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A Machine Learning Sentiment Analysis Approach on News Headlines to Evaluate the Performance of the Pakistani Government

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Abstract: The growing amount of unstructured online data presents challenges in efficiently organizing and summarizing relevant information, hindering knowledge development and opinion-building on various topics. Sentimental analysis is key technique to understand public views, as news significantly influences people's perceptions and emotions on various subjects, including politics, economics, and art. The study assesses Pakistani governments' performance using machine learning sentiment analysis of news headlines scraped from Dawn news, focusing on, PMLN, and PTI political party regimes, which hold the government authorities in last ten years. This study uses machine learning and pre-trained models for textual representation, recording term context and semantics, and incorporating feature reduction to enhance sentiment analysis accuracy by selecting useful features and applying labels. The SVM and sentiment intensity analyser model performed well, in experiments on two news headline datasets, from which gaining accuracy on the dawn news dataset with the sentiment intensity analyser pre-trained model. The system evaluates government efficacy using predicted labelled news, displaying sentiment scores from headlines from four regimes containing that ranking them and assessing their impacts.

Keywords*:* Sentiment Analysis (SA); Data Collection; Data Processing; Government Performance; Machine Learning (ML); Natural Language Processing (NLP); Pre-trained Models; Naïve Bayes (NB); Support Vector Machine (SVM); Linear Regression (LR)

1. Introduction

Newspapers and social media significantly influence opinions on various social, political, and religious issues, with articles potentially influencing society's overall perception. News websites provide valuable information for political campaigns and decision-making. By analysing this data, organizations can gather user opinions on government policies and gather input on potential candidates and political parties for future elections. Opinion mining, or sentimental analysis, is a technique for pulling positive, negative, neutral human emotions from written texts. SA is a technique utilized in natural language processing to categorize text output. Lexicon-based techniques use dictionaries to predict polarity, eliminating data pre-processing and classifier training. Machine learning techniques can be supervised or unsupervised. Researchers are combining classifiers and dictionaries to determine sentiment polarity on three levels, requiring annotators to annotate large amounts of data. Reading headlines provides a quick overview of a news story, while ML classification technique, such as support vector machines (SVM), naive Bayes (NB), and linear regression (LR) help understand opinions. Reviews, written in text format, provide opinions on various topics. Technological advancements have changed reading habits, with newspapers available both in print and online, with e-Papers offering current news.

News is information about current events or developments that the general public finds noteworthy or interesting. It is typically disseminated through a range of media platforms, such as websites, radio, television, and newspapers. In order to affect public opinion and decision-making, it is imperative to inform the public about events taking place locally, nationally, and globally. On the other hand, information is valuable, structured data, such as news and data from multiple sources. This ensures that information is organized and processed for effective communication. Since information has been given context, relevance, and a purpose, it is more than just raw data and enhances user comprehension. Data are just unprocessed, raw facts and numbers without any context. These are the basic elements that can be mixed and investigated to produce knowledge. For data to have meaning, it needs to be processed both qualitatively and quantitatively. The data must be sorted, evaluated, and presented in order to offer insight and comprehension. A set of actions taken in order to accomplish a specific objective is referred to as a process. Processes are useful in both artificial and natural systems because they transform inputs into desired outputs. Processes are useful in business, manufacturing, and daily life because they increase productivity, make tasks easier, and allow for the methodical accomplishment of goals.

Sentimental analysis (SA) uses machine learning classification model (ML) and natural language processing (NLP) to recognize emotional tone in news headlines, aiding in understanding consumer sentiment, industry trends, and news event effects. Sentiment analysis is crucial in media and journalism, providing insights into public perceptions, trends, and market movements by classifying headlines as positive, negative, or neutral. Sentiment analysis in news headlines is used for more than just gauging public opinion. It can also be a useful tool for decision-making processes, reputation management, and risk assessment. Sentiment analysis is a useful tool that media outlets and financial institutions can use to assess market sentiment and make better-informed editorial and investment decisions. Sentiment analysis has limitations due to sarcasm, irony, and linguistic cultural quirks, despite its potential advantages. Sentiment analysis models must constantly adapt due to the dynamic nature of language and the steady stream of new terms. Recent trends indicate that business owners, artists, organizations, agencies, and individuals are curious to know what the public thinks of their commodities, services, brands, and other offerings. Our dataset generated by social media may not be well structured and might need extensive processing before it can be used. Data models must be created to process these reviews [1].

This introduction lays the groundwork for examining the nuances of sentiment analysis within the framework of news headlines, as well as the approaches, difficulties, and practical uses of this technology in influencing our perception of public sentiment and its wider ramifications. Using natural language processing techniques (NLP), background sentiment analysis (SA) of news headlines evaluates the overall emotional tone expressed in the headlines of news articles. This analysis attempts to provide a brief overview of the dominant feelings connected to the news by identifying whether the headlines convey positive, negative, or neutral sentiments. Without reading the entire article, it assists stakeholders—like investors or the public—in determining how people perceive specific events/subjects.

Sentiment analysis is a natural language processing technique (NLP) that helps pin down the sentiments or emotion effect that is explicit in a text. This can be used with a variety of text dataset formats, like social media posts, customer reviews, news articles etc. The objective is to ascertain the attitude or opinion—whether positive, negative, or neutral—that is expressed in the text. Sentiment analysis for data, information, and news entails examining textual data to glean insights about the attitudes, sentiments, and responses of the public toward subjects or events. The terms are broken down as follows:

When discussing sentiment analysis, the term "data" refers to the textual data that has been collected from multiple sources. This could be any type of text-based content, such as news articles, customer reviews, social media posts, or anything else. After being gathered, the data is processed to create useful information. After that, sentiment analysis algorithms examine this data to determine and group the sentiments mentioned in the text. This focuses especially on using news articles to apply sentiment analysis techniques.

In last years, the influence of Machine Learning and Natural Language Processing on sentiment analysis to measure the sentiment of people has gained significant attention. This Research is conceptualized by Ammar Haider, investigates the features of machine learning algorithm in sentiment analysis prediction. The research methodology designed by the Author Hajira Noor. Co-Author Jawad Ahmad ensuring a robust framework for data collection and data pre-processing, the initial draft of this manuscript was approved by Dr. Arfan Jaffar. Co-Author Ammar Haider played a crucial role in the analysis and interpretation of the data, leading to significant findings that contribute to the existing body of knowledge on sentiment analysis on news headlines. The initial draft of this manuscript was authored by Hajira Noor and Ammar Haider, with Jawad Ahmad, Dr Fawad Nasim and Dr. Arfan Jaffar contributing to subsequent revisions and enhancements.

2. Literature Review

This study on the met averse, using AI and NLP, analysed articles from The Guardian (2021-2022). Positive sentiments (61%) emphasized innovations, while negative sentiments (30%) focused on social platform issues. The research provides concise insights into the met averse and its associations [4]. This study, based on 1200 tweets about Traveloka, assesses customer satisfaction using SVM, Logistic Regression, and Naïve Bayes. Using the Twitter API and Python's Scikit-learn, the research reveals SVM's superior accuracy in determining sentiment, providing insights into Twitter users' feelings about the mobile travel application [5].

During the COVID-19 peak in the UK, the Governor of the Bank of England's remarks on economic challenges and radical measures led to record losses in the financial market. This study links investor emotions to government policy announcements during the pandemic and concurrent Brexit, revealing a significant impact on market behaviour [6]. This study integrates Twitter data into government accounting to assess NYC street cleanliness using text mining and machine learning. By applying Naïve Bayes, Random Forest, and XGBoost, it offers an alternative performance measure, addressing class distribution issues.

The research extends to Facebook, revealing platform-specific differences in incremental value. Linking this data to government systems enhances operational evaluations, providing insights into costs and improving efficiency assessments [7]. This paper introduces LeBERT, a sentiment classification model combining lexicon, N grams, BERT, and CNN. Evaluated on diverse datasets, including Amazon and Yelp, LeBERT outperforms existing models with an 88.73% F-measure in binary sentiment classification [8]. This paper explores the intricate challenges and critical importance of detecting fake news on social media through the lens of data mining. Authored by Kai Shu, Amy Silva, Shuang Wang, Jiliang Tang, and Huan Liu, the study begins by acknowledging social media's dual role as a convenient news source and a breeding ground for intentionally misleading information.

Traditional fake news is contextualized, highlighting inherent psychological vulnerabilities that make consumers susceptible to misinformation. The authors provide a concise definition of fake news—intentionally false information created to mislead—and delve into the complexities of detecting such content on social media. The survey addresses the distinctive characteristics and challenges of fake news detection on social media, emphasizing the need for auxiliary information, such as user social engagements, to enhance detection algorithms. Challenges arising from big, incomplete, unstructured, and noisy data produced by user engagements with fake news are discussed. The comprehensive review encompasses fake news characterizations based on psychology and social theories, existing data mining algorithms, evaluation metrics, and representative datasets.

The authors introduce a mathematical formulation defining key components for fake news detection, including news articles, publishers, and content, and social news engagements. They outline news content features and social engagement features crucial for detection. The paper concludes by underscoring the increasing reliance on social media as a news source, the challenges posed by fake news, and the imperative for continued research in fake news detection, extending its applications beyond social media [9]. This paper delves into the critical issue of fake news proliferation on social media and proposes a novel approach for detection beyond traditional content analysis. Recognizing the intentional nature of fake news to mimic genuine information, the study introduces the TriFN framework.

This framework, rooted in the inherent tri-relationship among publishers, news pieces, and users during dissemination, simultaneously models the social context of partisan bias among publishers and user engagements. Experimental results on real-world datasets demonstrate the significant improvement in fake news detection offered by TriFN compared to baseline methods. The study not only showcases the framework's enhanced performance but also addresses challenges related to early fake news detection. In evaluating TriFN, the study employs standard metrics like Accuracy, Precision, Recall, and F1, utilizing 80% of news pieces for training and 20% for testing in repeated iterations. Comparative analysis against state-of-the-art fake news detection methods highlights TriFN's superiority. The research incorporates features extracted from various aspects, including Rhetorical Structure Theory (RST), Linguistic Inquiry and Word Count (LIWC), and social context features from Castillo. TriFN's effectiveness, especially in the early stages of news dissemination, underlines its potential for improving fake news detection in the dynamic landscape of social media [10].

This paper provides a thorough examination of the burgeoning issue of online fake news, emphasizing the potential societal consequences and the challenges associated with its detection. With the rapid growth of online social media as a primary means of communication, the ease of information sharing becomes a double-edged sword, facilitating the dissemination of misleading content. The study underscores the complexity of distinguishing between genuine and fake news due to the sheer volume and diverse nature of online information. It calls for a collaborative approach, combining human insights with technological advancements, to tackle the intricate task of identifying misinformation.

Through a comprehensive review of existing detection methods and datasets, the research contributes valuable insights into the characteristics of fake news and proposes an evaluation framework for building effective detection systems. Ultimately, the paper highlights the urgency of addressing the pervasive impact of fake news on various aspects of society [11].

This research focuses on the critical issue of automatic detection of fake news in online sources, particularly in social media feeds, news blogs, and online newspapers. The authors contribute by introducing two novel datasets designed for fake news detection, encompassing seven diverse news domains. They meticulously detail the collection, annotation, and validation processes, shedding light on linguistic disparities between fake and legitimate news content. The study conducts learning experiments to build accurate fake news detectors, accompanied by comparative analyses of automatic and manual identification methods. As the circulation of misinformation rises, especially on platforms like social media, the need for reliable computational tools to assess the credibility of online content becomes paramount. In constructing the fake news datasets, the authors adhere to established guidelines for corpus creation, ensuring the inclusion of both fake and real news items, homogeneity, and verifiable ground-truth.

The linguistic features employed for building fake news detection models encompass N-grams, punctuation characteristics, psycholinguistic features derived from the LIWC lexicon, and readability indicators. The paper concludes with an exploration of semantic differences between fake and legitimate news content across various domains, offering valuable insights into the distinct linguistic properties associated with deceptive news. Overall, the study provides a comprehensive approach to tackle the challenging task of automatic fake news detection, laying the foundation for further advancements in this critical area [12].

The study delves into the critical issue of fake news detection in the context of social media, presenting insights into the challenges posed by the pervasive spread of misinformation. The authors emphasize the evolving nature of news consumption on social media platforms, where the ease of registering as a news publisher without upfront costs contributes to the proliferation of false information. The research focuses on exploring various features for fake news detection, drawing on a dataset comprising BuzzFeed news articles related to the 2016 U.S. election.

They categorize features into linguistic, lexical, psycholinguistic, and semantic aspects, evaluating their discriminative power using classic and state-of-the-art classifiers. Notably, the study provides empirical results showcasing the effectiveness of these features in detecting fake news, with classifier performance metrics indicating promising results. The findings of the research extend beyond the technical realm, touching upon the practical implications of fake news detection. The authors discuss the challenges and opportunities in implementing fake news detection approaches in practice, considering the limitations of fact checking and the need for human expertise in sensitive subjects like politics. They propose a potential application where models predict the likelihood of news stories being fake, internally limiting their audience on social networks and search engines. The study advocates for a collaborative approach, suggesting that automatic fake news detection could assist fact-checkers as an auxiliary tool, enhancing the efficiency of identifying potentially false content. Despite acknowledging the necessity of human involvement in the final decision-making process, the research underscores the value of automatic detection in supporting fact-checkers and proposes avenues for future exploration, such as active learning solutions and the integration of larger labelled datasets to improve prediction performance [13].

The paper provides a comprehensive survey of natural language processing (NLP) techniques for detecting fake news, acknowledging the increasing challenge posed by the rapid growth of social networking platforms in disseminating misinformation. The authors emphasize the critical nature of fake news detection, which has real-world implications, including threats to public safety. Automatic detection of fake news is deemed essential to reduce human time and effort in identifying and preventing the spread of false information. The survey systematically reviews various task formulations, datasets, and NLP solutions developed for fake news detection. It also delves into related problems such as fact-checking, rumour detection, stance detection, and sentiment analysis. The paper categorizes task formulations into classification and regression, discussing the challenges associated with obtaining reliable labelled data for training models. The study evaluates and compares machine learning models, both non-neural network (e.g., Support Vector Machine, Naive Bayes Classifier) and neural network models (e.g., Recurrent Neural Network with LSTM), using datasets like LIAR, FEVER, and FAKENEWSNET. The findings showcase the performance of these models on different datasets, with attention mechanisms and additional metadata contributing to improved accuracy in some cases. The paper also raises critical discussions and recommendations for future research, including the need for more sophisticated truthfulness indices, diverse datasets that encompass various types of fake news, and careful consideration of the limitations of machine annotation in validating entire articles. Additionally, the survey emphasizes the potential of neural networks in replacing hand-crafted features and highlights the importance of attention mechanisms in enhancing fake news detection models [14].

The tutorial addresses the escalating threat of fake news and its detrimental impact on democracy, journalism, and economies, necessitating a comprehensive framework for systematic understanding and detection. It highlights the interdisciplinary nature of fake news research, involving experts from computer science, political science, journalism, social science, psychology, and economics. The tutorial's objectives include presenting fake news research challenges and directions, comparing fake news with related concepts like rumour, exploring fundamental theories from various disciplines, and examining diverse detection strategies under a unified framework. It also covers the state-of-the-art datasets, patterns, and models while addressing challenges for automatic fake news detection, particularly in the context of the upcoming 2020 U.S. presidential election. The context and motivation section emphasize the pervasive impact of fake news on public trust, elections, and economies. Noteworthy examples, such as the significant social media engagement during the 2016 U.S. presidential election, underscore the magnitude of the issue. The tutorial recognizes the motivations behind fake news activities, including economic benefits and the potential for individuals to exploit information gaps. It also identifies the tutorial's role in addressing both theoretical and technical aspects of fake news detection. The tutorial's outline covers fundamental theories, detection strategies, and challenges, emphasizing the need for a unified framework for fake news analysis. The target audience includes researchers, students, practitioners, and project managers across multiple disciplines, with a recommended background in data mining, machine learning, and natural language processing [15].

In this study, we provided a dataset of news headlines from the major Armenian press outlets that were released during the election season and were classified as positive, negative, or neutral by three analysts according to a target. With the most advanced pre-trained models, we conducted experiments with target-aware and target-unaware classifiers and demonstrated how these models can use target information to obtain a marginally significant advantage over predicting the overall sentiment in our data [16].

In this paper, we put forth a strategy for forecasting future stock price behaviour. For stock market prediction, we used a dataset from Kaggle called Daily News, which contained about 4116 images. i.e., either bullish or bearish using BERT based approach. We also employed the SVM and random forest classification algorithms. We found that the BERT model, with an accuracy of 86.25%, produced the best results after comparing the three models. Dealing with emotive keywords from tweets containing multiple keywords presents certain challenges. Handling the mispronunciation of words and phrases is also a challenge. In many cases, processing is restricted to extracting foreign words, long words, and their appropriate meaning. Work in emotional analytics can extend this research to neural convolution networks and potentially enhance pre word processing via deep neural networks [17] [37].

In summary, certain dataset sizes and technique pairings in machine learning pipelines work better for models like support vector machines (SVM) and naive bayes. My experiments greatly improved these models' performance scores in terms of F-1 scores and classification accuracy when compared to earlier research. It was discovered that preserving the semantic meaning of words in respect to context worked well for stock sentiment analysis in this classification task. The SVM and LSTM models with Hyperparameters and Word2Vec yielded better classification scores than the previously used RNN variants. This finding means that stock sentiment analysis will only get more intriguing over time, necessitating larger datasets and more powerful computers for future researchers to test their pipelines. According to my experimental findings, for a comparatively smaller dataset, the SVM, Passive Aggressive classifier, and my LSTM model variations performed better than the models from earlier work [38] [39]. Compared to optimizing the well-known pretrained models from earlier work, these models can be trained much more quickly. We can also circumvent the issue of not being able to train lengthy text data sequences that require numerous time steps. Our research also leads me to believe that the dataset and problem we choose can have an impact on a model's performance. Rather than choosing the most fashionable or well-liked model, these important factors should be taken into account before choosing a model. My focus in the future will be on word embedding’s' sub-linear connections, which the Word2Vec model is unable to capture. In order to circumvent this constraint, I plan to investigate Glove embedding’s. It creates word vectors with enhanced word analogy skills using an unsupervised algorithm. I'd also like to experiment with topic modelling. The Latent Dirichlet Allocation (LDA) is a tool that can produce sets of insights and analyse the relationships between different news elements. This could provide us with more in-depth and significant insights for our analysis of stock sentiment [18].

Recent times have seen the recognition of stock price prediction and the stock future trend as highly attractive and productive research problems by numerous researchers worldwide. In addition, to safeguard the economy from harm, the unexpected emergence of devastating viruses like Covid-19 necessitates automatic analysis and prediction. A brief overview of stock analysis and sentiment analysis is given in this paper. Next, it presents a highly effective system that combines the analysis of historical stock data with sentiment analysis of social news. The stock data variation during the Covid-19 period limits our system. Additionally, employing Stacked LSTM to apply the DL to the first phase predictions. Pre-processing techniques like feature selection and data normalization are used in historical data analysis to improve prediction performance. Similar text pre-processing techniques, like tokenization and parsing, are used in sentiment analysis. The Stacked-LSTM module then performs analysis on prediction vectors and yields more precise forecasts of upcoming trends. To assess performance, the suggested system is examined and tested on three stocks. In conclusion, the suggested system has an average prediction accuracy of 90%, 91.6%, and 92.3% for TSLA, AMZ, and GOOG, respectively, when it comes to stock movement predictions [19].

For entity-level sentiment and tone analysis in Croatian news headlines, we unveiled a dataset. The best results were obtained with representations of named entities and multi-task training when we tested neural benchmark models in single- and multi-task setups. Dataset cartography revealed a number of problematic scenarios for the model that may be resolved in later research. Future research might also take into account rephrasing the TSA task [20].

For text analysis, a comparison of supervised and unsupervised learnings was done. Sentiment analysis of labelled news headline data was done for supervised learning, and it was discovered that the Bi-LSTM model performed better than the machine learning ensemble model, with an accuracy of 84.92% compared to the ensemble model's 81.67%. The BiLSTM model performs better than the ensemble model because it considers the context of words, including those that occur before and after other words. Similar to this, two algorithms—LSA and LDA—were utilized for topic modelling in unsupervised learning. It was discovered that LDA outperformed LSA and generated a more homogeneous and balanced distribution of topics. Clustering graphs for both algorithms for different numbers of topics showed that the topics were more clearly visible in the case of LDA than LSA. Additionally, in order to improve topic classification in LDA, a trade-off between accuracy and topic count had to be made. Taking this into account, 24 topics with an accuracy of 81.34% were determined to be a better option because they each clearly showed the dataset and offered clear insight. While 24 topics were determined to be appropriate for this dataset, this isn't always the case for other datasets. The variable number of issues or subjects that have been discussed within that dataset determines how many topics should be chosen. This study provides a method for selecting the number of topics for a given dataset instead of using the hit-and-trial approach [21] [40].

3. Methodology

The study aims to develop a reliable system using Sentiment Analysis on news headlines to accurately measure government performance. By establishing a thorough data collection and pre-processing method, a customized model will be created to capture public sentiment about government activities, enhancing government performance measurement and showcasing machine learning's efficacy. The study examines the application of sentiment analysis to government performance evaluation, emphasizing the technology's ability to increase precision, accuracy, and nuanced public sentiment. It examines its effectiveness on various datasets, highlighting its generalizability and adaptability beyond traditional performance metrics, enhancing the responsiveness and timeliness of conventional measurement techniques.

3.1. Data Collection

Data collection have an important role in any research, data is the back bone of any research. In our research, we need the past news headlines to determine the performance of the governments of Pakistan, for this purpose we follow the multiple resources to collect the dataset like social media platforms, printed media and main stream media, from all the other sources only Dawn News have a huge archive of news headlines and description with the reliable and trusted sources. Dawn news archive have all the printed and mainstream news record publicly. We use these archives to collect the dataset of our required date ranges to continue the research in forward direction. Another Platform we use for data collection is Kaggle website. Both platforms are reliable and trusted, because both platforms are authentic dataset provider. Some of the Pakistani Government news headlines dataset is also available on Kaggle, which we use in our research along with the dataset scrape from dawn news archive site. Data Scraping is a widely used techniques to collect data from any site, we use python script to write a web scraping program which is helpful to scrap the headline data from dawn news archive site up to ten years. According to our problem statement, we need a long-term political news headlines dataset to continue our research to determine the performance of different governments who served in Pakistan. First tenure is start from June-2013 to May-2018, in which PML-N have the rights of government in Pakistan but the first tenure was divided into two durations, in first duration the prime minister was Nawaz Shareef from May-2013 to Aug-2017, and the remaining time of the first tenure was controlled by Shahid Khaqan Abbasi from PML-N. The second tenure was started from Aug-2018 to April-2022 in which Pakistan Tehreek-E-Insaf have the rights of government and Imran Khan was the prime minister of that tenure. The third tenure was starts from April-2022 to Aug-2023, in which PML-N gain the power of government and Shahbaz Shareef was the prime minister of Pakistan and now the current tenure is starts from Feb-2024 to today's data again government is under PML-N power and Shahbaz Shareef is the prime minister of Pakistan now. We are focusing on all these government tenures to identify which govt tenure is far better from all.

3.2. Data Cleaning

In data analysis and machine learning, data cleaning is an important pre-processing step. Removing or fixing undesired, incorrect, or superfluous components from the data such as extraneous words, symbols, or signs is the primary objective of data cleaning. This process improves the functionality and accuracy of a machine learning model by guaranteeing that the data fed into it is of the highest quality. We use panda's re-libraries. After cleaning data, we can manual labelling (assign label on cleaned data after reading news headline and news. Clear data makes it easier for the model to concentrate on pertinent information, which improves analysis and prediction. Removing unnecessary or incorrect information keeps the model from becoming confused by noise, which could impair its functionality. Clean data saves time and computational resources by allowing the model to process information more effectively. Before cleaning, you have to build your dataset, which may have a variety of errors, inconsistencies, and unnecessary data. Unwanted information may include specifics regarding, Common terms like "and," "the," and "is" typically don't significantly increase the meaning of text data. Characters that frequently don't provide helpful information, such as "@", "#", "!", etc. Extra characters that can block the data, such as spaces and newlines. You can carry out a variety of data cleaning tasks in Python by using libraries like Pandas, by listing stop words and removing them from the text using a filter. To remove unnecessary whitespace and fix inconsistent capitalization, use functions. The Data Frame is filtered by the filter political news function to only include rows where the category column corresponds to the designated category (in this case, political). The Data Frame rows are iterated over by the manual labelling function, which prints each headline and description for manual labelling. Since this section necessitates user interaction, it is commented out.

3.3. Data Pre-Processing

A critical stage in natural language processing (NLP) is data pre-processing, which is transforming unprocessed text into numerical representations that machine learning models can understand. Tokenization, word tokenization, frequency vectorization, and TFIDF are some of the methods used for this. Tokenization is the process of breaking text up into discrete components called tokens. Tokens may take a number of characters, words, or sub words, based upon the tokenizer in use. As a result, text is divided into words. This is what would happen if you tokenized "Data pre-processing is important": "Data", "pre-processing", "is", "important". Text is divided into separate characters as a result. Tokenizing "Data" would result in ['D', 'a', 't', 'a']. This breaks down words into smaller units, such as Word Piece or Byte Pair Encoding (BPE), which are useful for handling words that models such as NLTK and transform by hugging face do not have in their vocabulary. The process of frequency vectorization entails turning tokens into numerical vectors according to how frequently they appear in the text. This produces a matrix where documents are represented by columns and words (tokens) by rows. The quantity of tokens contained in a particular document is indicated by each entry in the matrix. For example, if we have two documents named "Data science" and "Science is fun," the count vectorized could produce the following output. Data pre-processing, which involves preparing raw data to make it suitable for creating and training machine learning classifiers, is an essential step in the data mining process. Real-world datasets are unsuitable for analysis without pre-processing because they are frequently inaccurate, inconsistent, or incomplete. Because these datasets are compiled from a variety of online and offline sources, they may include noise, missing values, and redundancy. Pre-processing is therefore necessary to turn this raw data into a clear and useful format.

3.4. Machine Learning Models

There are two types of machine learning models (MLM), first is supervised machine learning (SMLM) models, which is used for classification dataset to predict the specific labels of dataset and second is un-supervised machine learning models, which is used for regression dataset to categorize the specific groups or clusters of datasets. Our research problem is classification so we used the supervised machine learning models to classify the results of our dataset, we choose these models for training, Naïve Bayes, SVM (linear), SVM (poly), SVM (rbf), SVM (svc) with these kernels, Random Forest and Decision Tree. 80% of the dataset was used for training these models, and the remaining twenty percent was used for model testing. This is the accuracy of the supervised machine learning models that we trained on our dataset, and the sentiment predictions of the models are pretty good.

3.5. Pre-Trained Machine Learning

However, a large selection of pre-trained models is now accessible, which is ready to generate predictions on the pre-processed dataset. We choose these pre-trained machine learning classification models to predict the sentimental analysis on our dataset are these, sentimental analysis analyser provided by the Hugging face website used with transformers, sentimental analysis model provided by NLTK library, text blob model, pre-trained models provided by pipeline and Vader sentimental analyser. These are the models which we used to predict the sentiment label on our dataset. On pre-trained machine learning models, we use the complete processed news headlines dataset to predict the labels for our dataset, pre trained models are required lot of time to generate the prediction on our dataset. To measure the accuracy of these models, in order to determine the accuracy, precision, recall, and F1-Score of the predictions made by the pre-trained model, we compare the model prediction with our manually labelled dataset. This is how accurate the machine learning models that have already been trained are when compared to our manually labelled dataset.

3.6. Model Evaluation

In our classification problem, prediction of our machine learning models has been validated by finding the accuracy of the model by comparing the actual labels with the predicted labels. Moreover, to determine the precise result of the classification machine learning models, we obtain the F1-Score, recall, precision, and confusion matrix.

The definition of accuracy is the product of true positive and true negative divided by the product of false positive, false negative, true positive, and true negative. The accuracy formula can be found here.

$$Accuracy = \frac{True\,Positive + True\,Negative}{True\,Positive + True\,Negative + False\,Positive + False\,Negative}$$

Figure 1. Accuracy Formula

The number of actual positive and predicted positive labels for the model's outcome is referred to as precision. This is the precision calculation formula.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Figure 2. Precision Formula

The number of predictions that belong to a single labelled class in the dataset is referred to as recall. This is the formula for figuring out recall.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Figure 3. Recall Formula

The best evaluation metric for a machine learning model that uses classification is the F1-Score. The F1-Score is determined by calculating the precision and recall values. A model's output falls between 0 and 1, with 1 denoting an exceptional result. Because F1-score depends on precision and recall, it will be low if someone's value is low and high if someone's value is high. This is the F1-Score calculation formula.

$$F1 - Score = \frac{2(Precision * Recall)}{Precision + Recall}$$

Figure 4. F1-Score Formula

3.7. Our Contribution

We are working to measure the current and previous governments performance in Pakistan, our research will cover the different news headlines archives to gather dataset and perform different machine learning models and pre-trained models with the different pre-processing techniques to enhance the accuracy of our work. These outcomes will give a sufficient way to identify the progress and popularity of any government in the people of Pakistan.

4. Experiments and Result Evaluation

4.1. Experiments

The Proposed methodology is explained in methodology section in detail and implementation of the methodology is explained in this section. In this section, we explained all the experiments done on different machine learning models mentioned in methodology on the clean and pre-processed dataset of news headlines collected from dawn news and Kaggle website to predict the sentiment labelling on the news dataset to identify the performance of government of Pakistan from past ten years. There are 90,000 above rows of news headlines scraped from dawn news website and cleaned by using python libraries, after cleaning and selecting the political category news, only 40561 rows of political news headlines were left all the rows were manually analysis and assign the sentiment label to each row of dataset. While analysing the cleaned dataset, we observed that there are 22212 are positive news and 18349 news are negative base on 10 years of duration and 3 governments of Pakistan. These news headlines dataset is used to implement the models of machine learning mentioned in the above methodology.

After cleaning the data of news headline, pre-processing is required to convert the text into vectors to increase the understanding of machine learning models. These steps are used to perform pre-processing on our dataset mention below.

- In first step, we use the panda's library of python to read the dataset csv file of news headlines.
- In next we convert the complete dataset into lower alphabet by using python lower function.
- We use the NLTK library – tokenizer to convert the news headlines text into tokens.
- In next step we remove the stop words from dataset to enhance the dataset by implementing the stop words removal.
- The words are condensed to their most basic form using lemmatization and stemming.
- Merge the news headlines and news description into a single column.

- Apply porter stemmer to stem the news headlines text collected from dawn news website.
- Create the new csv file to store the updated form of data.
- Next apply the Frequency vectorization/ Bag of word to convert the news headlines text data into numerical vectors.
- Moreover, we apply some other vectorization techniques to convert textual data into numerical vectors to apply machine learning models on the dataset, like TFIDF etc.

The next stage is to use machine learning models to predict the sentiments of the news headlines after converting the textual data into numerical vectors. The supervised machine learning classification models that we employed in our study to make predictions on a dataset of news headlines include Gaussian Naive Bayes, Decision Tree, Random Forest, K-Neighbors, and Support Vector Machine. However, we also use the pre-trained models from the NLTK library, Text Blob, pipeline, Vader Sentimental Analysis models, and the hugging face website that transformers use. Our dataset, which contains 40,000 rows with labels above, is divided into training and testing datasets at a ratio of 80%–20% for supervised machine learning models. Eighty percent of the dataset is manually labelled for model training, and the remaining twenty percent is used to assess the accuracy of machine learning models that have been trained.

4.2. Results Discussion

In results and discussion, we explained all the machine learning classification models and pre-trained sentimental analysis models implemented on our dataset, in which 40561 rows of political cleaned news headlines dataset are available, in which 22212 are positive news and 18349 are negative news based on 10 years of duration.

4.2.1. Pre-Trained Models

To create the sentiment labels for the political news headlines dataset, we first apply pre-trained models to this dataset. We use hugging face, pipelines, transformers, NLTK (Natural Language Tool Kit), and other pre-trained model service providers to directly apply pre-trained models on your dataset without the need for model training. These models are capable of generating predictions on datasets without the need for model learning. We apply nine pre-trained models to our dataset in order to produce sentimental predictions. Once the predictions are generated, we apply a confusion matrix to the model's prediction and our manually labelled dataset in order to assess the model's accuracy. This yields the macro F1 score, macro recall score, and macro precision score. The pre-trained models' outcomes are listed in the table below.

Table 1. Pre-Trained Models Accuracy Score

Model	Provider	Pre-Processing	Accuracy	Precision	Recall	F1 Score
Sentiment Intensity Analyzer	Spacy – Vader Sentiment	Porter Stemmer – Word Tokenizer	0.995	0.993	0.995	0.994
Sentiment Intensity Analyser	NLTK	Word Tokenizer	0.89	0.82	0.87	0.86
Text Blob	Pipeline – Punkt	Porter Stemmer – Regex Tokenizer – Stop words	0.52	0.56	0.54	0.50
Sentiment Intensity Analyser	Vader Lexicon	Vader	0.993	0.996	0.997	0.991
Text-Classification	Hugging Face	Transformers	0.72	0.71	0.69	0.74
Bert For Sequence Classification	Hugging Face	Bert Tokenizer	0.92	0.91	0.93	0.91
Sentiment Analysis	Hugging Face	Transformers	0.61	0.83	0.37	0.51
Sentiment Intensity Analyser	NLTK	Vader Sentiment	0.995	0.992	0.990	0.991
Happy Word Prediction	Happy Transformer	Word Tokenizer	0.64	0.61	0.72	0.68

We used our dataset to test nine pre-trained models, each of which needed a different set of pre-processing steps in order to produce sentimental predictions. Pre-processing techniques such as Porter Stemmer, Word Tokenizer, Regex Tokenizer, Vader Sentiment, and Stop Words removal are employed to turn the text into tokens. Pre-trained models like Sentiment Intensity Analyser from NLTK, Vader Lexicon, Spacy, and Vader Sentiment are also implemented. Additional models include Text Blob, Text Classification, BERT, from all of these models, the sentiment intensity analyser provided by Spacy - Vader sentiment and pre-processed by Porter stemmer and word tokenizer performed well, with accuracy of 99.5%, precision of 99.3%, recall of 99.5%, and F1 Score of 99.4%. Happy Word Prediction was provided by hugging face using transformers. The Vader Lexicon-provided and Vader pre-processed sentiment intensity analyser had good performance as well, with accuracy of 99.3%, precision of 99.6%, recall of 99.7%, and F1 Score of 99.1%. The Vader Sentiment pre-processed and supplied by NLTK sentiment intensity analyser performed admirably as well, with accuracy of 99.5%, precision of 99.2%, recall of 99.0%, and F1 Score of 99.1%.

4.2.2. Machine Learning Classification Models

Second, we implement machine learning models on our dataset by using skit-learn library, our sentimental analysis prediction is classification problem, for that purpose we use machine learning classification models, in which naïve Bayes (Bernoulli, Multinomial, Gaussian), Support vector machine classification model, Random Forest classifier, decision tree classifier, and K nearest neighbour classifier. To turn the dataset into vectors, we employ TFIDF, frequency vectorization, and binary vectorization—three methods of data pre-processing. We face kernel dead issues in binary vectorization conversion due to large amount of dataset, so we skip the binary vectorization and continues our working with TFIDF and Frequency vectorization. Each model trained on two different vectors of each dataset, first dataset converted text to vector by using TFIDF model trained on that dataset and generate predictions and measure accuracy, after that again dataset is converted text to vectors by using frequency vectorization and machine learning classification models trained on that dataset and generate predictions accordingly. We use 80% of the dataset for training the models, and the remaining 20% is used to assess the machine learning models' accuracy. The confusion matrix, which calculates macro precision, macro recall, and macro f1 score based on model predictions and testing dataset labels, is used to measure the accuracy of the machine learning model. The models that have been used and their accuracy values are displayed in the table below.

Table 2. Machine Learning Models Accuracy Score

No	Model Name	Pre-Processing	Accuracy Score
Model 1	Decision Tree Classifier	TFIDF	Precision Score: 0.768 score for Recall: 0.767 F1 Score: 0.768
		Frequency	Precision Score: 0.784 score for Recall: 0.783 F1 Score: 0.783
Model 2	K Neighbours Classifier	TFIDF	Precision Result: 0.694 Recall Score: 0.688 F1 Score: 0.684
		Frequency	Precision Score: 0.655 Recall Score: 0.598 F1 Score: 0.554
Model 3	Random Forest Classifier	TFIDF	Precision Score: 0.772 Recall Score: 0.772 F1 Score: 0.772
		Frequency	Precision Score: 0.775 Recall Score: 0.776 F1 Score: 0.775
Model 4	SVM SVC	TFIDF	Precision Score: 0.896 Recall Score: 0.885 F1 Score: 0.898

	Frequency	Precision Score: 0.821 Recall Score: 0.840 F1 Score: 0.863

Using our dataset for sentimental analysis, we ran seven machine learning classification models. Since each model was trained using two distinct vectorization techniques, we were able to obtain a total of fourteen trained models for our dataset of political news headlines. The support vector machine classifier outperforms the other machine learning models in terms of accuracy and performance. When using TFIDF vectorization, the support vector classifier's macro f1 score is 89.8%, its macro precision is 89.6%, and its macro recall is 88.5%. However, the frequency vectorization macro f1 score of the support vector classifiers is 86.3%, the macro precision is 82.1%, and the macro recall is 84.0%. TFIDF vectorization decision tree classifiers have a macro f1 score of 76.8%, a macro precision of 76.8%, and a macro recall of 76.7%. The frequency vectorization decision tree classifiers, on the other hand, have a macro f1 score of 78.3%, a macro precision of 78.4%, and a macro recall of 78.3%. We apply every kind of naïve Bayes model. Compared to other types, Bernoulli naïve Bayes performs much better. With TFIDF vectorization, Bernoulli naïve Bayes has a macro f1 score of 78.4%, macro precision of 78.4%, and macro recall of 78.4%. However, the Bernoulli naïve Bayes with frequency vectorization macro f1 score is 78.4%, as well as 78.4% for macro recall and precision.

4.3. Government Performance

Our second phase of research is to measure the performance of government after finalizing the sentiment labels on our dataset by applying different models discuss in pervious section. According to our dataset range collected from the dawn news website and cleaned, there are Five regimes covered in our dataset, PML-N (Pakistan Muslim League Noon) PTI (Pakistan Tehreek Insaaf) again tenure of PML-N (Pakistan Muslim League Noon) and care taker setup before general elections and PML-N (Pakistan Muslim League Noon) after general elections. We ignore the care taker setup because their responsibility is to conduct general elections as per given timeframe. Now we have the four regimes in our research, according to our machine learning models results first regime is PMLN which have 44.2% positive news and 55.8% news are negative. Second regime is PTI which have 67.7% positive news which is the highest positive news from these four regimes and the negative news are 32.3% in our political news dataset. Third regime which is very short tenure is again PMLN which have high rate of negative news in these regimes, their negative news is 59.4% and the positive news are 40.6% and last regime which is now continue is again PMLN after the general elections conducted by the care taker setup and election commission of Pakistan, this regime of PMLN have 43.9% positive news and rest 56.1% is negative news. These results show that the second regime of PTI (Pakistan Tehreek Insaaf) have most popular government in last 4 regimes of Pakistan because the impact of positive and negative score shows the popularity of any government in their nation, PTI (Pakistan Tehreek Insaaf) 67.7% positive score have the highest positive score among all.

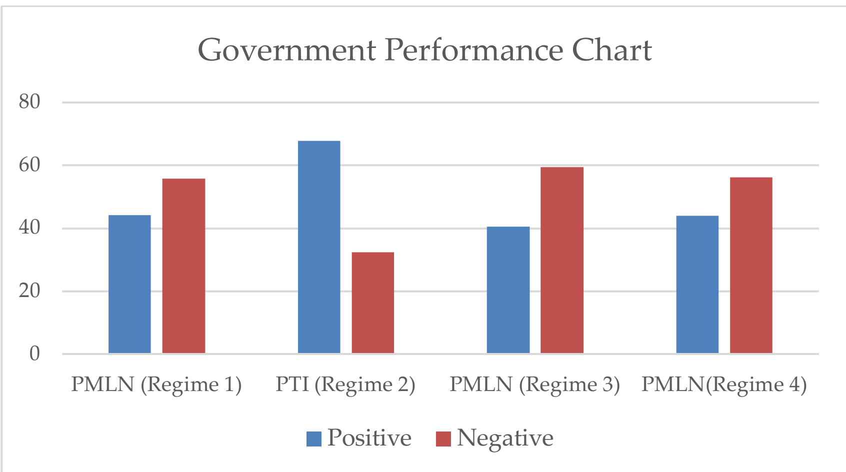

Figure 5. Government Performance Measure Chart

5. Conclusions

Sentimental Analysis of any content is very difficult challenge for researchers specially related to news headlines, each word plays important impact on the positivity and negativity of news. The beauty of this study is to measure the government performance regarding news headlines which will helpful to identify the political party have more impact in the country. New headlines have enough knowledge to decide that the news is positive or negative regardless without knowing detailed news description. Our study based on dawn news headlines dataset scraped for four regimes after cleaning and pre-processing process, pre trained sentimental analysis models and machine learning classifier models implemented on our dataset, and according to the results of both models we observe pre-trained models performed very well rather than machine learning classification models. After generating the prediction our second phase of research is measuring the performance of four regimes government. We observe that the PTI (Pakistan Tehreek Insaaf) have the better positive impact on country rather than other regimes. Furthermore, there are lot of other approaches which can be implement in future and news headlines dataset rapidly increasing on daily basis, the work of this study can be extended with the increasing of time and apply other techniques.

References

1. Sangam, S., & Shinde, S. (2019). Sentiment classification of social media reviews using an ensemble classifier. Indones. J. Electr. Eng. Comput. Sci, 16(1), 355.
2. Dor, D. (2003). On newspaper headlines as relevance optimizers. Journal of pragmatics, 35(5), 695-721.
3. Taj, S., Shaikh, B. B., & Meghji, A. F. (2019, January). Sentiment analysis of news articles: A lexicon-based approach. In 2019 2nd international conference on computing, mathematics and engineering technologies (iCoMET) (pp. 1-5). IEEE.
4. Tunca, S., Sezen, B., & Wilk, V. (2023). An explorator [] y content and sentiment analysis of the guardian metaverse articles using leximancer and natural language processing. Journal of Big Data, 10(1), 82
5. Diekson, Z. A., Prakoso, M. R. B., Putra, M. S. Q., Syaputra, M. S. A. F., Achmad, S., & Sutoyo, R. (2023). Sentiment analysis for customer review: Case study of Traveloka. Procedia Computer Science, 216, 682-690.
6. Paterson, A., Sakariyahu, R., Lawal, R., & Alabi, A. (2023). The Impact of Government Policy Responses to the COVID-19 Pandemic and Brexit on the UK Financial Market: A Behavioural Perspective. British Journal of Management.
7. Duan, H. K., Vasarhelyi, M. A., Codesso, M., & Alzamil, Z. (2023). Enhancing the government accounting information systems using social media information: An application of text mining and machine learning. International Journal of Accounting Information Systems, 48, 100600.
8. Mutinda, J., Mwangi, W., & Okeyo, G. (2023). Sentiment analysis of text reviews using lexicon enhanced bert embedding (LeBERT) model with convolutional neural network. Applied Sciences, 13(3), 1445.
9. Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake news detection on social media: A data mining perspective. ACM SIGKDD explorations newsletter, 19(1), 22-36.
10. Shu, K., Wang, S., & Liu, H. (2019, January). Beyond news contents: The role of social context for fake news detection. In Proceedings of the twelfth ACM international conference on web search and data mining (pp. 312-320).
11. Zhang, X., & Ghorbani, A. A. (2020). An overview of online fake news: Characterization, detection, and discussion. Information Processing & Management, 57(2), 102025.
12. Pérez-Rosas, V., Kleinberg, B., Lefevre, A., & Mihalcea, R. (2017). Automatic detection of fake news. arXiv preprint arXiv:1708.07104.
13. Reis, J. C., Correia, A., Murai, F., Veloso, A., & Benevenuto, F. (2019). Supervised learning for fake news detection. IEEE Intelligent Systems, 34(2), 76-81
14. Oshikawa, R., Qian, J., & Wang, W. Y. (2018). A survey on natural language processing for fake news detection. arXiv preprint arXiv:1811.00770.
15. Zhou, X., Zafarani, R., Shu, K., & Liu, H. (2019, January). Fake news: Fundamental theories, detection strategies and challenges. In Proceedings of the twelfth ACM international conference on web search and data mining (pp. 836-837).
16. Pérez, J. M., Zapata, E. R., Salgueiro, T. A., Furman, D., & Larrosa, P. N. F. (2023). A Spanish dataset for Targeted Sentiment Analysis of political headlines. Electronic Journal of SADIO (EJS), 22(1), 53-66.
17. Saxena, A., Jain, A., Sharma, P., Singla, S., & Ticku, A. (2023). Sentiment Analysis of Stocks Based on News Headlines Using NLP. In International Conference on Artificial Intelligence Techniques for Electrical Engineering Systems (pp. 124-135). Atlantis Press, Dordrecht.
18. Gaikwad, R. (2023). Comparison of Machine Learning and Deep Learning models for Stock Sentiment Analysis using News Headlines (Doctoral dissertation, California State U university, Northridge.

19. Sharaf, M., Hemdan, E. E. D., El-Sayed, A., & El-Bahnasawy, N. A. (2023). An efficient hybrid stock trend prediction system during COVID-19 pandemic based on stacked-LSTM and news sentiment an analysis. Multimedia Tools and Applications, 82(16), 23945-23977.
20. Barić, A., Majer, L., Dukić, D., Grbeša-zenzerović, M., & Šnajder, J. (2023, May). Target Two Birds with One STONE: Entity-Level Sentiment and Tone Analysis in Croatian News Headlines. In Proceedings of the 9th Workshop on Slavic Natural Language Processing 2023 (SlavicNLP 2023) (pp. 78-85).
21. Yadav, V. (2022). Sentiment Analysis and Topic Modeling on News Headlines (Doctoral d issertation, IOE Pulchowk Campus.
22. Kaliappan, S., Natrayan, L., & Rajput, A. (2023, September). Sentiment Analysis of News Headlines Based on Sentiment Lexicon and Deep Learning. In 2023 4th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 1044-1047). IEEE.
23. Pérez, J. M., Zapata, E. R., Salgueiro, T. A., Furman, D., & Larrosa, P. N. F. (2023). A Spanish dataset for Targeted Sentiment Analysis of political headlines. Electronic Journal of SADIO (EJS), 22(1), 53-66.
24. Limone, A., Gupta, M., Nagar, N., & Prajapat, S. (2023, September). Effect of financial news headlines on crypto prices using sentiment analysis. In UK Workshop on Computational Intelligence (pp. 209-219). Cham: Springer Nature Switzerland.
25. Gaikwad, R. (2023). Comparison of Machine Learning and Deep Learning models for Stock Sentiment Analysis using News Headlines (Doctoral dissertation, California State University, Northridge).
26. Iqbal, B. M., Lhaksmana, K. M., & Setiawan, E. B. (2023). 2024 Presidential Election Sentiment Analysis in News Media Using Support Vector Machine. Journal of Computer System and Informatics (JoSYC), 4(2), 397-404.
27. Hamed, S. K., Ab Aziz, M. J., & Yaakub, M. R. (2023). Fake news detection model on social media by leveraging sentiment analysis of news content and emotion analysis of users' comments. Sensors, 23(4), 1748.
28. Barić, A., Majer, L., Dukić, D., Grbeša-Zenzerović, M., & Šnajder, J. (2023, May). Target Two Birds With One SToNe: Entity-Level Sentiment and Tone Analysis in Croatian News Headlines. In Proceedings of the 9th Workshop on Slavic Natural Language Processing 2023 (SlavicNLP 2023) (pp. 78-85).
29. Sharaf, M., Hemdan, E. E. D., El-Sayed, A., & El-Bahnasawy, N. A. (2023). An efficient hybrid stock trend prediction system during COVID-19 pandemic based on stacked-LSTM and news sentiment analysis. Multimedia Tools and Applications, 82(16), 23945-23977.
30. Agarwal, A., Vats, S., Agarwal, R., Ratra, A., Sharma, V., & Gopal, L. (2023, March). Sentiment analysis in stock price prediction: a comparative study of algorithms. In 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom) (pp. 1403-1407). IEEE.
31. Glasserman, P., & Lin, C. (2023). Assessing look-ahead bias in stock return predictions generated by gpt sentiment analysis. arXiv preprint arXiv:2309.17322.
32. Mo, K., Liu, W., Xu, X., Yu, C., Zou, Y., & Xia, F. (2024). Fine-Tuning Gemma-7B for Enhanced Sentiment Analysis of Financial News Headlines. arXiv preprint arXiv:2406.13626.
33. Samin, T., Mouri, N. A., Haque, F., & Islam, M. S. (2024, May). Sentiment Analysis of Bangladeshi Digital Newspaper by Using Machine Learning and Natural Language Processing. In 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT) (pp. 149-153). IEEE.
34. Wagner, T., Guhl, D., & Langhals, B. (2024). The Impact of Data Preparation and Model Complexity on the Natural Language Classification of Chinese News Headlines. Algorithms, 17(4), 132.
35. Lefort, B., Benhamou, E., Ohana, J. J., Saltiel, D., Guez, B., & Jacquot, T. (2024). Sentiment Analysis of Bloomberg Markets Wrap Using ChatGPT: Application to the NASDAQ. Available at SSRN 4780150.

36. Thimmaiah, K. (2024). Perform the Stock Prediction Using the Sentiment Analysis and Time Series Forecasting Approaches to Determine the Optimal One (Doctoral dissertation, Dublin Business School).
37. Shaker, B., Ullah, K., Ullah, Z., Ahsan, M., Ibrar, M., & Javed, M. A. (2023, November). Enhancing grid resilience: Leveraging power from flexible load in modern power systems. In 2023 18th International Conference on Emerging Technologies (ICET) (pp. 246-251). IEEE.
38. Munir, A., Sumra, I. A., Naveed, R., & Javed, M. A. (2024). Techniques for Authentication and Defense Strategies to Mitigate IoT Security Risks. Journal of Computing & Biomedical Informatics, 7(01).
39. Ali, H., Iqbal, M., Javed, M. A., Naqvi, S. F. M., Aziz, M. M., & Ahmad, M. (2023, October). Poker Face Defense: Countering Passive Circuit Fingerprinting Adversaries in Tor Hidden Services. In 2023 International Conference on IT and Industrial Technologies (ICIT) (pp. 1-7). IEEE.
40. Sajid, M., Malik, K. R., Almogren, A., Malik, T. S., Khan, A. H., Tanveer, J., & Rehman, A. U. (2024). Enhancing intrusion detection: a hybrid machine and deep learning approach. Journal of Cloud Computing, 13(1), 1-24.
41. Shah, A. M., Aljubayri, M., Khan, M. F., Alqahtani, J., Sulaiman, A., & Shaikh, A. (2023). ILSM: Incorporated Lightweight Security Model for Improving QOS in WSN. Computer Systems Science & Engineering, 46(2).