses the combination of computational linguistics and information retrieval techniques, which is the focus is not on the topic that a specific document has but, in the opinion or sentiment, it expresses (Esuli and Sebastiani, 2006). Sentiment analysis can be performed at the sentence, word, document, or phrase level (Taj et al., 2019). The two-class sentiment analysis helps in classifying news articles into positive or negative content and could give a much quicker insight into the content reported by news media outlets.

For automation of sentiment analysis, different methods have been designed for predicting sentiments and opinions from words. There are numerous natural language processing algorithms used to do sentiment analysis such as the Naïve Bayes, Support Vector Machine, Random Forest, and neural networks (Llombart, 2017). To use any classification algorithms in natural language processing, the text being processed must be presented in a vector form with real values that encodes a word meaning such that the words with close proximity in the vector are anticipated to have a related meaning, this process is called word embedding. Some of the most popular techniques for word embedding are Bag of words, Term Frequency-Inverse Document Frequency (TF-IDF), word2vec, and Bidirectional Encoder Representations from Transformers (BERT). Most of the time researchers have utilized the Bag of words technique together with the Support Vector Machine to improve the results for sentiment detection (Doddi et al., 2014). The study of sentiment analysis is performed using the classical machine learning models, but for further improvement of the results for sentiment analysis application, deep learning and neural network models with transfer learning abilities are used (Syeda,2022).

Deep learning models have outclassed traditional machine learning algorithms in various classification tasks, including news categorization, sentiment analysis, question answering, and natural language inference (Minaee et al., 2021). Asthana (2021) applied a DistilBERT pretrained model to do sentiment analysis task on the coverage of Covid-19 for online news articles. The study aimed to check the political bias in the news articles by classifying Covid-19 news articles into positive and negative sentiments. The news sentiment was then compared with other countries to check for evidence of political bias in the coverage of the Covid-19 pandemic across different media publications. The DistilBERT model achieved an accuracy of 92.7% when fine-tuned on the Stanford Sentiment Treebank – 2 (SST-2) datasets, therefore it was concluded that the model is suitable to perform binary sentiment classification on the news articles. So far we have seen that the BERT, RoBERTa, and DistiBERT perform best for binary sentiment analysis in Bengali language and coverage of Covid-19 news articles but none of the studies attempted to apply the models on the news articles that are domain specific such as financial news, sport news, and entertainment news . And the studies do not show how we can further use the sentiment scores and labels obtained from those pretrained models to solve real life problems. Therefore, the principal study interest is to use the pretrained BERT on the financial news articles to compute the sentiment scores and labels that will enable us to investigate the coverage of the financial news in the African emerging markets between the local and global news outlets. Then we further check whether the sentiment of the news correlates with the exchange rates for the African emerging markets such as South

Africa and Nigeria to detect whether there exists some possible bias in news reporting about Africa countries by the global news outlets.

1.2.1 Aim

The aim of the study is to use the transformer model to detect the financial news bias from global media outlets compared to the local media outlets.

1.2.2 Objectives

The objectives of the study are to.

i) Build a transformer model for the sentiment analysis task
ii) Compute the news sentiment scores for local and global media outlets
iii) Evaluate the news coverage from global media outlets to local media outlets
iv) Test the significance of the relationship between global and local news coverage with an economic indicator such as exchange rates from African emerging markets.

1.2.3 Research questions

i) How to build a transformer model for the sentiment analysis task?
ii) How to compute sentiment scores from the news articles?
iii) How does the coverage of global media outlets in certain countries compare with local media coverage?
iv) Does the sentiment of the global and local news coverage correlate with the economic indicator such as exchange rates from African emerging markets?

1.3 Significance of the study

Major western news media outlets play a critical role in proving information about the financial, political, and nation building stories of the countries especially for African countries to its foreign investors (Black, 1995). The top five biggest investors to South Africa are all from foreign countries or continent which are US, Malaysia, UK, Switzerland, and Germany (Heese, 2017). This study assesses financial news bias by comparing the local and global media outlets on the African emerging markets using the exchange rates, as the previous studies accused the major western global media outlets of fundamentally always reporting negative news regarding African Countries. Therefore, this study aims to provide answers in the debate on whether the global media outlets are biased in reporting financial news for African countries or not. It is significant to assess the credibility of global news outlets in covering financial news because many financial institutions from the western developed countries that provides funding or financial support for African countries rely on the information reported by the global media outlets to make decisions about possible investments opportunities. Therefore, the study use the transformer model called pretrained BERT model to do sentiment analysis on the financial news for two African countries South Africa and Nigeria. The pretrained BERT model is chosen as the best model to perform the task because it outperforms the traditional machine learning model in terms of accuracy when it comes to the natural language processing tasks such as sentiment classification which requires high language understanding. Then we use the sentiment scores and labels obtained from the BERT model to assess the news bias between the local and global media outlets.

1.4 Dissertation outline

The dissertation is structured as follows:

Chapter 1: Introduction

Chapter 1 introduces the problem statement, rationale, aim and objectives, research questions, and significance of the study.

Chapter 2: Literature review

Literature review discuss the past related studies regarding the news coverage sentiment analysis, machine learning models for sentiment analysis, deep learning models for sentiment analysis, transformer models for sentiment analysis, the results obtained, and the conclusions.

Chapter 3: Methodology

Methodology discusses the data collection process and information, fine tuning the transformer model for sentiment analysis, and methods used to compare the sentiment labels and scores obtained from financial news titles.

Chapter 4: Results

The results chapter give the computed sentiment labels, sentiment scores, hypothesis testing results, and the data analysis.

Chapter 5: Conclusion

This chapter gives brief conclusions and summary based on the results obtained from Chapter 4, answers the research aim and questions, outline the significance contributions and limitations of the study, and provide recommendations for future work.

Chapter 2: Literature review

2.1 Introduction

This chapter gives a piece of brief information about sentiment analysis on the news articles, and methods used. The chapter also reviews ideas, conclusions, and possible hypotheses reached by previous studies on news sentiment analysis using deep learning and machine learning models, especially with the transformer model.

2.2 The News

Technology has opened a new window of information sharing. The publishing of news articles has become easier and faster with the help of blogs, micro-blogging websites, and social media outlets, moving away from the traditional methods of printing news articles (Samuels and McGonigal, 2017). News provides people with information about the current global news such as sports, entertainment, politics, and financial news. News have always been a significant source of information to shape the perception of market investments (Gupta, 2020). Financial news is one of the most interesting news domains worldwide since it provides information required by investors to make educated predictions about upcoming events, to minimize the risk of losing investments. The same cannot be said about crime, sports, or political news, because when people read those types of news, they are only focused on one question which is what happened (Rocci and Palmieri, 2007).

The international and foreign news selection is characterized by dramatic, erratic, and unsophisticated amazement, by negative or contention events involving exclusive people or countries. Conflict and negativity account for two of the most dominating news values in journalism (Harcup and O'Neill, 2001). News values are the criteria that influence the selection of stories and events for publishing. Hence it is no surprise that negative and conflicting news are found to be serving the interests of the media audiences (Obijiodor, 2001). The news media phrase, ‘if it bleeds, then it leads’ was formulated to mirror the intuition among journalists that news stories about conflicts, tragedy, bloodshed, and crime sell more newspapers than the coverage of stories about good news (Pooley, 1989). Robertson et al., (2023) investigated the effects of emotional and negative words on the news consumption using the viral news stories dataset downloaded from online, and it was found that the use of negative words in the news increased the news consumption rates compared to the use of positive words which seem to decrease the news consumption rates. This raises concerns about the credibility of the news since they have the power to shape people's opinions and moods in the communities. Therefore, there is a need for a balanced news flow, regardless of whether it is negative, positive, or neutral news. There is much research on the credibility of the news, but the focus is based more on the public confidence in the media outlets rather than the credibility of certain news establishments or the quality of news coverage for stories and events (Fico, et al., 2004). Due to the goals of the news, organizations and their sponsors' news articles are not guaranteed to be free from bias (Budak et al., 2016). News bias can also be seen through the selective publishing of news content (Gangula et al., 2019).

2.3 Sentiment analysis

Sentiment analysis is defined as a recent specialty at an intersection of computational linguistics and information retrieval which is not concentrated on the topic that a specific document has but, in the opinion, it expresses (Esuli and Sebastiani, 2006). As previously stated, sentiment analysis is performed at either sentence, word, document, or phrase level (Taj et al., 2019). Sentiment analysis at the sentence level investigates the polarity of sentences, analysing phrases and clauses, word-level analyses what people hate or like, and document-level analyses the polarity of a document concerning a single entity. The natural language processing techniques such as the sentiment analysis task has been widely used by researchers in attempts to detect news bias from news articles by evaluating the dominant news content as positive or negative news (Swati et al., 2015; Schumaker et al., 2009; Singh and Jain, 2021). Existing studies have produced many sentiment analysis techniques which include both unsupervised and supervised methods. Supervised techniques include the Support Vector Machine, Naïve Bayes, and maximum entropy, while unsupervised techniques include various methods that exploit syntactic patterns, sentiment lexicons, and grammatical analysis. Nonetheless, deep learning techniques proved to be powerful and produced state-of-the-art outputs in numerous applications including the sentiment analysis task. Therefore, the application of deep learning techniques in sentiment analysis has become very popular recently (Zhang et al.,2018).

2.3.1 Challenges in sentiment analysis

Automatic sentiment analysis on its own has limitations in analysing the opinions expressed in a document, sentences, or words. The judgment of the opinion could be subjective, the same way human language can provoke arguments amongst people about a particular sentence where different judgments are presented. The key challenges faced by the researchers interested in sentiment analysis are applying sentiment analysis on negated expressions, challenges in figurative expressions, and challenges in multilingual sentiment analysis (Mohammad, 2017). These challenges occur since machine learning algorithms are difficult to accurately in order to understand and analyse emotions as a human brain does.

i. Challenges of negated expressions

Negations are words or phrase that shows that you reject or disagree with something. Popular examples are words such as no, never, not, shouldn't, and cannot. Negated expressions are significant in linguistics because they have an impact on the polarity of the words in the sentences and tend to make positive sentences to be negative. The negation effects may be limited to the words that are exactly next to it, or it can extend to other words in the sentences. Therefore, this poses a new challenge for sentiment analysis techniques to accurately determine the polarity of the sentences by considering the range of words that are affected by negated words (Farooq et al., 2016).

ii. Challenges in figurative expressions

Figurative expressions are statements that are not intended to be comprehended literally. Figurative language such as metaphor, sarcasm, and irony are remarkable challenges in sentiment analysis (Hercig and Lenc, 2017). In terms of sarcasm language, Rosenthal et al., (2014) found that the sentiment analysis system accuracy drops significantly by 25% when analysing sarcasm tweets compared to non-sarcasm tweets.

iii. Challenges in multilingual sentiment analysis

In sentiment analysis, the English language is the most used because of its advantages for the availability of resources such as dictionaries, corpora, and lexicons. But researchers over the years showed more interest in performing sentiment analysis tasks using different languages. Therefore, the researchers are forced to create new dictionaries, corpora, and lexicons for different languages which is a very challenging task (Chandni et al.,2015).

2.3.2 Application of sentiment analysis

The main areas of research in sentiment analysis are Sentiment Prediction, Text Summarization for Opinions, Product Feature Extraction, Subjectivity Detection, Aspect Based Sentiment Summarization, Contrastive Viewpoint Summarization, and detecting opinion spam (Vohra et al., 2013). Sentiment analysis studies in those areas of research are applied in many fields such as marketing, politics, finance, and sociology for the purpose of customer support, social media monitoring, market predictions, analysing customer feedback, and many others (Alessia et al., 2015).

2.4 Machine Learning Algorithms

Machine learning is defined as an approach to computer science that gives the ability and allows the computer algorithms to learn without direct programming (Mahesh, 2020). Machine learning algorithms are assembled into different grouping that depends on the anticipated result of the algorithm. There are different types of machine learning algorithms which include unsupervised learning, supervised learning, semi-supervised, learning to learn, reinforcement learning, and transduction. Supervised learning is an approach where a model is developed using input features with the corresponding labels and the unsupervised learning is an approach where machine learning algorithms look for patterns in the dataset without given pre-existing labels. Learning to learn is an approach where as a result of previous training experience, the algorithm learns its own inductive bias. Semi-Supervised learning is an approach where the machine learning algorithm use the combination of both unlabelled and labelled datasets to generate a classifier or appropriate function. Reinforcement learning is where the algorithm uses the observations of the world to learn the blueprint on how to behave. Therefore, every behaviour is characterised by an effect in the environment. Subsequently, the environment gives the response that monitors and instruct the learning algorithm. Transduction – supervised learning -- predicts new outputs based on new inputs, training inputs, and training outputs (Ayodele, 2010).

2.4.1 Challenges of machine learning algorithms

Some of the challenges in machine learning algorithms are lack of training dataset, poor quality dataset, model overfitting, and model underfitting (Belkin et al., 2019). Managing machine learning algorithms present additional difficulties beyond the classical software systems, especially when building a classifier over one input table and the major challenge of the machine learning model is that the behaviour depends on the data being processed, therefore making the application of machine learning more complex (Schelter et al., 2018).

2.4.2 Application of machine learning algorithms

The machine learning algorithms use the data in building the model, then the model can be used to predict new unknown values based on the data trends and historical data it was built on. These machine learning algorithms can be applied in different fields such as finance, image processing, health, media, computer vision, retail, manufacturing, automated trading, travel, automotive, natural language processing, aerospace, and many others (Kumar et al., 2020).

2.4.3 Machine learning algorithms in sentiment analysis

There are numerous natural language processing algorithms used to do sentiment analysis such as the Naïve Bayes, Support Vector Machine, Maximum entropy, and many others. To use any classification algorithms in natural language processing, the text being processed must be represented in a form of a real-valued vector that encodes the meaning of a particular word such that the words that are closer to each other in the vector are expected to have a similar meaning, this process is called word embedding. Over the past, word embedding evolved from classical machine learning embeddings to neural embeddings. Some of the most popular techniques for word embedding are Bag of words, Bidirectional Encoder Representations from Transformers (BERT), word2vec, and Term Frequency-Inverse Document Frequency (TF-IDF). Most of the time researchers have utilized the Bag of words technique together with some machine learning algorithms at most the Support Vector Machine to improve the results for sentiment detection (Doddi et al., 2014).

For automation of sentiment analysis, different methods have been designed for predicting sentiments and opinions from words. Taj et al., (2019) explored an unsupervised approach for sentiment analysis using news articles from the BBC news dataset. The sentiment analysis is done on a document level to check news article documents that indicate negative, positive, or neutral opinions. 2225 BBC news articles were used, having five area topics: technology, politics, sport, business, and entertainment news. For text pre-processing, the news texts from the documents were transformed to lowercase, and stop words were removed since they contribute little to sentiment analysis. TF-IDF was used to identify important words by checking which words occur frequently. WordNet dictionary was used to find the opinions on those important words. The extraction sentiment operator was used to calculate the sentiment score of the news document, where texts having a +1 score are considered positive sentiment and a -1 score are considered negative sentiment. The news articles were categorized as negative, neutral, and positive based on the sentiment score. It was found that news articles about technology and entertainment had more negative sentiment and whereas sport and business had a more positive sentiment.

Kalyani et al., (2016) aimed to develop a model that predicts financial news polarity which could be used to predict market trends. The trends were predicted by evaluating the news sentiment of which negative sentiment suggests a high probability that stock price will drop whereas positive sentiment suggests a high probability that stock price will go up. News articles about a specific company and its stock prices were collected during the same period. Before analysing the news articles, stop words were removed since they do not contribute to sentiment analysis. Support Vector Machine, Random Forest, and Naïve Bayes were used as the sentiment detection algorithms to classify texts into negative or positive sentiments. The three algorithms that were used performed best in their task of detecting news articles' sentiments. It was concluded that given the news sentiment, the model can be used to predict stock trends.

Fong et al., (2013) presented different machine-learning techniques for doing sentiment analysis. The texts were classified into three categories neutral, positive, and negative. It was found that it is efficient to use a Naïve Bayes classifier for sentiment analysis since it produces better results compared to classifiers such as maximum entropy and decision tree. But Firmino Alves et al., (2014) and Shirsat et al., (2019) showed that when comparing the Support Vector Machine technique and the Naïve Bayes technique for news sentiment analysis tasks, the Support Vector Machine slightly outperforms the Naïve Bayes technique.

2.5 Deep learning algorithms

Deep learning is an emerging area within machine learning that offers techniques for learning feature representations in an unsupervised or supervised approach within a hierarchy (Barahona, 2016). Deep learning models have outperformed traditional machine learning algorithms in various applications including sentiment analysis and produce state-of-the-art prediction results (Minaee et al., 2021). Therefore, with this evidence of the high success of the deep learning models in many application domains, deep learning models are the most preferred models in sentiment analysis in recent years (Zhang et al., 2018). Deep learning models can learn data representation by themselves, and it lessens the need for feature engineering and makes the models transferable over different tasks (Vaswani et al., 2017).

2.5.1 Challenges in deep learning algorithms

Deep learning algorithms are designed to imitate how human brains work by using neural networks and progressively learn to give solutions accurately. But just like any other algorithms, deep learning systems do have some significant challenges which include big data required to train the model, model overfitting, and Hyperparameter optimization. The major limitation is the one that the deep learning models requires a large amount of labelled data to train on so that excellent results could be obtained. With the limited labelled data across many fields, the supervised deep learning models suffer from overfitting, therefore it is difficult to use deep learning models in many fields since obtaining enough labelled data requires a large amount of time and is expensive (Gong et al., 2022). With the large dataset being a minimum requirement, then training the deep learning model will be very computationally expensive as well. Some of the more complex deep learning models take weeks training using the machines equipped with sophisticated Graphics Processing Units (Tyagi and Rekha, 2020).

2.5.2 Application of deep learning algorithms

Deep learning algorithms have given a breakthrough in solving many problems that have been giving the artificial intelligence community challenges for the past decades. The algorithms proved to be excellent at finding very complicated structures in high-dimensional data, therefore they are popular in many domains of business, media, science, and government. The deep learning algorithms have produced state-of-the-art results for important tasks such as image processing, question answering, speech recognition, language translation, sentiment analysis, and topic classification (LeCun et al., 2015). Deep learning models are usually compared to the tool that underlie the human mind, and some researchers also believe that the models will continue to improve at an unexpected rate, and they will soon conquer many applications under different fields (Tyagi and Rekha, 2020).

2.5.3 Deep learning algorithms in sentiment analysis

Syeda (2022) aimed to find state-of-the-art outputs for sentiment analysis and classification of the financial news with classical classifiers such as Naïve Bayes and the transfer learning models such as BERT and FinBERT. The Naïve Bayes produced an accuracy of 0.678, while the two transfer learning models BERT and FinBert have produced good classification accuracies of 88.2% and 91.3%, respectively. Therefore, it was concluded that the transfer learning models BERT and FinBert are better than the traditional machine learning classifiers such as Naïve Bayes for doing financial news sentiment analysis. Saha et al., (2020) aimed to do analysis the sentiment of the news articles in Bengali using the unique mode called Long Short-Term Memory (LSTM), which is just the Recurrent Neural Network (RNN) based deep learning approach and compared its classification accuracy with the three classical machine learning techniques such as Decision Tree, Support Vector Machine, and Naïve Bayes. The LSTM-based deep learning RNN architecture outperformed all three machine learning techniques with an accuracy of 85%.

As is seen in recent years that deep learning models such as LSTM, convolutional neural network, and RNN techniques have been preferred in doing sentiment analysis, but they also have some significant limitations. All these deep learning techniques have problems in capturing long sentences, which usually results in gradient disappearing or gradient not updating (Li et al.,2020). Recently a paper by Vaswani et al., (2017) developed and introduced a deep learning model approach called the Transformer model, which resolves the problems of gradient disappearing and overshooting.

2.6 The Transformer model

The transformer model is a deep learning model that allows the self-attention mechanism, by differentially weighting the significance of each part of the input data. The transformer architecture is developed around neural networks and attention mechanisms that allow the algorithms to comprehend text more accurately than other neural models such as short-term memory networks and recurrent neural networks (Karita et al., 2019). The transformer architecture has been widely used in different fields such as speech processing, natural language processing, and computer vision. Initially, this technique was presented as a sequence-to-sequence model used for doing machine translation, but over the years, the transformer models proved to achieve state-of-the-art results on other various tasks (Lin et al.,2021). On natural language processing tasks, the neural networks and transformer model are preferred due to their transfer learning abilities. Transfer learning is a method used to transfer the knowledge acquired from prior activities to associate it with the new activity. One of the significant elements of transfer learning models is to help in the further pre-training of the model on the language that is domain-specific so that the models can learn the semantic correlations in the sentences, especially when dealing with financial sectors (Syeda, 2022).

The same as other deep learning models such as RNNs, CNNs, and LSTM, the transformer models are developed to operate on the sequential input data, such as natural language. But transformer models are designed to process the whole input sentence at once if we are dealing with a natural language sentence, unlike RNNs that process one word at a time. Therefore, the transformer model with self-attention mechanism will allow more parallelization than all other neural models and result in reduced training times and help in modelling long-range dependencies (Vaswani et al.,2017). The transformers are the encoder-decoder model, the encoder will convert the inputs into a vector representation. After that, the encoded inputs are passed through to the decoder, where the decoder attempts to convert those vectors into an understandable language or natural language. Each encoder and decoder, consist of a feed-forward neural network and a self-attention layer shown below in the structure by Vaswani et al., (2017)

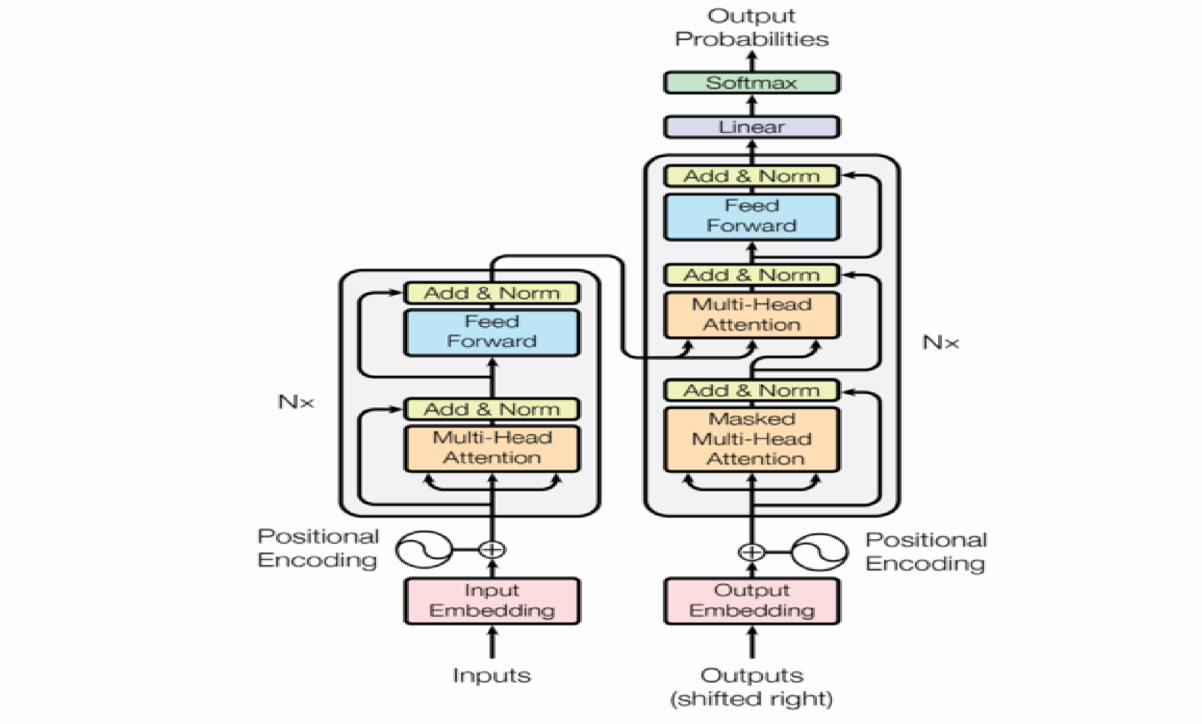


Figure 2.1: Transformer architecture

2.6.1 Challenges in transformer models

The transformer models are a significant improvement from the deep learning models such as the RNNs and LSTM, but they also have their share of limitations. The transformer attention only deals with the fixed length of sentence strings Vaswani et al., (2017). The sentences must be divided into several segments before being used as input, splitting text into segments causes context fragmentation, which leads to a significant amount of context being lost.

2.6.2 Application of transformer models

The transformer models have been successful over the years in fields such as machine translation, sentiment analysis, text summarization, and question answering just like the classical deep learning models such as RNNs. Transformers is a library inverted by Hugging Face that provides transformer-based pre-trained models and architectures. Transformer models are applied in standard deep learning frameworks such as PyTorch and TensorFlow (Wolf et al.,2020).

2.6.3 Sentiment analysis with the transformer model

The self-supervised and pre-trained models of the transformers have significantly improved the notion of transfer learning in the field of natural language processing across different tasks with the help of the self-attention mechanism. Especially in sentiment tasks such as product reviews and news topics (Vaswani et al.,2017). The attention mechanism in the transformer model helps to speed up the training process and produce the model for down sampling to different sizes of private datasets. Singla and Ramachandra (2020) aimed to use self-supervised models such as RoBERTa, BERT, and A Lite BERT (ALBERT) model and analyse their performance when fine-tuning a non-benchmarking dataset for multi-class sentiment analysis. BERT is a language model that is created to pre-train deep bidirectional representations from the untagged text by cooperatively conditioning both the right and the left context in all layers. The RoBERTa was designed to clone the BERT model by increasing the training dataset and tweaking hyperparameters. ALBERT is the lite BERT model designed to overcome longer training times and memory limitations. The Area under ROC Curve (AUC) score and F1 score was used to evaluate the performance of the models. The BERT model achieved the best results of all transformer models with an accuracy of 85%. Therefore, it was concluded that the best model to perform multi-class sentiment analysis on a non-benchmarking dataset is the BERT model.

Singh and Jain (2021) used the transformer models to do sentiment analysis by classifying news headlines into positive, negative, and neutral. The models were fine-tuned by training them on the news headlines dataset. The four transformer models explored were the XLnet base-cased, robustly optimized BERT approach (RoBERTa) base, BERT base-cased, and Distilled BERT (DistilBERT). The performance of these transformer models has been observed to be a significant improvement from prior deep learning models and machine learning classifiers for sentiment analysis tasks. BERT base-cased transformer model performed best in classifying the news sentiment with an accuracy of 93.6% and an F1 score of 93.6%. Similar conclusions were reached by Mathew and Bindu (2021) that the transformer models RoBERTa, BERT, DistillBERT, and ALBERT, are superior when applied to a sentiment analysis task over deep learning models such as LSTM.

Raha et al., (2021) aimed to point out fake news related to covid-19 from social media platforms like Facebook, Instagram, and Twitter. At first, the baseline models such as the Naïve Bayes model, linear classifier, bagging model, boosting model, and Support Vector Machine. The models were applied together with two different words embedding techniques word2vec and TF-IDF to get vector representations of the posts and sentences. Then the transformer architecture was used to fine-tune various transformer models such as BERT, ELECTRA, and RoBERTa on the covid-19 training dataset. The explicit data pre-processing was not performed to allow the models to fully learn the patterns of input, including plenty of hashtags to assist in fake news detection. Hugging Face's 6 transformers library was utilized for finetuning the pre-trained transformer models. The results showed that none of the baseline models with both word embedding techniques had managed to outperform any of the transformer models with fake news detection accuracy.

Sousa et al., (2019) used the BERT model to perform sentiment analysis on financial news articles to extract meaningful information to help investors in making informed decisions about the behaviour of the stock markets. This pre-trained model was fine-tuned on 582 financial news documents manually labelled as negative, positive, and neutral. The BERT model achieved a good accuracy of 72.5%. A similar study was performed by Fazlija and Harder (2022), where the aim was to obtain sentiment information from financial news articles and make use of the sentiment scores to predict the patterns of the stock markets. To try obtaining the best results, the BERT model was used. The pre-trained model was fine-tuned on the financial dataset that was labelled, then the model was used on the financial news articles from different news media outlets to compute the sentiment scores. It was concluded that the sentiment scores from the financial news content help predict the patterns of the stock markets.

This study will make use of the BERT model to do news title sentiment analysis and fine-tune it on the labelled dataset that is large enough. This transformer model was chosen because of its excellent accuracy in sentiment classification tasks over other deep learning and traditional machine learning models.

2.7 Conclusion

Sentiment analysis can be done on sentence, document, or phrase level, for the purpose of product reviews, customer service, and many others. Over the years, researchers used machine learning and deep learning models to do sentiment analysis, and deep learning models achieved more accurate results than machine learning models. Even with good accuracy obtained, the deep learning models were faced with challenges of gradient disappearing, not updating, and overshooting. In the year 2017, researchers at Google introduced the deep learning model called the transformers model, which tends to solve the problems that the prior deep learning models encountered, with great success. The transformer model BERT is widely used for sentiment analysis because of its good accuracy compared to other transformer models.

Chapter 3: Methodology

3.1 Introduction

This chapter outlines the data collection process, data analysis, and the methods used to perform the experiments. The study makes use of the news article titles as secondary unstructured data from local and global media outlets to determine the nature of the relationship with the exchange rates for South African and Nigerian financial news coverage. Then, we assess media bias based on the results obtained from the test of significance for correlation coefficient.

For comparing and investigating the relationship between exchange rates and financial news content using the test of significance for the correlation coefficient. The sentiment corresponding to the financial news content must be computed, this process is called sentiment analysis. Sentiment analysis is done using the deep learning model called the BERT model, because of the transfer learning feature and its good accuracy for different natural language processing tasks.

3.2 Dataset

This study makes use of the unstructured dataset in a form of titles of the news articles collected from both the global and local media outlets coverage. The datasets are extracted from the Global Database of Events, Language, and Tone (GDELT) project using key words. Two countries with the most emerging markets from the African continent are used, which are South Africa and Nigeria. The news articles headlines were obtained from both local and global media outlets with information about financial economics for both countries. For each country, the news titles are downloaded as a CSV file for the period from April 2021 to March 2022 containing 60 news articles each month, bringing the total number of news articles for each of the four datasets to exactly 720 news articles titles. The currency or exchange rates of each month from April 2021 to March 2022 for the United States Dollar (USD) against the South African Rand (ZAR) and Naira (NGN) are also collected to make necessary comparisons with the financial news content. The monthly exchange rates for Rands and Naira against the USD are obtained from the following links https://fred.stlouisfed.org/series/dexsfus and USD NGN Historical Data - Investing.com, respectively. The news datasets contain columns for URL, Mobile URL, date published, and news titles.

3.2.1 News dataset Analysis

For each of the four-news media outlet's coverage, 720 news articles were selected from April 2021 to March 2022 with the financial economy information about South Africa and Nigeria. For each month 60 news articles are downloaded and selected from different media organizations covering financial news.

Media outlet	Period	Articles per month	Articles per period	Domain
RSA local media coverage	April 2021 to March 2022	60	720	Financial news
RSA global media coverage	April 2021 to March 2022	60	720	Financial news
NIG local media coverage	April 2021 to March 2022	60	720	Financial news
NIG global media coverage	April 2021 to March 2022	60	720	Financial news

Table 3. 1: News collection information

Both the datasets for South Africa and Nigeria, regarding local and global media outlets reported, contain no missing content in the title, URL, and date columns. However, there are missing contents or values in the mobile URL column in all the datasets, of which we are not interested in, and all the data types in the columns are the objects as shown in Figure 3.1 below.

South African local news coverage

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 720 entries, 0 to 719
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   URL        720 non-null    object
 1   MobileURL  578 non-null    object
 2   Date       720 non-null    object
 3   Title      720 non-null    object
dtypes: object(4)
memory usage: 22.6+ KB
```

Nigerian local news coverage

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 720 entries, 0 to 719
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   URL        720 non-null    object
 1   MobileURL  578 non-null    object
 2   Date       720 non-null    object
 3   Title      720 non-null    object
dtypes: object(4)
memory usage: 22.6+ KB
```

South African global news coverage

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 720 entries, 0 to 719
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   URL        720 non-null    object
 1   MobileURL  543 non-null    object
 2   Date       720 non-null    object
 3   Title      720 non-null    object
dtypes: object(4)
memory usage: 22.6+ KB
```

Nigerian global news coverage

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 720 entries, 0 to 719
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   URL        720 non-null    object
 1   MobileURL  660 non-null    object
 2   Date       720 non-null    object
 3   Title      720 non-null    object
dtypes: object(4)
memory usage: 22.6+ KB
```

Figure 3. 1: Global and Local news coverage dataset features

Figure 3.2 and figure 3.3 below shows the distribution of stop words for South African and Nigerian news coverage used in the financial news articles, respectively.

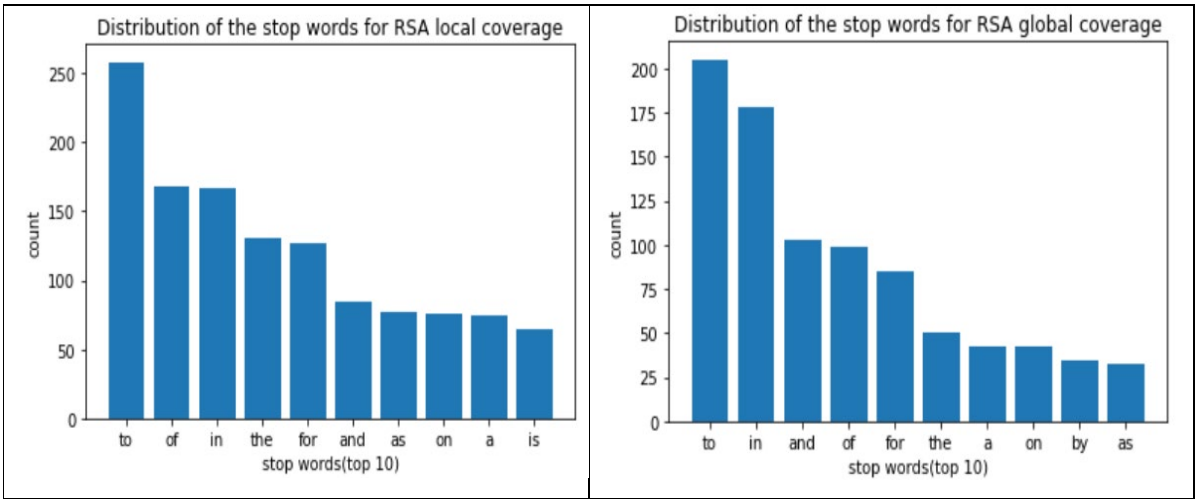


Figure 3. 2: RSA news title stop words distribution

For both the South African local and global news coverage, the most used stop word is “to” with over 200 mentions, followed by “of”, “in”, “and”, and “the”. The difference in stop word usage has no specific reason, is a matter of language, grammar, and language preference used by the journalists.

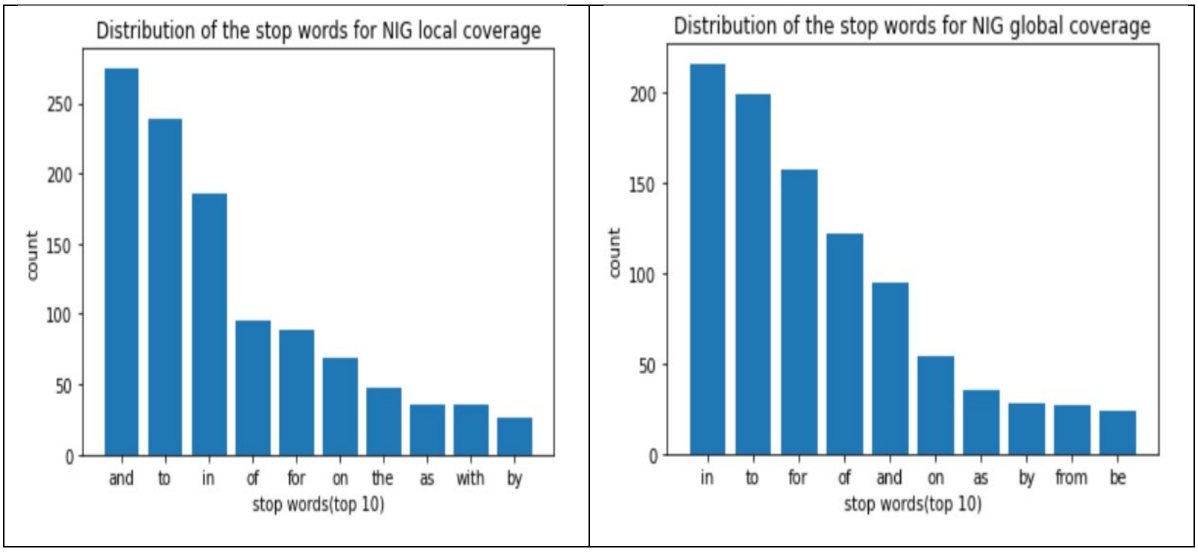
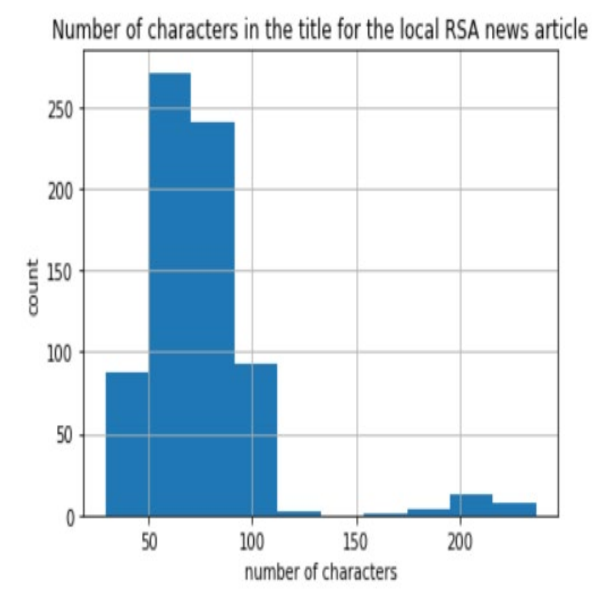
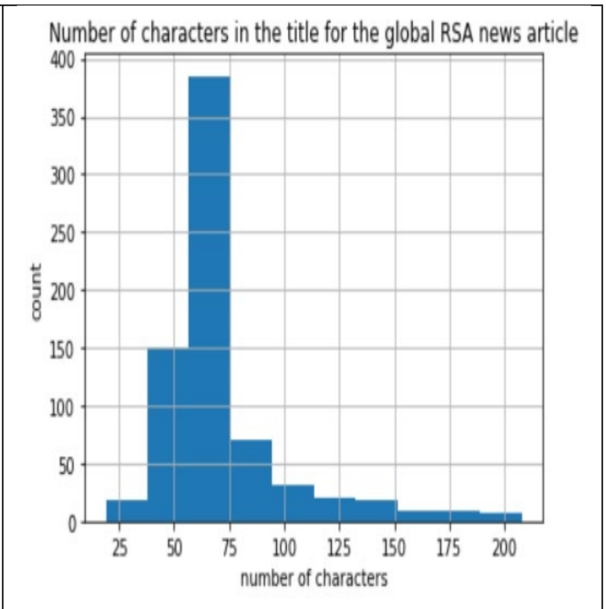


Figure 3. 3: NIG news title stop words distribution

For both the Nigerian global and local news coverage, the most used stop words are "in" and "and" respectively, with over 200 mentions each, followed by "to", "for", and "of".

Figure 3.4 and figure 3.5 below shows the distribution of the number of characters for South African and Nigerian news coverage that are used in the financial news titles, respectively.





Minimum = 29 characters	Minimum = 19 characters
Maximum = 237 characters	Maximum =208 characters

Figure 3. 4: RSA news title characters distribution

For South African local news coverage, the minimum number of characters used in the title is 29 characters and the maximum is 237 characters. For South African global news coverage, the minimum number of characters used in the title is 19 characters and the maximum is 208 characters. Therefore, based on the number of characters per news title for the local against global news coverage, we can conclude that the South African local media news titles use more characters compared to global media news titles this might be due to knowing more information about the content being reported.

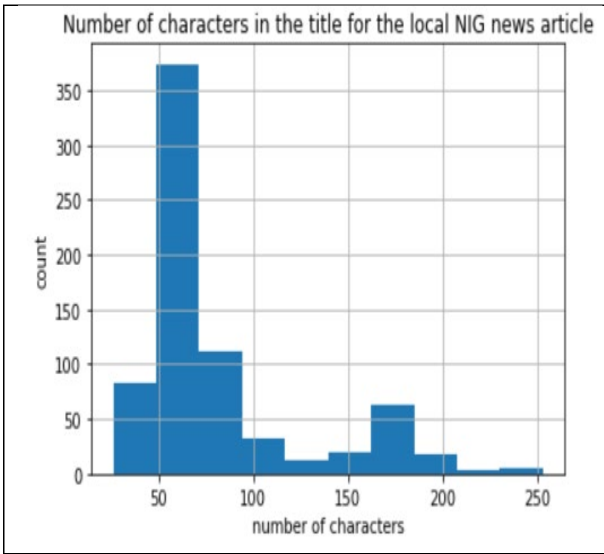
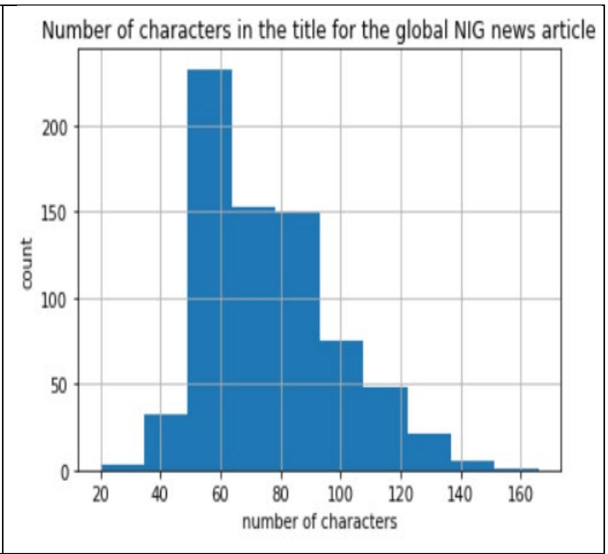
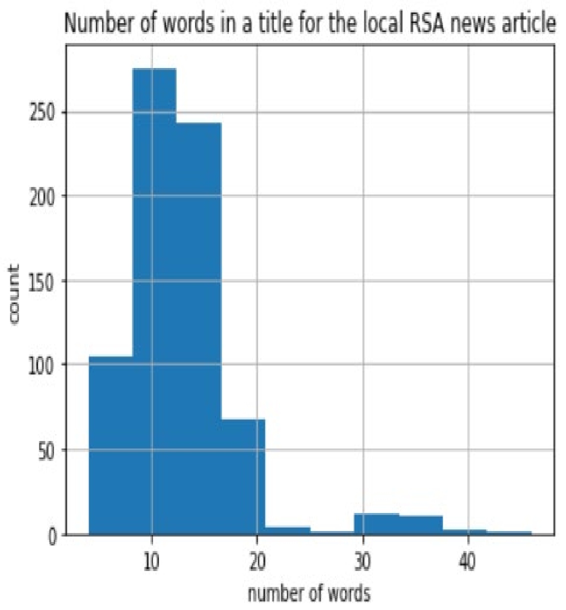
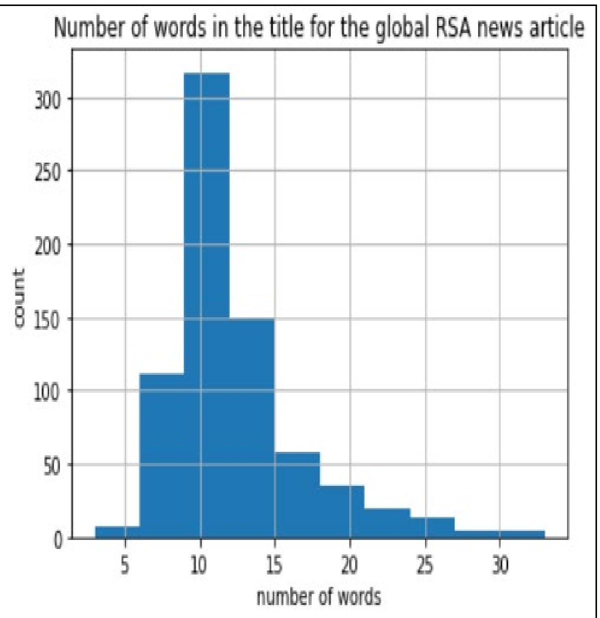
	
Minimum = 26 characters	Minimum = 20 characters
Maximum = 253 characters	Maximum = 166 characters

Figure 3. 5: NIG news title characters distribution

For Nigerian local news coverage, the minimum number of characters used in the title is 26 characters and the maximum is 253 characters. For Nigerian global news coverage, the minimum number of characters used is 20 characters and the maximum is 166 characters. Therefore, based on the number of characters per news article for the local against global news coverage, we can conclude that the Nigerian local media news titles use more characters compared to global media news titles. These results are similar to those for South African news coverage, both the local news coverage for South Africa and Nigeria uses more characters in writing news titles compared to the global media coverage.

Figure 3.6 and figure 3.7 below shows the distribution of the number of words for South African and Nigerian news coverage used in the financial news titles, respectively.

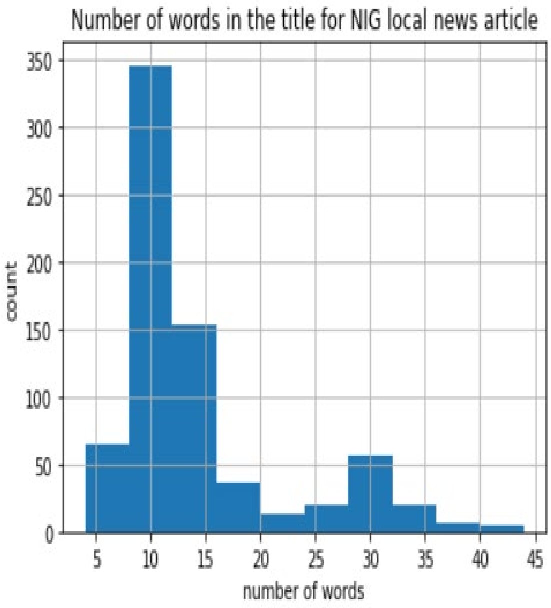


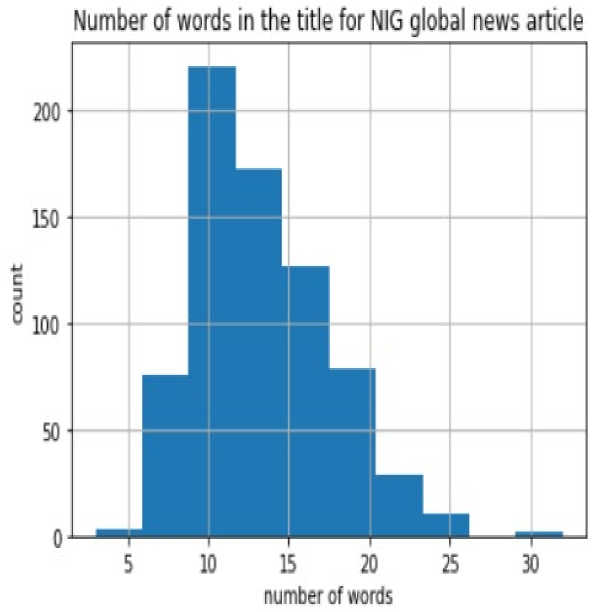


Minimum = 4 words	Minimum = 3 words
Maximum = 46 words	Maximum = 33 words

Figure 3. 6: RSA news title words distribution

The South African local news coverage has a minimum of 4 words and a maximum of 46 words in the news titles, while for the global news coverage there is a minimum of 3 words and a maximum of 33 words in the news titles. The average number of words used in the local news titles is 13 words with a mode of 13 words compared to the global news titles with an average of 12 words and a mode of 10 words. Therefore, based on the number of words for each news title for the local media against the global media coverage, we conclude that the South African local news coverage uses more words in writing news titles compared to the global news coverage.





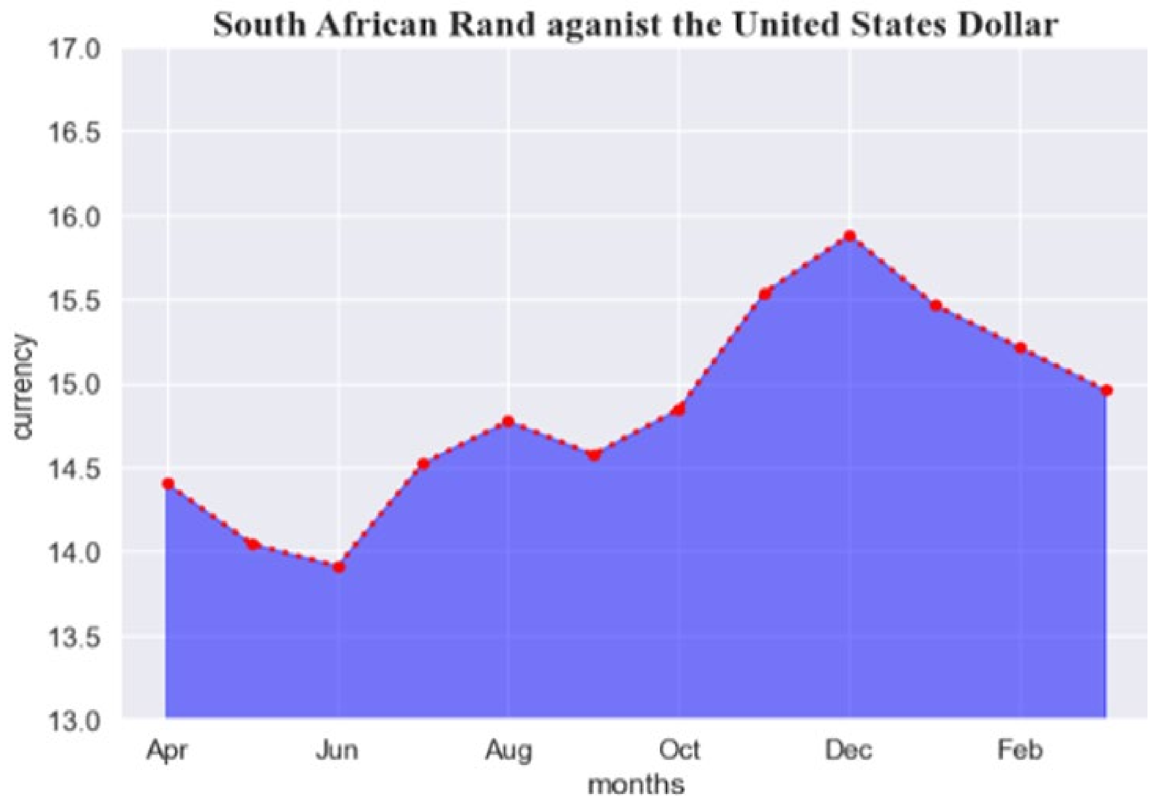
Minimum = 4 words	Minimum = 3 words
Maximum = 44 words	Maximum = 32 words

Figure 3. 7: NIG news title words distribution

The Nigerian local news coverage has a minimum of 4 words and a maximum of 44 words in the news title, while for the global news coverage there is a minimum of 3 words and a maximum of 32 words in the news titles. The average number of words used in the local news titles is 14 words with a mode of 8 words compared to the global news titles with an average of 14 words and a mode of 9 words. Therefore, based on the number of words for each news title for the local media against the global media coverage, we conclude that the Nigerian local news coverage uses more words in writing news titles compared to the global news coverage. The same conclusion was also reached on South African news coverage when comparing the number of words used in titles between the local and global media coverage.

3.2.2 Exchange rates dataset analysis

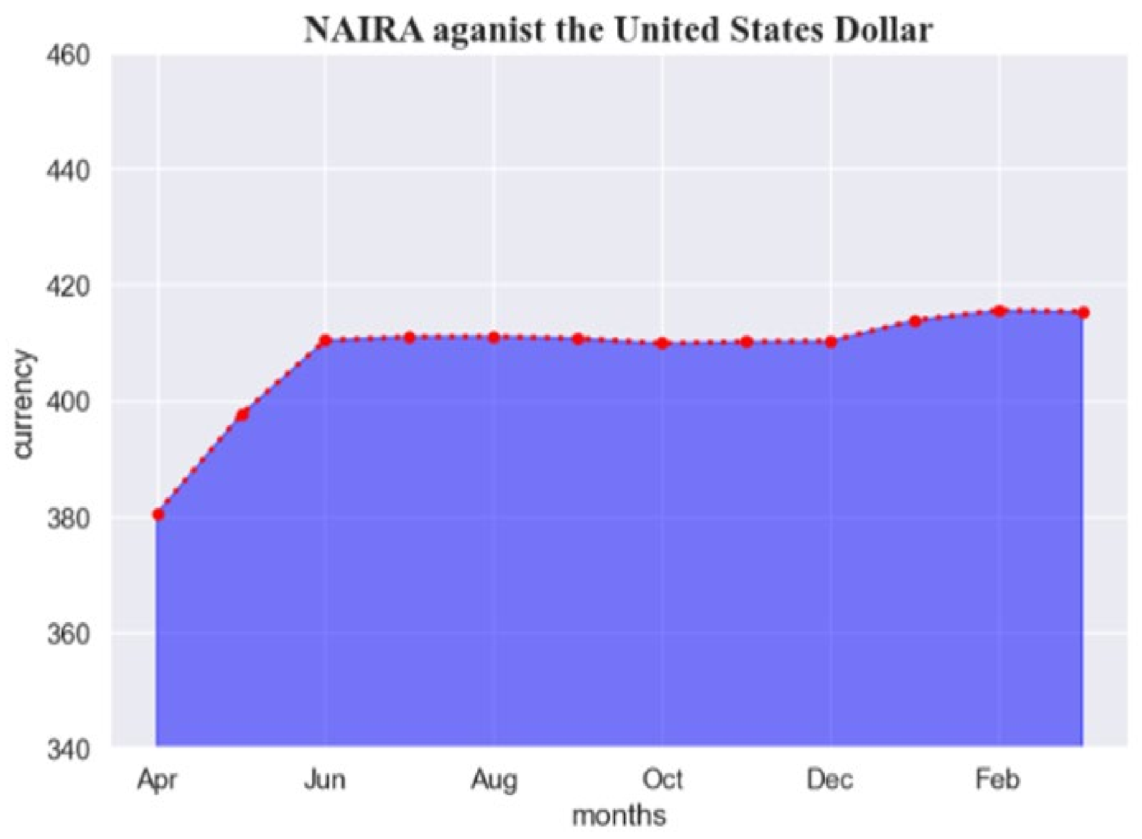
Figure 3.8 and Figure 3.9 below show the South African and Nigerian currency value against the United States dollar from April 2021 to March 2022, respectively.



Minimum = 13.913 Rands per Dollar
Maximum = 15.882 Rands per Dollar

Figure 3. 8: RSA exchange rates over a year period

The graph above shows the average currency rate per month from April 2021 to March 2022 for the South African Rand against the United States Dollar. The minimum exchange rate between ZAR and USD is 13.913 per USD which was in June 2021 and the maximum is 15.882 per USD which was in December 2021.



Minimum = 380.550 Naira per Dollar	
Maximum = 415.581 Naira per Dollar	

Figure 3.9: NIG exchange rates over a year period

The graph above shows the average currency rate per month from April 2021 to March 2022 for Nigerian NAIRA against the United States Dollar. The minimum exchange rate between NAIRA and USD is 380.55 per USD which was in April 2021 and the maximum is 415.581 per USD which was in February 2022.

3.3 Development of the transformer model for sentiment analysis

The transformer model for sentiment analysis is done in three steps namely pre-processing, model fine-tuning, and the last step which is post-processing. The pre-trained BERT base cased model is used to avoid training a model from scratch, which results in reduced computational costs and computational overload. This pre-trained model allows us to use a domain-specific dataset to fine-tune the BERT model for any sentiment analysis task, whether two-class, three-class, or multiclass classification, while in this case, we make use of two-class classification. The coding was done using python through Jupyter Notebook.

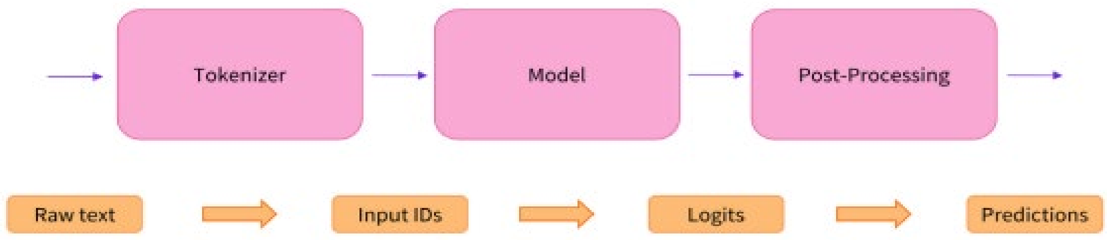


Figure 3.10: Sentiment analysis process

3.3.1 Pre-processing

Before we can start to fine-tune the model, we start by installing datasets transformers from the *huggingface_hub* platform. In this study, we use the Internet Movie Database (IMDB) dataset to fine-tune our model for sentiment analysis.

```
!pip install datasets transformers huggingface_hub

from datasets import load_dataset
dataset = load_dataset("imdb")
```

The IMBD dataset consists of exactly 25,000 reviews for movies that are labelled by sentiment for testing a model and 25,000 movie reviews for training it. After downloading and uploading the dataset, we introduce a tokenizer to offer the ability to process text and include a padding and truncation approach to handle sentences of any length. This is done by applying the pre-processing function over the entire dataset using *dataset.map* method.

```python
from transformers import AutoTokenizer

tokenizer = AutoTokenizer.from_pretrained("bert-base-cased")

def tokenize_function(examples):
    return tokenizer(examples["text"], padding="max_length", truncation=True)

tokenized_datasets = dataset.map(tokenize_function, batched=True)
```

To allow the model to train faster and to avoid possible machine overloading, we only selected a subset of 5000 over 25000 movie reviews at random to finetune our sentiment analysis model.

```python
small_train_dataset = tokenized_datasets["train"].shuffle(seed=42).select(range(5000))

small_eval_dataset = tokenized_datasets["test"].shuffle(seed=42).select(range(5000))
```

3.3.2 Fine-tuning the model

For finetuning the pre-trained model phase, we start by importing the Auto Model for Sequence Classification from the Transformers. The Auto Model for Sequence Classification is the class that is used to obtain the text classification model from the checkpoint. Then, using both the Auto Model sequence Classification class and the pretrained method, we load our model and specify that it is the BERT-base-cased and the number of labels expected is equal to two classes since we are looking to classify sentences into either positive or negative. In the IMDB dataset, Label 0 means negative sentiment and Label 1 is a positive sentiment.

```python
from transformers import AutoModelForSequenceClassification

model = AutoModelForSequenceClassification.from_pretrained("bert-base-cased", num_labels=2)
```

The next step is to finetune the hyperparameters. This is done by importing the training arguments class that has various training options concerning tuning the hyperparameters. In this study, we use the default training hyperparameter options, so that we can get optimal settings. The only two settings that we change are to specify where the checkpoints for training should be saved and for the evaluation metric to be reported at the end of each iteration or epoch using the evaluation strategy parameter, this is mainly to monitor the accuracy during model fine-tuning.

```
from transformers import TrainingArguments, Trainer

training_args = TrainingArguments(output_dir="test_trainer", evaluation_strategy="epoch")
```

The accuracy of the predictions is measured by calling the compute on metric function.

```
import numpy as np

from datasets import load_metric

metric = load_metric("accuracy")

def compute_metrics(eval_pred):

    load_accuracy = load_metric("accuracy")

    load_f1 = load_metric("f1")

    logits, labels = eval_pred

    predictions = np.argmax(logits, axis=-1)

    accuracy = load_accuracy.compute(predictions=predictions, references=labels)["accuracy"]

    f1 = load_f1.compute(predictions=predictions, references=labels)["f1"]
    return {"accuracy": accuracy, "f1": f1}
```

The next step is to create a trainer object with the test dataset, training dataset, Training arguments, evaluation accuracy, and the pre-trained model. After creating a trainer object, we call *Train()* to fine-tune our model.

```
from transformers import Trainer

trainer = Trainer(

    model=model,

    args=training_args,

    train_dataset=small_train_dataset,

    eval_dataset=small_eval_dataset,

    compute_metrics=compute_metrics,

)
```

```
trainer.train()
```

3.3.3 Postprocessing

In the post-processing phase after tuning our model, we call evaluate () to evaluate the validation loss, accuracy, runtime, and f1 score per epoch.

```
trainer.evaluate()
```

Next, we save the tokenizer and our fine-tuned model and assign the names to be able to use them to make sentiment classifications on our financial news titles.

```
save_directory = "save"
tokenizer.save_pretrained(save_directory)
model.save_pretrained(save_directory)
```

```
token1 = AutoTokenizer.from_pretrained(save_directory)
```

```
model1 = AutoModelForSequenceClassification.from_pretrained(save_directory)
```

To make the model easily accessible and less complicated to use, we import the pipeline from transformers and specify that is for sentiment analysis, then also inject our fine-tuned model and tokenizer. The pipeline will then replace the default model with our fine-tuned model.

```
from transformers import pipeline

classifier = pipeline("sentiment-analysis",model = model1, tokenizer = token1)
```

And whenever the series of sentences are passed into the pipeline classifier, the model will produce the sentiment label and sentiment scores of five decimal places for each of the sentences.

3.4 Computing sentiment scores for news titles

All four news articles' data are uploaded into the Jupyter Notebook using the panda's data frame for both the countries, South Africa and Nigeria. When the datasets are uploaded, we equate news article titles to the index column so that the titles could be selected easily because this will separate the news titles from the rest of the data content such as Date, URL, and Mobile URL. Below is the uploaded dataset for South African local news coverage.

```
df1 = pd.read_csv('RSAAPRIL2021.csv' ,    index_col = 'Title')
df2 = pd.read_csv('RSAMAY2021.csv'    ,   index_col = 'Title')
df3 = pd.read_csv('RSAJUNE2021.csv'   ,   index_col = 'Title')
df4 = pd.read_csv('RSAJULY2021.csv'    ,  index_col = 'Title')
df5 = pd.read_csv('RSAAUGUST2021.csv' ,   index_col = 'Title')
df6 = pd.read_csv('RSASEPTEMBER2021.csv', index_col = 'Title')
df7 = pd.read_csv('RSAOCTOBER2021.csv' ,  index_col = 'Title')
df8 = pd.read_csv('RSANOVEMBER2021.csv' , index_col = 'Title')
df9 = pd.read_csv('RSADECEMBER2021.csv' , index_col = 'Title')
df10 = pd.read_csv('RSAJANUARY2022.csv',  index_col = 'Title')
df11 = pd.read_csv('RSAFEBRUARY2022.csv', index_col = 'Title')
df12 = pd.read_csv('RSAMARCH2022.csv'  ,  index_col = 'Title')
```

When we further use the index on news titles columns on each of the datasets, the news titles that are produced are divided with the commas and inverted commas, which is all the requirements that are needed for the model classifier to calculate the sentiment scores and assign the labels automatically for all the titles of each dataset.

```
a = df1.index
b = df2.index
c = df3.index
d = df4.index
e = df5.index
f = df6.index
g = df7.index
h = df8.index
i = df9.index
j = df10.index
k = df11.index
l = df12.index
```

The results contain 60 news titles for each month from April 2021 to March 2022 respectively, which are made suitable to be fed manually into the *classifier ([])*. The *classifier ([])* produces 60 sentiment labels with negative or positive sentiment and 60 sentiment scores based on the news article titles contained by results a to l.

```
results = classifier([])
for result in results:
        print(f"label: {result['label']}, with score: {round(result['score'], 5)}")
```

3.5 News coverage comparison

The main aim of this sub-section is to describe the methods used to summarise and check the relations between the news content, the type of news outlet, and the exchange rates.

3.5.1 Average sentiment scores

For every 60 articles in a month for both the global and the local media outlets, the mean is used to measure the average of the sentiment scores, similarly on the currency rates, it is used to measure the centre of ZAR and Naira exchange rates data against the USD data.

$$Average\ sentiment\ score\ per\ month = \frac{The\ sum\ of\ all\ sentiment\ scores\ per\ month}{n}$$

Were,

n = The total number of news articles for each month.

3.5.2 Contingency table

The contingency table is used to summarise, count, and analyse the data by providing early possible relationships between two or more categories of variables. In this case, the contingency table is used to count, summarise, and give the preliminary analysis of the relationship between the news headline's sentiment scores (positive and negative) and news outlets (Global media and Local media).

news outlets	Headlines polarity		Total
	Negative	Positive	
Global media	a	b	a + b
Local media	c	d	c + d
Total	a + c	b + d	n

Table 3. 2: Contingency table for news sentiment labels

Were,

a = The number of news titles with negative sentiment labels from the global media,

b = The number of news titles with positive sentiment labels from the global media,

c = The number of news titles with negative sentiment labels from the local media,

d = The number of news titles with positive sentiment labels from the local media

n = The total number of news titles

3.5.3 Test of significance

The test of significance is the test used to check the significance of the relationships between the random variables. Pearson's correlation test is used to test whether there exists a significant relationship between the local and global media outlet's sentiment scores and is used to check the significance of the relationship between global media sentiment monthly scores with the monthly exchange rates for ZAR and Naira.

Step 1: Hypothesis

For testing the relationship between the local news sentiment with the global news sentiment for both countries South Africa and Nigeria.

H_O: There is no significant relationship between local news sentiments and global news sentiments.

H_1 : There is a significant relationship between local news sentiments and global news sentiments.

For testing the relationship between the news sentiment with the exchange rates for both countries South Africa and Nigeria.

H_O: There is no significant relationship between news sentiments and exchange rates.

H_1 : There is a significant relationship between news sentiments and exchange rates.

Step 2: Significance level (α)

The test of significance for the correlation coefficient is performed at an 85% confidence level in all our hypotheses.

$\alpha = 0.15$

Step 3: Decision

If the p-value is less than the significance level ($\alpha = 0.15$), then reject the null hypothesis and conclude that there is sufficient evidence to conclude that there is a significant linear relationship between the local news sentiment scores and global news sentiment scores, or the news sentiment scores and exchange rates because the correlation coefficient is significantly different from zero. Otherwise, fail to reject the null hypothesis and conclude that there is insufficient evidence to conclude that there is a significant linear relationship between the local news sentiment scores and global news sentiment scores, or the news sentiment scores and exchange rates because the correlation coefficient is not significantly different from zero, tested at 15% significance level.

3.6 Conclusion

The news article dataset was downloaded for GDELT Project from both the local and global news media outlets in South Africa and Nigeria. The pretrained transformer model for text classification is fine-tuned by a sample of 5000 two labelled movie review datasets from the IMDB. To compare the news coverage for the local and global news media outlets, the contingency table and the test of significance for the correlation coefficient are used.

Chapter 4: Results

4.1 Introduction

This chapter reports the findings of the study based on the methodologies used to gather information, develop the models, and perform tests of significance. To measure the performance of the transformer model for sentiment analysis, the accuracy, F1 score, Training loss, and validation loss are computed. The model is used to produce the sentiment scores, and those sentiment scores are used to perform the test of significance for the correlation coefficient while comparing them with the currency exchange rates for South Africa and Nigeria.

4.2 The transformer model for sentiment analysis

The pre-trained transformer model is fine-tuned using 5000 samples from the IMDB dataset for two labels, negative or positive sentiment. Table 4.1 below shows the F1 score, Training loss, accuracy, and validation over three iterations.

Table 4. 1: Training results

Epoch	Training Loss	Validation Loss	Accuracy	F1
1	0.509100	0.318483	0.873400	0.871576
2	0.307900	0.396134	0.896800	0.900616
3	0.214200	0.491581	0.897600	0.896816

For the maximum of 3 epochs, the model achieved a good accuracy of 89.76 percent for the final epoch, and the accuracy gradually increased from 87.41 percent for the first epoch and 89.68 percent for the second epoch. Only three epochs were computed due to the limited computing capabilities and the kind of model we are fine-tuning. The model also has an F1 score of 89.68%, a validation loss of 49.16%, and a training loss of 21.42% at the end of the training.

4.3 Sentiment scores

The transformer sentiment analysis model fine-tuned in section 3.3, is used to compute the sentiment scores and labels from each of the news articles collected from the local and global media outlets about financial news for South Africa and Nigeria from April 2021 to March 2022. Then the average sentiment scores and exchange rates for each month are computed and recorded.

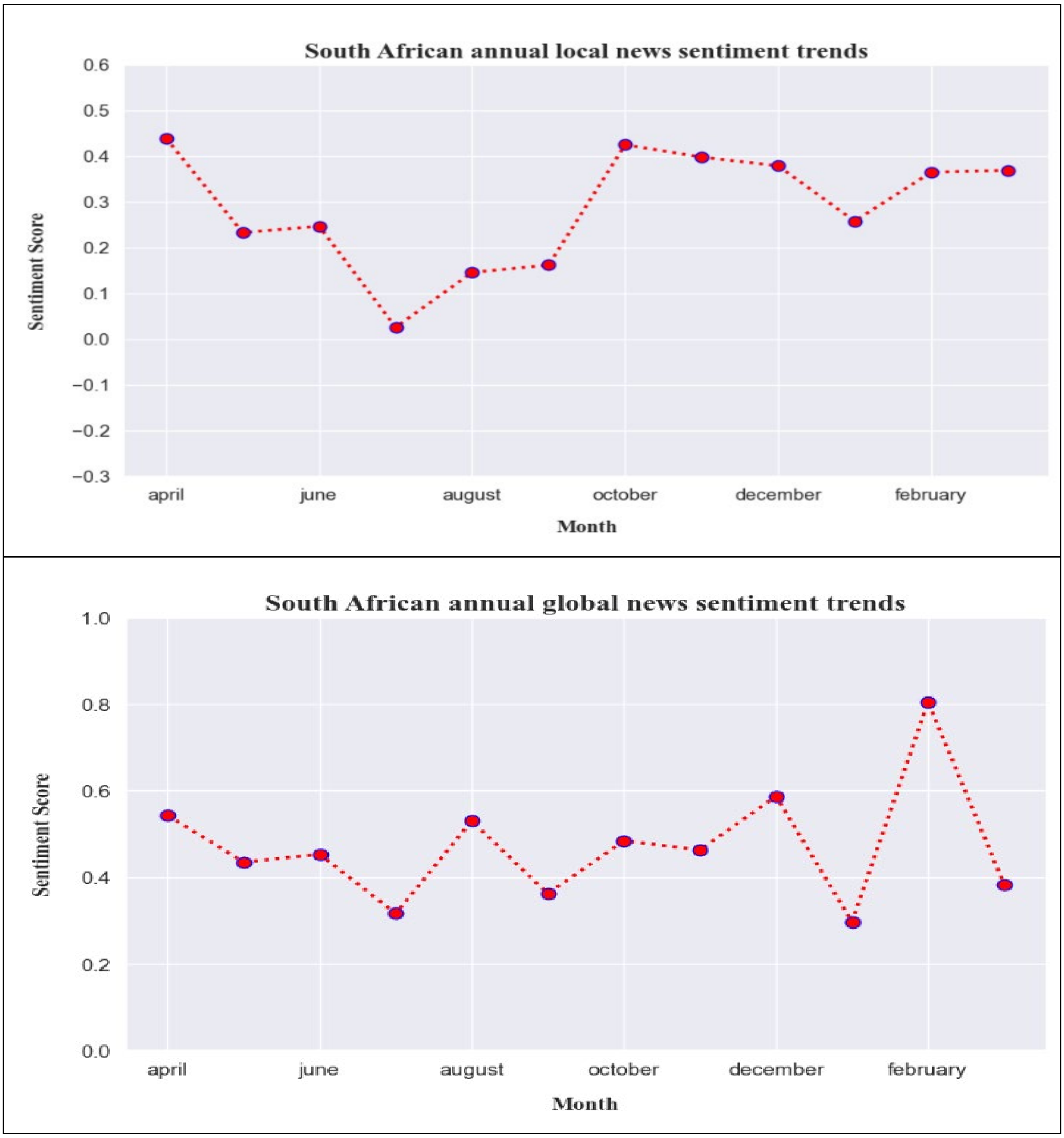


Figure 4. 1: South African news sentiment scores

Figure 4.1 above represents the line graphs for average monthly sentiments between April 2021 to March 2022 from the South African local and global news coverage. The two graphs show similar trends in most of the points, even though the sentiment scores are not equal. We can observe similar trends from April 2021 to August 2021 and from December 2021 to February 2022. The only different trends are from August 2021 to September 2021, November 2021 to December 2021, and February 2022 to March 2022. It was expected for both the graphs to show a sudden drop in positive news or an increase in negative news reporting in July 2021, because South Africa experienced a wave of looting and rioting which destroyed many businesses and these events drove the negativity in the financial news coverage.

Date	RSA local average sentiment scores	RSA average sentiment scores	Average exchange rates for Rand against Dollar
April 2021	0.439	0.543	14.405259
May 2021	0.233	0.435	14.044250
June 2021	0.247	0.453	13.913068
July 2021	0.026	0.316	14.523750
August 2021	0.146	0.530	14.774405
September 2021	0.162	0.362	14.576932
October 2021	0.425	0.484	14.846667
November 2021	0.398	0.463	15.538068
December 2021	0.379	0.587	15.881800
January 2022	0.258	0.297	15.566429
February 2022	0.365	0.805	15.212000
March 2022	0.369	0.383	14.959783

Table 4. 2: South African sentiment scores and exchange rates

Table 4.2 above shows the average sentiment scores from the local and global media coverage for South Africa and the average exchange rates for Rand against Dollar. For local news average sentiment scores, the minimum score is in July 2021 with an average positive sentiment score of 0.026, while the maximum score is in April 2021 with an average positive sentiment score of 0.439. For global news average sentiment scores, the minimum score is in January 2022 with an average positive sentiment score of 0.297, while the maximum score is in February 2022 with an average positive sentiment score of 0.805.

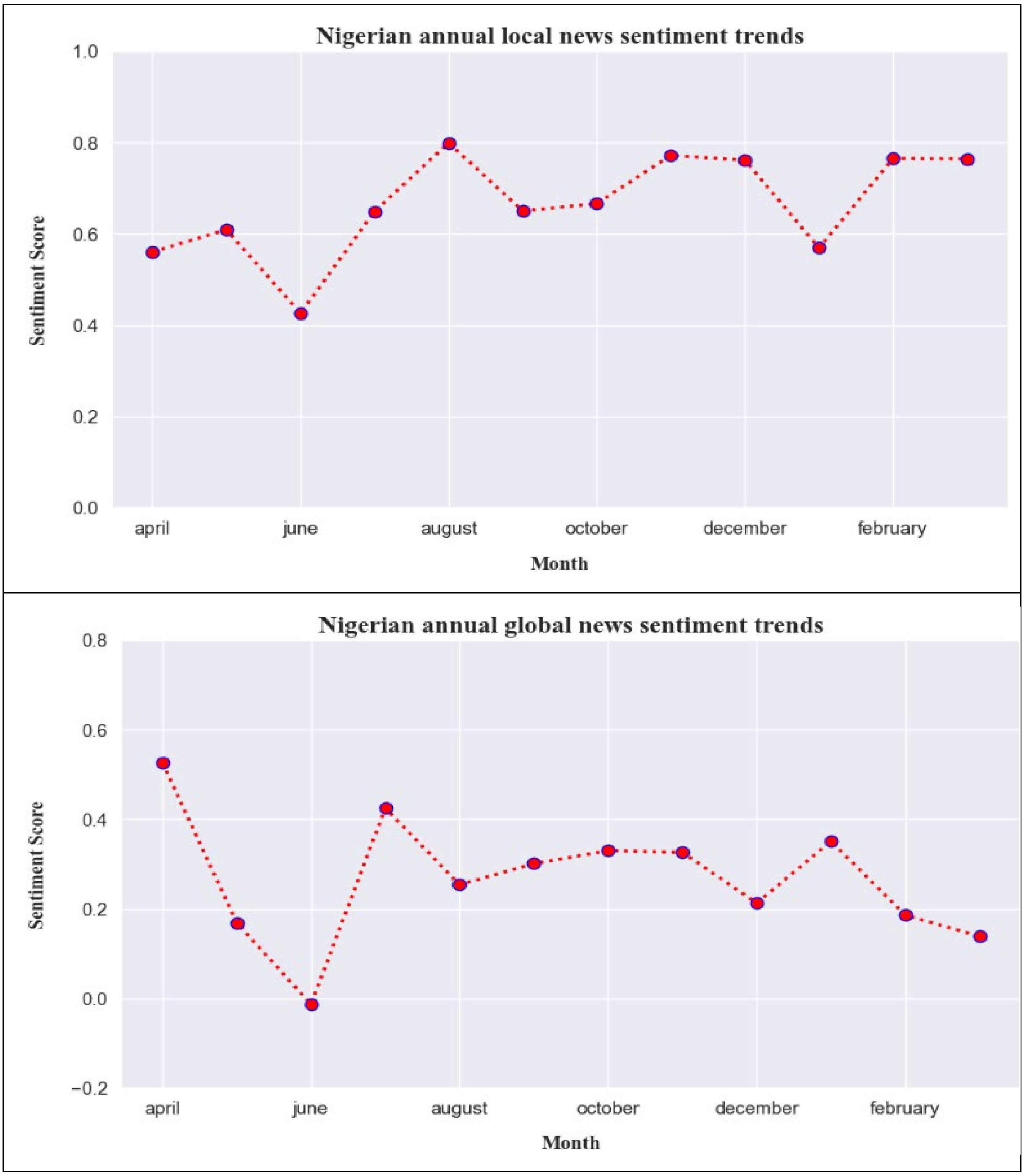


Figure 4. 2: Nigerian news sentiment scores

Figure 4.2 above represents the line graphs for average monthly sentiments between April 2021 to March 2022 from the Nigerian local and global news coverage. The two graphs do not show any similar trends in most of the points over months, the only visible similar trend is from May 2021 to July 2021.

Date	NIG local average sentiment scores	NIG average sentiment scores	Average exchange rates for Naira against Dollar
April 2021	0.560	0.526	380.550000
May 2021	0.609	0.169	397.583810
June 2021	0.426	-0.013	410.393333
July 2021	0.649	0.425	411.000000
August 2021	0.799	0.254	411.054545
September 2021	0.650	0.301	410.726818
October 2021	0.666	0.330	409.879524
November 2021	0.772	0.326	410.159545
December 2021	0.761	0.213	410.263478
January 2022	0.569	0.351	413.840952
February 2022	0.765	0.186	415.580500
March 2022	0.764	0.139	415.353478

Table 4. 3: Nigerian sentiment scores and exchange rates

Table 4.2 above shows the average sentiment scores from the local and global news coverage for Nigeria and the average exchange rates for Naira against Dollar. For the local news average sentiment scores, the minimum score is in June 2021 with an average positive sentiment score of 0.426, while the maximum score is in August 2021 with an average positive sentiment score of 0.799. For global news average sentiment scores, the minimum score is in June 2021 with an average negative sentiment score of -0.013, while the maximum score is in April 2021 with an average positive sentiment score of 0.526.

The average monthly sentiment scores for South Africa and Nigeria from both the local and global news media suggest that the majority of the news that is reported is positive rather than the negative news, but the levels of average monthly sentiment scores seem to differ from country to country on how the local and global medias cover the news. For the case of South Africa, the local and global media outlets seem to be consistently reporting the same polarity of the news, this might suggest that is either both the local and global news media outlets are biased or not biased. For the case of Nigeria, the local and global media outlets seem to report different news content, this suggest that either the local or global news outlets might found to be bias. The common thing about the South African and Nigerian news coverage is that the levels of positive against negative news are different comparing the local and global news coverage.

4.4 News coverage comparison

This section uses the average monthly news sentiment scores, exchange rates, and sentiment labels to investigate biases in the financial news coverage between the local and global news media outlets for South Africa and Nigeria. The two methods used to compare news coverage are the test of significance and the contingency table.

4.4.1 Contingency table

The contingency table is used to summarize the sentiment labels obtained from news titles into the local media outlet or global media outlet and provide an early relationship between the sentiment label and the type of news media outlet.

The type of news media outlet	Sentiment label		Total
	Negative	Positive	
Local media outlets	257 (35.7%)	463 (64.3%)	720
Global media outlets	187 (26.0%)	533 (74.0%)	720
	444	996	1440

Table 4. 4: Contingency table for South African news

From Table 4.4 it is seen that for both the local and global media outlets, the news titles with positive sentiment labels are more dominant than those with negative sentiment labels. The local media outlets report 35.7% of negative news, while the global media outlets report only 26.0% of negative news about South Africa in financial news. Therefore we can conclude that the South African local news outlets report more of negative news than the global news about South Africa. The claims that global news outlets report more of negative news than positive news are not true in this case because local news outlets are the media outlets that reports more negative news with a difference of 9.7% compared to global news outlets.

The type of news media outlet	Sentiment label		Total
	Negative	Positive	
Local media outlets	122 (16.9%)	598 (83.1%)	720
Global media outlets	262 (36.4%)	458 (63.6%)	720
	384	1056	1440

Table 4. 5: Contingency table for Nigerian news

From Table 4.5 it is seen that from both the local and global news media outlets that the titles with positive sentiment labels are more dominant than those with negative sentiment labels. The local news media outlets report 16.9% of negative news, while the global media outlets report only 36.4% of negative news about Nigeria in financial news. In both countries, local and global media outlets report more positive financial news than negative news. Therefore, we can conclude that the Nigerian global news outlets report more of negative news than the local news outlets about Nigeria. The claims that global news outlets report more of negative news than positive news are true in this case because global news outlets are indeed the news media outlets that reports more negative news with a difference of 19.5 % compared to local news outlets. This might be the case that indeed the global news outlets are bias in reporting African countries such as Nigeria as stated in the literature review or this might that indeed the financial news supposed to be more negative news articles. Hence the next step is to do hypothesis testing using sentiment scores and exchanges rates to determine whether each respective news media outlet, local or global are bias or not.

4.4.2 The test of significance for the correlation coefficient

The test of significance is used to check whether the relationship between average local news sentiment scores and the average global news sentiment scores is significant or not, and check with the average exchange rates for Rand and Naira. The information used in this section is obtained from Table 4.2 and Table 4.3.

RSA local average sentiment scores against RSA global average sentiment scores	
Correlation coefficient	0.48209103
Significance level	0.15
P-value	0.112

Table 4. 6: Local and global news sentiment scores for South Africa

From Table 4.6, the correlation coefficient is 0.482 meaning there is a low positive correlation between South African local news average sentiment scores with the South African global news average sentiment scores. To confirm whether this low positive correlation is significant or not, we use the hypothesis.

H_O: There is no significant relationship between the South African local news sentiment scores and the South African global news sentiment scores.

H_1 : There is a significant relationship between the South African local news sentiment scores and the South African global news sentiment scores.

Since the p-value (0.112) is less than the significance level (0.15), we reject the null hypothesis (H_O) and state that there is sufficient evidence to conclude that there is a significant linear relationship between the South African local news sentiment scores and the South African global news sentiment scores because the correlation coefficient is significantly different from zero, tested at 15% significance level.

RSA local average sentiment scores against exchange rates for Rand against Dollar	
Correlation coefficient	0.38937425
Significance level	0.15
P-value	0.211

Table 4. 7: Local news sentiment scores and exchange rates for South Africa

From Table 4.7, the correlation coefficient is 0.389, meaning there is a low positive correlation between South African local news average sentiment scores with the South African average exchange rates. Next, we test whether the relationship is significant or not.

H_O: There is no significant relationship between the South African local news sentiment scores and the South African average exchange rates.

H_1 : There is a significant relationship between the South African local news sentiment scores and the South African average exchange rates.

Since the p-value (0.211) is greater than the significance level (0.15), we fail to reject the null hypothesis (H_O) and state that there is insufficient evidence to conclude that there is a significant linear relationship between the South African local news sentiment scores and the South African average exchange rates because the correlation coefficient is not significantly different from zero, tested at 15% significance level.

RSA global average sentiment scores against exchange rates for Rand against Dollar	
Correlation coefficient	0.22789969
Significance level	0.15
P-value	0.476

Table 4. 8: Global news sentiment scores and exchange rates for South Africa

From Table 4.8, the correlation coefficient is 0.228, meaning there is a negligible correlation between South African global news average sentiment scores with the South African average exchange rates. Next, we confirm whether indeed correlation is negligible.

H_O: There is no significant relationship between the South African global news sentiment scores and the South African average exchange rates.

H_1 : There is a significant relationship between the South African global news sentiment scores and the South African average exchange rates.

Since the p-value (0.476) is greater than the significance level (0.15), we fail to reject the null hypothesis (H_O) and state that there is insufficient evidence to conclude that there is a significant linear relationship between the South African global news sentiment scores and the South African average exchange rates because the correlation coefficient is not significantly different from zero, tested at 15% significance level.

NIG local average sentiment scores against NIG global average sentiment scores	
Correlation coefficient	0.07272905
Significance level	0.15
P-value	0.822

Table 4. 9: Local and global news sentiment scores for Nigeria

From Table 4.9, the correlation coefficient is 0.073, meaning there is a negligible correlation between Nigerian local news average sentiment scores with the Nigerian global news average sentiment scores. Next, we confirm whether indeed correlation is negligible.

H_O: There is no significant relationship between the Nigerian local news sentiment scores and the Nigerian global news sentiment scores.

H_1 : There is a significant relationship between the Nigerian local news sentiment scores and the Nigerian global news sentiment scores.

Since the p-value (0.822) is greater than the significance level (0.15), we fail to reject the null hypothesis (H_O) and state that there is insufficient evidence to conclude that there is a significant linear relationship between the Nigerian local news sentiment scores and the Nigerian global news sentiment scores because the correlation coefficient is not significantly different from zero, tested at 15% significance level.

NIG local average sentiment scores against exchange rates for Naira against Dollar	
Correlation coefficient	0.37888992
Significance level	0.15
P-value	0.225

Table 4. 10: Local news sentiment scores and exchange rates for Nigeria

From Table 4.10, the correlation coefficient is 0.379, meaning there is a low positive correlation between Nigerian local news average sentiment scores with the Nigerian average exchange rates. Next, we test whether the relationship is significant or not.

H_O: There is no significant relationship between the Nigerian local news average sentiment scores and the Nigerian average exchange rates.

H_1 : There is a significant relationship between the Nigerian local news average sentiment scores and the Nigerian average exchange rates.

Since the p-value (0.225) is greater than the significance level (0.15), we fail to reject the null hypothesis (H_O) and state that there is insufficient evidence to conclude that there is a significant linear relationship between the Nigerian local news average sentiment scores and the Nigerian average exchange rates because the correlation coefficient is not significantly different from zero, tested at 15% significance level.

NIG global average sentiment scores against exchange rates for Naira against Dollar	
Correlation coefficient	-0.46954593
Significance level	0.15
P-value	0.124

Table 4. 11: Global news sentiment scores and exchange rates for Nigerian

From Table 4.11, the correlation coefficient is -0.4695, meaning there is a low negative correlation between Nigerian global news average sentiment scores with the Nigerian average exchange rates. Next, we confirm whether the correlation coefficient is significant or not.

H_O: There is no significant relationship between the Nigerian global news average sentiment scores and the Nigerian average exchange rates.

H_1 : There is a significant relationship between the Nigerian global news average sentiment scores and the Nigerian average exchange rates.

Since the p-value (0.124) is less than the significance level (0.15), we reject hypothesis (H_O) and state that there is sufficient evidence to conclude that there is a significant linear relationship between the Nigerian global news average sentiment scores and the Nigerian average exchange rates because the correlation coefficient is significantly different from zero, tested at 15% significance level.

For South Africa financial news coverage, it is seen that both the local and global media outlets cover the same content which is more positive news than negative news and both do not correlate with the exchange rates. Since both the global and local financial news do not correlate with the exchange rates, then we can conclude that financial news coverage for South Africa from both the local and global media outlets are biased, meaning that there are some possible elements such as news consumption rate and news value used to determine which financial news gets coverage rather fair selection of stories as seen also in chapter two under the news section. For Nigerian financial news coverage, there is a significant difference in news content between the local media outlets and global media outlets. The Nigerian local financial news content does not correlate with the exchange rates. The Nigerian global financial news content has a significant negative relationship with the exchange rates. This make sense because the decrease in positive sentiment news means the exchange rates are increasing, therefore they should be a negative relationship. We can conclude that in the Nigerian financial news coverage, the local media outlets are biased while the global news media outlets are fair. From our analysis, there is no significant evidence to suggest that the global news outlets are reporting bias negative financial news about Nigeria countries.

4.5 Conclusion

The transformer model for sentiment analysis achieved excellent results with an accuracy of 89.76%, therefore it is evident that the model is well-trained to be used to compute the sentiment scores and labels. Both the global and local media outlets report more positive financial news content than negative content for both South Africa and Nigeria. From the test of significance, it was found that for South Africa both the local and global media outlets were biased, while for Nigeria it was found that only the local news media outlets were biased and the global news media outlets were fair in reporting financial news.

Chapter 5: Conclusion

5.1 Introduction

This chapter gives a summary of the key findings of the research, answers the research objectives and address the research aim, reports the main significant contributions of the study, discuss any weaknesses or limitations of the study, and finally presents recommendations for future research purpose.

5.2 Summary and conclusions

This study aimed to use the transformer model to detect the financial news bias from global media outlets compared to the local media outlets. To fulfil the aim of the study, four objectives need to be achieved, which are to develop the transformer model for sentiment analysis, compute the news sentiment scores on the news articles using the transformer model, compare the news coverage from the local and global media outlets for South African and Nigerian news coverage, and then test whether the sentiment scores from the local and global news media outlets correlate with the economic indicator such as the exchanges rates for emerging markets countries, South Africa and Nigeria.

The transformer model for sentiment analysis was developed by using the pretrained transformer for text classification and fine-tuned on the 5000 movie reviews downloaded for IMDB. The model achieved a good accuracy of 89.76% over three iterations. It was observed that the training loss decreases as the validation loss increases, and this suggests that the model is overfitting. This is because we are fine-tuning a pre-trained on a different dataset that is not large enough, but the overfitting does not have any significant impact on our model's ability to correctly classify and compute sentiment scores from sentences. The model was tested to do sentiment classification on several comments of which all were correctly classified.

To compute the sentiment scores and labels, the news titles were extracted from the rest of the content for both the local and global news for South African and Nigerian datasets. Then the news titles for each month from April 2021 to March 2022 were injected into the transformer model classifier. The transformer model classifier then computed the sentiment scores for every news title for all the months and produced also the corresponding sentiment label of whether the sentiment score is negative or positive. After then the average sentiment scores for each month were computed and recorded along with the average monthly exchange rates for Rand and Naira against the Dollar.

When we compare the sentiment labels and sentiment scores between the global and local news coverage for both countries, we see that the coverage of positive financial news is dominant in the local and global news coverage for both countries. When looking at the line graphs for the South African local and global news average sentiment scores, we found that there are similar trends in many data points in our graphs. While for the Nigerian local and global news average sentiment scores, the line graphs do not show any similar trends in most parts.

The last step was to apply the test of significance for the correlation coefficient to check whether there exists a significant relationship between the average monthly sentiment scores for local news and global news, and further to check whether they correlate with the exchanges to detect if there is a possibility of news bias. For the South African news coverage, it was found that there is a significant relationship between the local and global financial news content, but all of them do not significantly correlate with the exchange rates for the rand against the dollar. For the Nigerian news coverage, it was found that there is no significant relationship between the local and global financial news content, but only the global news coverage correlates significantly with the exchange rates for Naira against the dollar.

Nigeria and South Africa are the largest emerging markets in Africa, therefore the financial news must not be biased, to increase the chances of attracting potential investors. For South Africa financial news coverage, in terms of the local and global news, we can conclude that they are both biased since they don't correlate with the countries' exchange rates. For Nigerian financial news coverage, only the global news correlates with the exchange rates of the country, therefore we can conclude that the local news coverage is biased, and the global news coverage is not biased. The news bias detected might be due to news media outlets using factors such as the news consumption rates and news value to determine which stories are to be published. From the information obtained above, we can conclude that the transformer model was used successfully to assess news bias between the local and global media outlets for both South Africa and Nigeria, but there is no sufficient evidence that suggests that the global news media outlets are biased in covering the negative financial news for African emerging markets, considering that both the local news media outlets for South African and Nigeria it was found that the financial news content reported does not correlate with their respective exchanges rates, therefore there are some elements of biasness to those news also. We observe that is not the matter of how the big western media outlets are biased in covering news in African but is how the media outlets cover news in African in general regardless of whether is from local or global news outlets.

5.3 Significant contributions

The pretrained transformer model for sentiment analysis was recently introduced. These models are considered the state-of-the-art accuracy for many application areas such as computer vision, natural language processing, and many others. The use of transformer model for sentiment analysis is widely used in classifying customers reviews, movie reviews, and many others, but there are limited studies done on using the model to mine the sentiments in the financial news and making good use of those sentiment scores such as when the sentiment scores are used to assess customers reviews and movie reviews. From the results we obtained, the transformer model proves to be more accurate for performing sentiment analysis using the news data compared to the classical deep learning and machine learning discussed in the literature review.

5.4 Limitations of the study

The news datasets were downloaded from the GDELT project of which there are very limited financial news articles uploaded, especially for African countries such as South Africa and Nigeria. This limited us to working with 60 news articles per month so that the information we are using could be more accurate. One major limitation of this study is no access to a computer with high processing abilities. In this study, initially, the aim was to fine-tune the model using the complete IMDB dataset, which is about 25000 movie reviews, but the computer could not execute the results at a reasonable duration. Therefore, we opted for using a sample of 5000 over 25000 movie reviews and fine-tuning the model only for three iterations. Because of the less dataset that was used, the training loss is decreasing as the validation loss increased, this suggests that the model might be overfitting the dataset.

5.5 Recommendations and future work

To avoid possible overfitting of the model when doing sentiment analysis on the news, future researchers may consider using a more sophisticated computer to be able to use large datasets and more iteration when fine-tuning the model. For further exploration into whether global news media outlets are biased when covering the African emerging markets, it was seen that South African and Nigerian news coverage gives different conclusions, therefore using more countries could eliminate this problem. Since this study shows that the local and global news media outlets are biased in covering the financial news, this raises some questions such as does news media outlets tend to cover certain content or topics that interest the readers, rather than covering the factual truth of the events occurring.

5.6 Conclusions

The transformer model sentiment analysis achieves a good accuracy of 89.76%, but there are some issues of possible overfitting. There is no evidence that suggests that the global news media outlets are biased when covering the financial news about African emerging markets compared to local news media outlets. For both African countries South Africa and Nigeria, the local and global news outlets report more positive financial news than the negative news, but the monthly average sentiment score levels between the local and global news coverage seem to differ from country to country. For further to our pretrained BERT model to achieve more accurate results, larger news datasets and larger fine-tuning datasets are needed, together with a more sophisticated computer with excellent Graphics processing unit.

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