EXTENSIVE ANALYSIS OF PRESIDENTIAL SPEECHES USING NLP AND MACHINE LEARNING ALGORITHMS

BY

GROUP 3

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DECLARATION

I, Derick Dankwah, Yamoah Owusu Romeo, Apaflo Godson Teye and Keil Kofi Boateng declare that the submission is our own work towards the award of a BSc. In Information Technology. And that to the best of our knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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Abstract

This project presents an extensive analysis of the State of the Nation Address (SONA) delivered by the various Presidents of Ghana across the years, using Natural Language Processing (NLP) and machine learning algorithms and techniques. The SONA is a crusial yearly event that outlines the economic, social, and governance status of the country Ghana, yet it often contains ambiguous or misleading information, necessitating rigorous scrutiny. Our research addresses the challenge of verifying the truthfulness of statements made in these speeches by developing a machine learning model that classifies speech segments into distinct categories of truthfulness (truth/lie).

Leveraging advanced NLP techniques such as tokenization, lemmatization, and part-of-speech tagging, we preprocess the SONA texts to prepare them for analysis. We employ various machine learning models, including Support Vector Machines (SVM), Random Forests to perform classification tasks on the processed data. The significance of this study lies in its potential to streamline the analysis of political communication, providing a data-driven approach to identify instances of deceit and improve transparency in governance.

By developing a user-friendly system for fact-checking, our research aims to empower analysts, journalists, and the general public to critically engage with presidential speeches, thereby enhancing accountability and integrity in political discourse. In the long run, this study contributes to the broader field of political analysis, offering insights into the effectiveness of SONA and its implications in Ghana.

Chapter 1

Introduction

This aspect of the research contains information on the background of study, problem statement, objectives and the organization of the study.

1.1 Background Of Study

The State of the Nation Address (SONA) is an annual speech to Parliament given by the President of the Republic of Ghana, covering the economic, social, and financial state of the country, as mandated by Article 67 of the 1992 Constitution of Ghana (Ghana Web, 2024.).The SONA was first implemented under the administration of the second President of the Fourth Republic of Ghana, John Agyekum Kufuor. Records indicate that during his 18 years in office, former President Jerry John Rawlings did not deliver a single State of the Nation Address, despite the constitutional requirement (Ghana Constitution, 2024). Former President John Agyekum Kufuor was the first to adhere strictly to the constitutional mandate, delivering the SONA at the beginning and close of every parliamentary session. Since then, the SONA has become a consistent feature of Ghana's political landscape (Ghana Web, 2024.). Interestingly, the tradition of delivering such an address in person before a joint session of Congress dates back to George Washington, who first fulfilled this presidential duty on January 8, 1790, in New York City(*State of the Union*, 2022).

The SONA warrants critical analysis and scrutiny as it is one of the President’s most significant formal governance and communication events, providing a blueprint for the nation’s developmental agenda for the year (Sikanku, 2022). With how important these speeches are one would think that they are written to perfection without any flaw or deceit behind them but that is not the case. A blog by Julius Yao Petetsi on the Ghana Times website expressed how a State of the Nation Address (SONA) by then-President Nana Addo Dankwah Akufo-Addo did not accurately reflect the true state of the country. He continued to explain how a minority was able to detect instances of deceit in the speech and expressed in a paragraph that in the view of Mr Iddrisu, the success reported by the president in the various sectors of the economy including health, education, roads, security amongst others were just a rehatch of the promises that won him the election(JULIUS YAO PETETSI, 2022). The problem with deceit and false information in these speeches is that it can be very difficult to detect, especially when the information is outdated.

Artificial intelligence is developing at an incredibly fast pace. The potential is enormous and it's hard to see where it will end. Artificial intelligence is based on maths and logic. We know the work processes, but we don't always know how the AI arrives at a particular solution. Therefore, as researchers and society, we must make demands on the use of technology, both in legislation and morally. In Ghana, there is a need for a system that can analyze these SONA speeches by the various presidents, categorize them, and identify instances of deception and false information. In this study, we employ Natural Language Processing (NLP) and machine learning algorithms to perform a classification analysis of the SONA texts. We aim to classify segments of the speeches based on sentiment (positive/negative) and truthfulness (truth/lie), thereby uncovering patterns in political communication. Using NLP techniques such as tokenization, lemmatization, and parts of speech tagging, we pre-process the text data to make it suitable for analysis(Chai, 2023). We then apply various machine learning models, including Support Vector Machines (SVM), Random Forests, and neural networks, to classify the speech segments. This approach not only enhances our understanding of the content and tone of the addresses but also contributes to the broader field of political discourse analysis(Sagar, 2023). By leveraging advanced computational methods, this research aims to shed light on the dynamics of presidential communication in Ghana, providing a data-driven perspective on the effectiveness and transparency of the State of the Nation Addresses.

1.2 Problem Statement

In Ghana the analysis of SONA is important to individuals as it gives an overview of the current position and stand of the governance as well as the economic condition of the country which is the reason why most press institutions give a commentary on it when it is delivered, and example being a commentary of the Ghana state of the nation address which was published on the Ghana Investment promotion website(Benjamin A. Alomatu, 2024). Most of the analysis done on SONA are from these online sources or the internet and recent research has proven that the internet isn't a reliable place for information. The information on the analysis can be twisted to the view or to suit the way the analyser(*LibGuides: Evaluating Information Sources: Should I Trust Internet Sources?*, n.d.).

SONA speeches are lengthy and to be able to understand and grasp which aspects of the speech is true or false a huge amount of research is needed on that single document. Rigorous fact checking and analysis is required which can be time consuming and put significant toll on the individual. In addition to text analysis being time consuming it is also very costly as efficient analysis would require the person who wants the analysis to pay multiple people to work on efficient fact-checking of the information he or she wants to derive from the set of data(Phillip P. Adu, 2022).

There are various text analysis automated systems however most of the ones available aren't really focussed on deriving the facts in SONA and the ones available incorporate analysis of information which could be termed as irrelevant in our research(Shashank S. Gupta, 2018). There is a need for a simpler analysis of SONA text speeches and classification to reduce the strain of traditional methods of classification of text speeches(Phillip P. Adu, 2022).

1.3 Objectives

1.3.1 Main Objective

The primary objective of this research is to develop a machine-learning model that can accurately categorize speech content into distinct segments based on sentiment (positive/negative) and truthfulness (truth/lie).

1.3.2 Specific Objectives

This research seeks to:

1. Make Fact SONA fact checking easier.
2. Using Python and NLP libraries to pre-processed scanned texts this is transforming the speeches so it can be understood by the computer or the model.
3. Perform fact-checking and use pre-labelled and pre-process data to perform classification, whether claim it is true or false.

1.4 Significance of Study

This study will provide a much simpler alternative to the robust and difficult to use analysis systems. It also provides a specific outcome as it is focussed mainly on identifying deceit or truthfulness in SONA speeches. By locating or identifying instances of deceit and false delivery of information, the study adds to greater transparency in political communication. The research can hold political leaders accountable for the accuracy of their statements, thereby promoting integrity in governance and the nation as a whole.

The research aims to aid individual that will indulge in the analysis of SONA speeches have a system that can reduce fact-checking tasks so they can accurately and efficiently analyse the text without much problems or stess.The study offers a data-driven on the effectiveness and transparency of SONAs, helping government officials, researchers, and the public in understanding the presidents and the information they share to us Ghanaians.

1.5 Organisation of study

This study is a five parts study with aspects of the stufy including labelled chapters, from Chapter One to Chapter Five. Chapter one encompases the introduction of the study. This aspect of the study contains the background of the study, problem statement, main as well as the specific objectives, and the significance of the study. Chapter two is where the literature review that backs our study will be. In Chapter three we discuss the steps and the procedures as well as various tools and techniques needed to complete the work. We explain how we build the models and perform text analysis with SONA speeches. We also discuss the data types, and the data collection methods. In chapter four, we discuss the results of our study. In this section of the work we discuss the results we were able to derive from the methodology we implemented in our work and how efficient and effective the model was able to process the text data analyse and classify them. Chapter 5 concludes the study. It contains a summary of the entire work as well as expectations for the future and some recommendations for future works. In addition, all references used in the development of this stufy will be added at the end of the final chapter.

Chapter 2

Literature Review

Introduction

This chapter is the literature review of this research where definition of concepts, and subtopics as well as related works and some summary of works can be found.The conclusion is the final part of this chapter given an overview of the literature review.

2.1 Definition of Concepts

2.1.1 State of The Nation Address (SONA)

The State of the Nation is an annual address to Parliament given by the President of the republic of Ghana covering economic, social, and financial state of the country according to Article 67 of the 1992 constitution of Ghana(Ghana Web, n.d.)

2.1.2 Machine Learning

According to a webpost on the MIS website Machine learning is a subfield of artificial intelligence, which is broadly defined as the capability of a machine to imitate intelligent human behavior. Artificial intelligence systems are used to perform complex tasks in a way that is similar to how humans solve problems(*Machine Learning, Explained | MIT Sloan*, 2021).

2.1.3 Natural Language Processing

Natural language processing (NLP) is the discipline of building machines that can manipulate human language or data that resembles human language in the way that it is written, spoken, and organized. It evolved from computational linguistics, which uses computer science to understand the principles of language, but rather than developing theoretical frameworks, NLP is an engineering discipline that seeks to build technology to accomplish useful tasks. NLP can be divided into two overlapping subfields: natural language understanding (NLU), which focuses on semantic analysis or determining the intended meaning of text, and natural language generation (NLG), which focuses on text generation by a machine(*Natural Language Processing (NLP) [A Complete Guide]*, 2023).

2.1.4 Text Classification

Text classification is a machine learning technique that automatically assigns tags or categories to text. Using natural language processing (NLP), text classifiers can analyze and sort text by sentiment, topic, and customer intent – faster and more accurately than humans(*Go-to Guide for Text Classification with Machine Learning*, 2020).

2.1.5 Text Pre-processing

Text Processing pertains to the analysis of text data using a programming language such as Python. Text Processing is an essential task in NLP as it helps to clean and transform raw data into a suitable format used for analysis or modelling(GeeksforGeeks, 2024).

2.2 Subtopics

2.2.1 Text Classification in State of the Nation Addresses

Text classification is an important aspect in Natural language (NLP) that involves categorizing text into predefined labels. In the area of State of the Nation addresses, text classification can be used to identify key themes, sentiments, and policy areas discussed in these speeches (Devlin et al., 2019). This process mostly involves several steps of text pre-processing, including tokenization, stemming, and stop-word removal, to prepare the text for classification algorithms (Ehud & Dale, 2020).

2.2.2 NLP Techniques for Text Pre-processing

Effective text pre-processing is important for the success of text categorizing tasks. Techniques such as tokenization, which breaks down text into individual words or tokens, and stemming, which reduces words to their root forms, are commonly used in the pre-processing of text before implemented in a model (*Speech and Language Processing*, n.d.) Stop-word removal is another essential step, as it eliminates common words that do not contribute to the meaning of the text (Manning et al., 2008). These pre-processing steps help in reducing the of the text data and improve the performance of classification algorithms.

2.2.3 Machine Learning Algorithms for Text Classification

Various machine learning algorithms can be employed for text classification tasks. Traditional algorithms like Naive Bayes, Support Vector Machines (SVM), and decision trees have been widely used due to their simplicity and effectiveness(Kowsari et al., 2019a). However, recent advancements have seen the rise of deep learning models, particularly those based on neural networks, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), which have shown superior performance in text classification tasks (Yin et al., 2020).

2.2.4 State of the Nation Address Analysis Using NLP

Analyzing State of the Nation addresses using NLP techniques involves extracting meaningful insights from the text. This can include identifying the frequency of key terms, sentiment analysis, and topic modeling to understand the main issues addressed by the speaker (Bhatia et al., 2019). Such analyses can provide valuable information about the political and social priorities of a country at a given time.

2.2.5 Challenges in Text Classification of State of the Nation Addresses

One of the primary challenges in text classification of State of the Nation addresses is the complexity and variability of the language used. Political speeches often contain nuanced language, rhetorical devices, and context-specific references that can be difficult for algorithms to interpret accurately (Jurafsky & Martin, 2020). Additionally, the need for large labelled datasets for training machine learning models poses a significant challenge, as manual annotation can be time-consuming and resource-intensive.

2.2.6 Future Directions in NLP for Political Speech Analysis

The future of NLP in the analysis of political speeches lies in the integration of more sophisticated models and techniques. Advances in transfer learning, such as the development of pre-trained models like BERT (Bidirectional Encoder Representations from Transformers), have the potential to enhance the accuracy and efficiency of text classification tasks (Devlin et al., n.d.) Moreover, the incorporation of multimodal data, such as combining text with audio and video analysis, could provide a more comprehensive understanding of political speeches (Müller et al., 2020).

2.3 Review of Related Works or Systems

A survey conducted by (Q. Li et al., 2022) reviewed the differences and the pros and cons or text classification using Natural language processing as compared to the traditional methods of doing classification. It provides an overview of text classification methods and approaches from 1961 to 2022. And concluded that the more ambitious the classification needed to be performed the more challenging and complex implementation of the model would be. The research provides a comprehensive understanding of other techniques used in the classification of text and the different deep learning models available.

Convolutional neural networks were utilized to develop a sentiment analysis of online products in a reserach by. The aim was analysis to classify online product reviews as positive, negative or neutral. This model had a 92 percent accuracy for categorizing data. Evaluation was done with various methods and it was a nice addition to research utilizing natural language processing methods.

A guide provided on how decision are to be taken before utilizing analysis for true, false or neutral contents by (Barberá et al., 2021) show that two reasonable approaches to corpus selection yield radically different corpora and advocate for the use of keyword searches rather than predefined subject categories provided by news archives. (Barberá et al., 2021) demonstrate the benefits of coding using article segments instead of sentences as units of analysis and show that, given a fixed number of coding, it is better to increase the number of unique documents coded rather than the number of coders for each document. Finally, (Barberá et al., 2021) find that supervised machine learning algorithms outperform dictionaries on a number of criteria.

A research paper written by (Kowsari et al., 2019b) expressed the growing level of text document in the world and how there is a need for the automation of these files in by utilizing Natural language processing. (Kowsari et al., 2019b) also emphasized the significance of text pre-processing before feeding text data into any model as well as the various techniques utilized to complete text classifications.

A paper by Francis Adoma acheampong on text-based emotion detection investigated deep learning techniques for recognizing emotion expressed in text information or data through various social media platforms namely Facebook and twitter as well as customer reviews and chat conversation(Acheampong et al., 2020). The research centred around transformer-based approaches like BERT, and how such models have achieved state of the art performance in emotion recognition tasks. The study which focused on emotion classification metrics had issues with cross-domain generation and interpretability of emotion detection(Acheampong et al., 2020).

Multilingual text classification model for social media analysis was developed based on deep learning and the aim was to accurately categorize social media posts in multiple languages. The project involved the use of pre-processed texts and a trained deep neural network architecture. It achieved a high classification accuracy of 90% across multiple tests and was evaluated using standard metrics such as precision and recall as well as f-1 score(Zade & Ajani, 2022).

(Salminen et al., 2020)designed and implemented a machine learining system for automatically detecting hate speech and toxic content in online forums and other social media platform and utilized support vector machines which was the supervised model used after data preprocessing had taken place. It got an F-1 score of 0.90 compared to traditional machine learnig approaches and was a huge addition to research in the field of machine learning. However the study also had challenges deleting speeches which were unbiased(Salminen et al., 2020).

The Automated fact-checking research by (Thorne et al., 2018) which seeked to unvestigate the use of natural language processing and machine learning techniques for automatically verifying the factual accuracy of claims and statements utilized a created database or dataset which contained claims and associated evidence then proceded to incorporate this into a network based model. The research played a pivotal role in combating misinformation particularly form online sources(Thorne et al., 2018).

Learning towards conversational AI: The paper discusses the evolution of open-domain dialogue systems, highlighting their ability to handle unrestricted conversation topics compared to task-oriented systems. As well as the frameworks utilized in bringing dialogue models to life. It also emphasised how dialogue systems should be informative and controllerble(Fu et al., 2022).

2.4 Summary of Related Topics/Research

Project Name	**Citation**	**Main Objectives**	**Methodologies**	**Results**	**Evaluation On Metrics**	**Conclusion**
Sentiment Analysis of Online Product Reviews	(L-, 2023)	Develop a sentiment analysis model to classify online product reviews as positive,	preprocessed the text data, and trained a deep learning-based sentiment classification model using convolutional	CNN-based sentiment analysis model achieved an accuracy of 92% in positive,	The model was evaluated using standard classification metrics such as accuracy,	valuable insights for businesses to understand customer perceptions and improve

		negative, or neutral.	neural networks (CNNs).	negative, and neutral categories.	precision, recall, and F1-score.	their products or services.
Fake News Detection using Machine Learning	(Raja & Raj, 2022)	Design and implement a machine learning-based system to detect fake news in social media posts.	Collected a dataset of real and fake news articles, extracted textual features using natural language processing techniques, and trained various machine learning models	The random forest classifier achieved the highest accuracy of distinguishing fake news from real news.	The models were evaluated using accuracy, precision, recall, and F1-score metrics.	Machine learning-based fake news detection can be an effective tool to combat the spread of misinformation on social media platforms.
Automated Abstractive Text Summarization using Deep Learning	(Karuna et al., 2023)	The objective is to construct an abstractive text summarizer using deep learning	The algorithm which is been used here is the Long Short Term Memory model (LSTM) which is a type of RNN model.	Summerized text accurately	The models were evaluated using accuracy, precision, recall	Performed assigned tasks allocated to it.
An intent recognition pipeline for conversational AI	(Chandrakala et al., 2024)	Investigate the state-of-the-art in intent detection techniques for conversational AI systems, such as chatbots and	review on intent detection approaches, including rule-based, machine learning, and deep learning methods, and their applications in	The survey identified the key challenges, techniques, and performance metrics in intent detection for	The review was based on a systematic analysis of the existing literature, with a focus on the strengths, limitations,	Intent detection is a crucial component of conversational AI, and continued research in this area can lead to more natural

		virtual assistants.	various domains.	conversational AI, and highlighted emerging trends and future research directions.	and comparative performance of the discussed approaches.	and intelligent human-computer interactions.
Automated Text Summarization using Deep Learning	(Barberá et al., 2021)	Develop a deep learning-based model for generating abstractive summaries of text documents.	Employed a sequence-to-sequence neural network architecture, specifically a transformer-based model, to learn the mapping from input text to concise summaries.	The deep learning-based text summarization model outperformed traditional extractive and abstractive summarization techniques in terms of ROUGE scores and human evaluation.	The summarization model was evaluated using standard metrics like ROUGE.	Accomplised Research goal.
Emotion Recognition from Text using Deep Learning	(Kowsari et al., 2019b)	Investigate the use of deep learning techniques for recognizing emotions in text data.	The study reviewed the existing literature on emotion recognition from text, covering various deep learning architectures (e.g., recurrent	The review found that deep learning models, particularly transformer-based approaches like BERT, have achieved state-of-the-	The reviewed studies were evaluated based on standard emotion classification metrics, such as accuracy, F1-score, and area under	Emotion recognition from text using deep learning has numerous applications in customer experience management, mental health monitoring, and human-

			neural networks, transformers)	art performance in emotion recognition tasks.	the curve (AUC).	computer interaction
Multilingual Text Classification for Social Media Analysis	(Acheampong et al., 2020)	accurately categorize social media posts in multiple languages	The project involved the use of pre-processed texts and a trained deep neural network architecture	It achieved a high classification accuracy of 90% across multiple tests	The models were evaluated using accuracy, precision, recall, and F1-score metrics.	Achieved focus of study and was fairly accurate.
Automated Hate Speech Detection in Online Communities	(Salminen et al., 2020)	Design and implement a machine learning-based system for automatically detecting hate speech and toxic content	The researchers collected a dataset of user-generated content from various online platforms, annotated the data for the presence of hate speech, and trained supervised learning models	The deep learning-based hate speech detection models achieved superior performance compared to traditional machine learning approaches	F1-score, and area under the receiver operating characteristic (ROC) curve.	Achieved focus study.
Automated Fact-Checking using Natural Language Processing	(Thorne et al., 2018)	Use of NLP and machine learning techniques for automatically	Created the FEVER (Fact Extraction and Verification) dataset and then	FEVER dataset, with the best-performing systems	The fact-checking models were evaluated using	The fact-checking models were evaluated using standard metrics like accuracy,

		verifying the factual accuracy of claims or statements	developed neural network-based models to classify the claims as supported	reaching an F1-score of over 0.65.	standard metrics like accuracy, precision, recall, and F1-score, as well as task-specific measures like FEVER score.	precision, recall, and F1-score, as well as task-specific measures like FEVER score.
Learning towards conversational AI: A survey	(Chandrakala et al., 2024)	The goal of the paper is to address dialogue act (DA) classification in domain-independent conversations.	Retrieval based methods, Generation based methods and Hybrid based methods	Informative	Word-overlap measures, embedding based measures and metrics based questions	Research aimed on open Was up for more scrutiny
Article Classification using Natural Language Processing and Machine Learning	(Dien et al., 2019)	The goal of the experiments was a feasibility and automatic classification system of articles.	The input data were pre-processed, extracted, vectorized and classified using machine learning techniques including Support Vector Machines, Naïve Bayes,	The experiments were carried out on two data sets of articles with the accuracy of over 91%, using natural language processing and support vector	The models were evaluated using accuracy	Accomplised Research goal.

			and k-Nearest Neighbours.	machines technique		
Text Summarization Evaluation Using Original Documents	(Foysal & Böck, 2023)	Aim make the text summarization method much simpler and easier	A proposed approach uses original content as reference for evaluation	Informative	SUSWIR metric evaluates semantic similarity, relevance, redundancy, and bias avoidance	Effective evaluation of machine-generated summaries without human reference summaries
Text Classification Based on Machine Learning and Natural Language Processing Algorithms	(H. Li & Li, 2022)	For text classification technology, this paper combines the technical requirements and application scenarios of text classification with ML to optimize the classification.	For the application of natural language processing (NLP) technology in text classification, this paper puts forward the Trusted Platform Module (TPM) text	In the experiment of distinguishing spam from legitimate mail by text recognition, all performance indexes of the TPM algorithm are superior to other algorithms,	The models were evaluated using accuracy, precision, recall, and F1-score metrics.	When F1 value is used for evaluation, the proposed method also shows relatively better performance than other methods

			classification algorithm.	and the accuracy of the TPM algorithm on different datasets is above 95%.		
Efficient English text classification using selected Machine Learning Techniques	(Luo, 2021)	Classification of English texts and documents	In this paper, they implemented the Support Vector Machines (SVM) model in classifying English text and documents.	90% when using more than 4000 features.	The models were evaluated using accuracy, precision, recall, and F1-score metrics.	proposed approach can also be implemented in R, Tensors flow, Python, or Matlab simulation tool.
Text Classification Using Machine Learning and Deep Learning Models	(Kolluri et al., 2020)	Understanding the best way to utilize text classification alongside Machine learning models	This research uses various diagrams and flowcharts to express how informative and practical classification is done	Informative	Text classification methods as well as supervised and unsupervised learning review	The research highlighted the necessity of machine learning in streamlining the tasks and activities

Universal Language Model Fine-tuning for Text Classification	(Howard & Ruder, n.d.)	The main objective of the paper is to introduce Universal Language Model Fine-tuning (ULMFiT), a novel transfer learning method for natural language processing (NLP) that enables effective fine-tuning of language models across various text classification tasks.	ULMFiT is structured in three key stages eneral-domain Language Model Pretraining, arget Task Language Model Fine-tuning and Target Task Classifier Fine-tuning	The results of ULMFiT demonstrate a significant performance improvement across six standard text classification tasks, achieving error reductions of 18-24% compared to state-of-the-art methods.	The paper evaluates ULMFiT using standard metrics relevant to text classification, such as accuracy and error rates	In conclusion, ULMFiT represents a significant advancement in transfer learning for NLP, allowing for effective and efficient fine-tuning of language models across diverse tasks without the need for extensive labeled datasets or complex architectures.
Deep Learning Based Text Classification: A Comprehensive Review	(Haque et al., 2022)	The primary objective of this paper is to provide a comprehensive review of over 150 deep learning (DL) models	The authors categorize the deep learning models into several architectures, including Recurrent Neural	The findings showcase that deep learning models significantly outperform classical machine learning	The evaluation metrics used in the analysis include accuracy, precision,	he paper concludes that deep learning has revolutionized text classification, surpassing traditional

		developed for text classification	Networks (RNNs), Convolutional Neural Networks (CNNs), Transformers, and Capsule Networks.	methods in various text classification tasks	recall, and F1-score.	methods in accuracy and efficiency.
Benchmarking Zero-shot Text Classification: Datasets, Evaluation and Entailment Approach	(Yin et al., n.d.)	The primary aim of this study is to benchmark the challenging task of zero shot text classification	The authors introduce a novel approach to 0SHOT-TC by developing datasets that cover diverse aspects of classification, including topic detection, emotion detection, and situation framing.	The results demonstrate the effectiveness of the proposed approach, showing improved performance in both evaluation setups	The evaluation metrics focus on traditional classification accuracy, precision, recall, and F1-score, tailored for both the label-partially-unseen and label-fully-unseen scenarios.	The study concludes that zero-shot text classification can be effectively approached through a unified framework that leverages textual entailment.

EDA: Easy Data Augmentation Techniques for Boosting Performance on Text Classification Tasks	(Wei & Zou, n.d.)	paper aimed to address the lack of standardaized data augmentation in NLP by introducing a set of simple operations that might serve as a baseline for future investigation.	EDA consists of four simple but powerful operations: synonym replacement, random insertion, random swap, and random deletion which is used to achieve classification in this research.	EDA demonstrates particularly strong results for smaller datasets	EDA's improvement was negligible when using ULMFit	Continued work on this topic could explore the theoretical underpinning of the EDA
A recent overview of the state-of-the-art elements of text classification	(Mirończuk & Protasiewicz, 2018)	The aim of this study is to provide an overview the state-of-the-art elements of text classification..	The quantitative analysis uncovers the research trends in text classification.	Informative	The quantitative analysis outlines different aspects of text classification.	This study will help readers acquire the necessary information about these elements and their associated techniques.

2.5 Summary of Literature review

The literature review has highlighted the various concepts in NLP and Machine learning as well as highlighted similar works and how they have been implemented. Existing research provides a solid understanding of the importance of text classification and analysis. The table gives a brief overview on what to expect when dealing with works or research similar to the owns in the table. This chapter allows or shows how important Natural Language Processing is and how it is prevailing very rapidly in out now economy or society. The systems implemented in most of the projects although prevailed were not perfect which goes to show that there is much needed improvement in how we handle NLP and machine learning systems and with time there should be better data retrival, classification and databases as well as models which will make the implementation of robust systems easier.

Chapter 3 Introduction

The third chapter of this project lays down the methodology implemented in order to achieve the aims of this project as well as the objectives which were stated earlier the previous chapters. This chapter will involve a detailed documentation of all the steps involved in text analysis of the SONA speeches as well as how we intend to implement the NLP and Machine learning models into our project. This section of the document will contain sections like data collection methos, system Architecture, system components, algorithms, operational methods and the summary of the documentation which will be provided at the end of this chapter.

3.1 Research Design

3.1.1 Research Philosophy

The research philosophy adopted for this study is positivism. This approach is suitable as it emphasizes the use of quantitative methods which is objective measurements and the statistical, mathematical, or numerical analysis of data collected through polls, questionnaires, and surveys, or by manipulating pre-existing statistical data using computational techniques. This research relies on researching and finding truths or lies in the text speeches using this philosophy will be of great help to the development of the project. The goal is to produce results that are reliable, simple, and structured.

3.1.2 Research Type

This research is deductive and quantitative in nature as it begins with a hypothesis about the ability to classify SONA statements as fulfilled or unfulfilled promises based on text analysis.

The study primarily employs quantitative methods to analyse and classify the text data, making it a quantitative research type.

3.1.3 Sampling Strategy

In this study, the population consists of all existing SONA speeches. Since the aim of the research is to gather all Ghanaian SONAs in existence there is no need for sampling of the speeches. This approach ensures comprehensive coverage and avoids sampling errors which may occur. Accuracy is a big benefit since analysing the entire population removes sampling errors and provides a complete picture of the data.

3.1.4 Data Collection

This is the first and one of the most crucial part of the project. The task to be completed in this section is to collect all SONA from the year 2000 to the current year at the time of writing this documentation 2024, these speeches which are to be collected are necessary for text analysis.

3.1.5 Data Collection Methods

The Sona speeches are going to be collected across various government and news websites namely Ghanaweb, GhanaToday, CityFmOnline , Wikipedia and the largest database coming from the official parliament of Ghana Website.

3.1.6 Data Requirements

There is a need for data collected to be strictly text as the objective of the project is to do analysis on only text data and label or classify it. Also, data collected will be pdfs which will then be converted to csv for model training.

3.2 System Architecture

3.2.1 Data Labelling

Collecting of all SONA data is the easy part of the project, here comes the hard part. Here out job will be to scan through the collected SONA documents and identify claims in the speeches and get corresponding year and speaker then proceed to create a csv file that will house all data so it can be used to train the model.

3.2.2 Data Pre-processing

After the data has been collected there is a need for us to convert the SONA claims in the csv file into a format that will make the computer understand the claims and provide effective and efficient classification. We will be using pre-processing techniques like

3.2.3 Feature Extraction Module

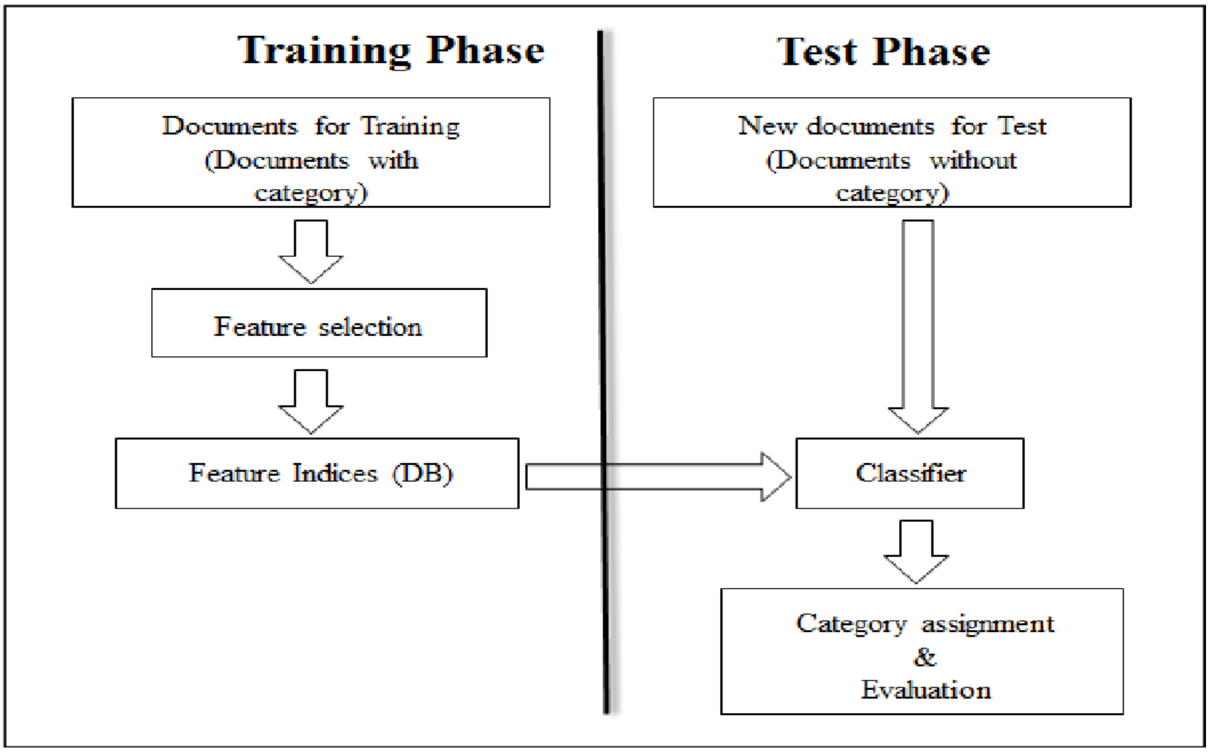
Raw text data cannot be used by the computer, it is important to convert the text data into numerical values so that it can be used by the computer. Feature extraction converts the text into a structured numerical format that algorithms can process. Properly extracted features can significantly improve the accuracy and efficiency of the classification model.

3.2.4 Machine Learning Classification Module

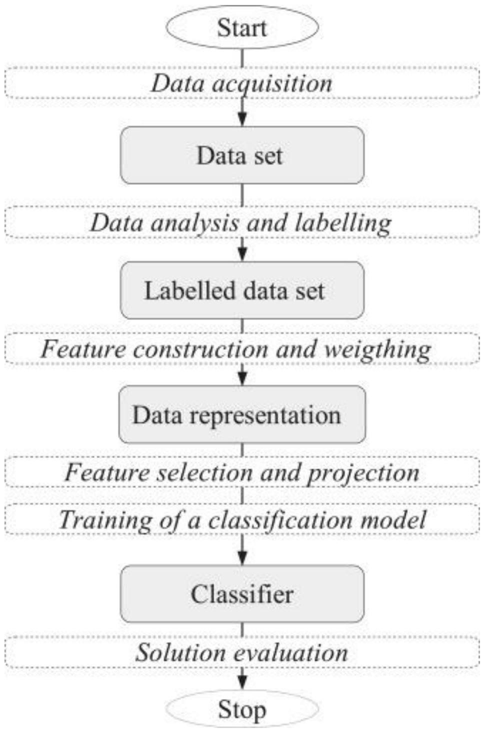
Classification models can learn patterns from labelled training data, this will be useful for classifying fulfilled and unfulfilled promises in the SONA texts and then predict the category for new, unseen statements. The model likely to be implemented will be Support Vector Machines or Logistics regression.

3.2.5 Evaluation and Refinement Module

Evaluates model performance and refines the models based on feedback and performance metrics.



Workflow



3.3 System Components

3.3.1 Backend

The system is first and foremost a backend project. Handling large amounts of text SONA speeches, utilizing machine learning and Natural language processing and creating a database storage are all primary features of the backend. Since this project will be utilizing all this aspects in the work its safe to say that the project is a backend project.

3.3.2 Algorithms

The algorithms used in this project are:

Logistics regression, Random Forest Classifiers , Decision Tree Classifier and Gradient boosting model

3.4 Operational Methods

3.4.1 Fact-Checking and Accountability:

The text classification model can be used to systematically analyze new SONA speeches and identify promises that are classified as "fulfilled" or "unfulfilled".This information can be used to hold the government accountable and track their performance in delivering on their stated commitments.The insights can be shared with the public, media, and other stakeholders to increase transparency and democratic oversight.

3.4.2 Policy Evaluation and Policymaking:

The analysis of past SONA speeches can provide valuable insights into the government's policy priorities, focus areas, and the evolution of their agenda over time.These insights can inform the evaluation of existing policies and the development of new policies that better address the needs and concerns of the citizens.Policymakers can use the findings to align their agenda and resource allocation with the promises and commitments made in the SONA.

3.4.3 Citizen Engagement and Awareness:

The project outcomes can be used to create interactive visualizations and reports that help citizens better understand the government's performance and the fulfillment of promises.This can empower citizens to engage more actively in the political process and hold their representatives accountable.The analysis can also be used to educate the public on the importance of the SONA and its role in the democratic process.

3.4.4 Academic Research and Teaching:

The dataset of SONA speeches and the associated analysis can be a valuable resource for academic researchers studying political discourse, rhetoric, and the relationship between promises and outcomes.The project can be used as a case study in courses on political science, public policy, data analysis, and natural language processing.Researchers can build upon the existing work to explore new research questions and expand the scope of the analysis.

3.4.5 Media and Journalism:

Journalists and media outlets can leverage the project's findings to enhance their reporting on the government's performance and the fulfillment of promises.The analysis can be used to fact-check claims made in the SONA and provide a more objective and data-driven perspective on the government's achievements.Media organizations can collaborate with the project team to integrate the analysis into their coverage and amplify its impact.

3.5 Limitations Of Project

The project faces several challenges and limitations. Due to the largeness of the document or SONA text accuracy may be a problem and since the text is also supposed to be pre-processed some valuable information may be lost in the process as well. Also, data that will be used to train model is information available online and may be untrue. The scalability and processing speed of the system are also important considerations, as analysing and classifying the text of multiple SONA speeches over time can be computationally expensive. There may also be ethical and legal considerations around the use of SONA speeches, which could be considered sensitive or confidential government information. The interpretability and explain ability of the machine learning models used for text classification are also important considerations, as complex models may struggle to provide transparent and interpretable explanations for their predictions. Although the model will be useful now further on along the line it can't be determined if it will retain its usefulness.

3.6 Conclusion

This project elaborates on all the aspects and process involved in producing a classification analysis utilizing natural language processes and machine learning algorithms. It also explains how the project is going to be used therefore speaking on its importance as well as the various stages the data goes through to bring about a useful project.

Chapter 4 Results And Analysis

Introduction

This section of the project houses the current state of all classification done as well as some insightful findings and observation about how our model works. Various information including dataset used and how it affects the classification.

4.1 Dataset Overview

This dataset that was utilized in the analysis consisted of 2,609 viable entries and it was a pre-labelled dataset gotten from the careful analysing of all pdf data collected. The dataset was labelled with the following headings for easy identification during the process of training of model

1. Id: A sequential name starting from zero to help with indexing of the claims and help with collection of claim in the IDE
2. Date: Year of speech delivered allowed for easy identification of year a claim was delivered

3. Speaker: Name of the president delivering speeches this was added to the claim dataset to enable the model identify patterns in speech giving or various presidents
4. Claims: The individual claims identified and extracted from the text.
5. Label: A binary label 0, and 1 for claims

The dataset was very imbalanced as it had over 2,489 true statements and only 120 false statements this affected the ability for the model to distinguish between the true statements from the false ones, although the model could easily identify true statements it struggled with false claims. The Dataset was separated into training and testing for selected algorithms

4.2 Dataset Pre-processing Overview

The data pre-processing steps which involved critical steps in order to help the machine learning models understand the patterns in data were as follows:

1. Text Cleaning: Non-alphanumeric characters were removed, and the text was converted to lowercase.

2. Tokenization and Lemmatization: Claims were tokenized into words, and lemmatization was applied to reduce words to their base forms, removing common English stop words.

3. Label Encoding: The speaker variable was transformed into numerical format using Label Encoder to facilitate its integration into modeling.

The preprocessed claims were then vectorized using TF-IDF Vectorization, resulting in a matrix representation of the text data, which was combined with the encoded speaker information to create a comprehensive feature set used for model training.

4.3 Model Training and Model Evaluation

Three different classification models were trained and evaluated: Random Forest Logistic Regression, and Decision Tree. The models were assessed on both training and testing datasets.

4.3.1 Random Forest Model

The Random Forest model displayed exceptional accuracy on the training set, achieving 99.09%, but its performance on the test set was slightly lower, with an accuracy of 93.30%. The model was highly accurate in identifying true claims, with a recall of 98% for true claims (Class 1). However, it struggled with false claims (Class 0), achieving a 4% recall on the test set, which reflects its difficulty distinguishing false claims from true ones due to the dataset imbalance.

Model Performance Overview

Metric	Training Set	Testing Set

Accuracy	99.09%	93.30%
Confusion Matrix	[95,0] [19,1973]	[1,24] [11,486]
Precision(class 0)	83.33%	8.33%
Recall(class 0)	100%	4%
F1-Score (Class 0)	90.91%	5.41%
Precision (Class 1)	100%	95.29%
Recall (Class 1)	99.05%	97.78%
F1-Score (Class 1)	99.12%	96.52%

4.3.2 Logistic Regression.

The Logistic Regression model achieved a respectable training accuracy of 96.93%, while its accuracy on the test set was 91.57%. This model demonstrated a balanced performance, with a recall of 95.57% for true claims (Class 1), indicating its effectiveness in identifying positive instances. However, it faced challenges with false claims (Class 0), recording a recall of only 12% on the test set. This discrepancy highlights the model's struggle with classifying negative instances, particularly in the context of imbalanced data.

Model Performance Overview

Metric	Training Set	Testing Set
Accuracy	96.93%	91.57%
Confusion Matrix	[95,0] [64, 1928]	[3, 22] [22, 475]
Precision(class 0)	59.75%	12%
Recall(class 0)	100%	12%
F1-Score (Class 0)	74.80%	12%
Precision (Class 1)	100%	95.57%
Recall (Class 1)	96.79%	95.57%
F1-Score (Class 1)	98.37%	95.57%

4.3.3 Decision Tree

The Decision Tree model exhibited a very high training accuracy of 99.09%, but its test set accuracy dropped significantly to 84.10%. The model excelled in identifying true claims, achieving a recall of 87.26% for Class 1. However, it encountered considerable difficulty with false claims (Class 0), obtaining a recall of only 24% on the test set. This performance indicates the model's tendency to overfit the training data, resulting in challenges to generalize effectively to unseen data, especially in the presence of class imbalance.

Model Performance Overview

Metric	Training Set	Testing Set
Accuracy	99.09%	84.10%
Confusion Matrix	[95,0] [19,1973]	[6, 19] [64, 433]

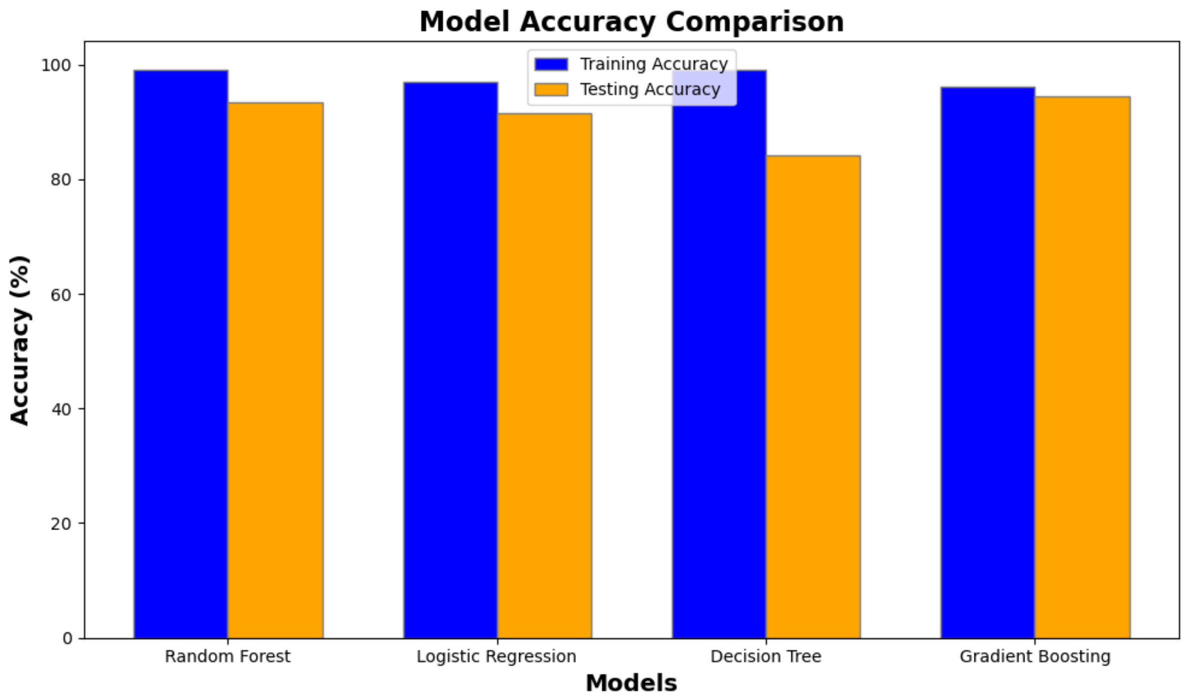
Precision(class 0)	83.33%	8.57%
Recall(class 0)	100%	24%
F1-Score (Class 0)	90.91%	12.63%
Precision (Class 1)	100%	95.80%
Recall (Class 1)	99.05%	87.17%
F1-Score (Class 1)	99.12%	96.52%

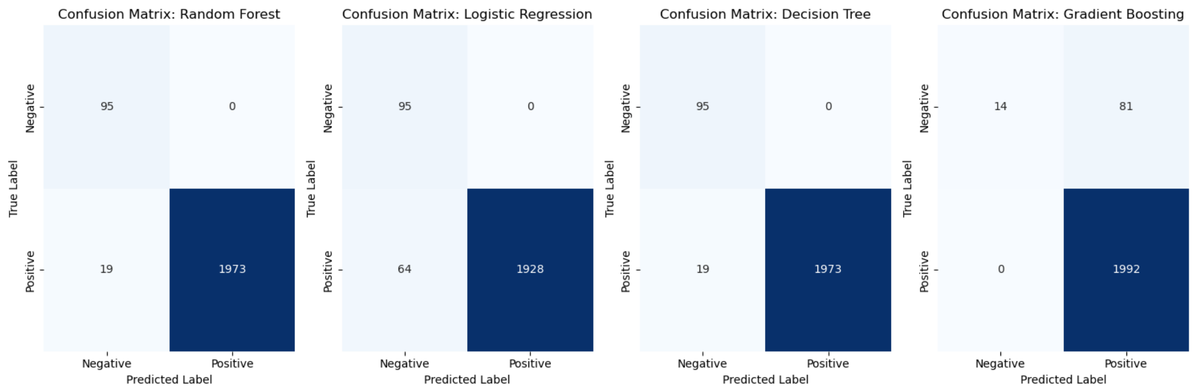
4.3.4 Gradient Boosting

The Gradient Boosting model demonstrated a training accuracy of 96.12%, while achieving a test set accuracy of 94.44%. The model performed well in identifying true claims, achieving a recall of 99.19% for Class 1, showcasing its effectiveness in capturing positive instances. Conversely, it struggled with false claims (Class 0), attaining a recall of only 0% on the test set. This stark contrast indicates that the model was unable to correctly classify any false claims, likely due to the dataset's imbalance and the model's focus on minimizing errors for the majority class.

Model Performance Overview

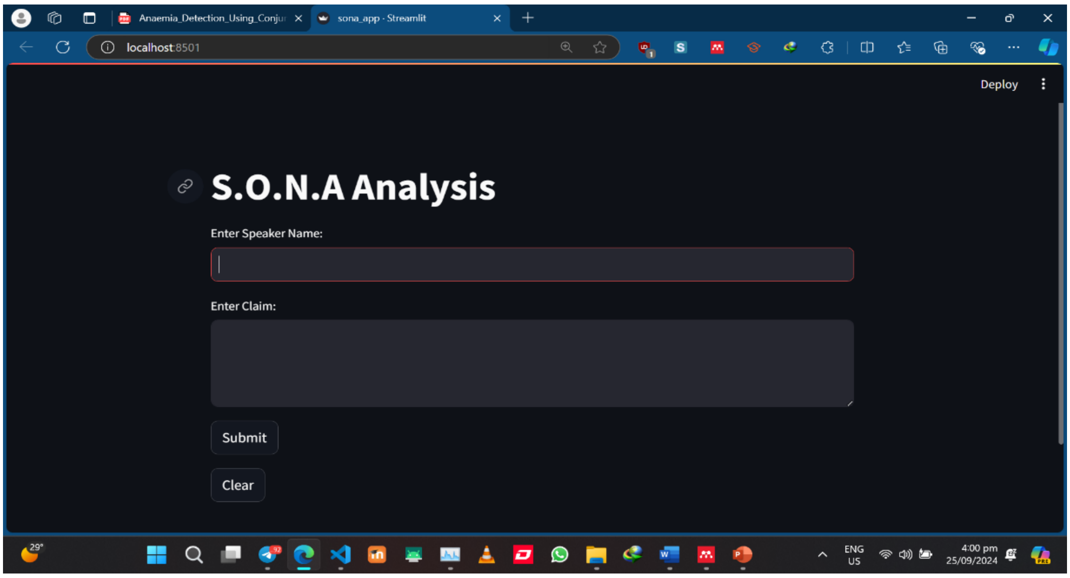
Metric	Training Set	Testing Set
Accuracy	96.12%	94.44%
Confusion Matrix	[14,81] [0,1992]	[0,25] [4,493]
Precision(class 0)	100%	0%
Recall(class 0)	100%	0%
F1-Score (Class 0)	14.74%	0%
Precision (Class 1)	25.69%	95.17%
Recall (Class 1)	96.09%	99.19%
F1-Score (Class 1)	100%	97.52%

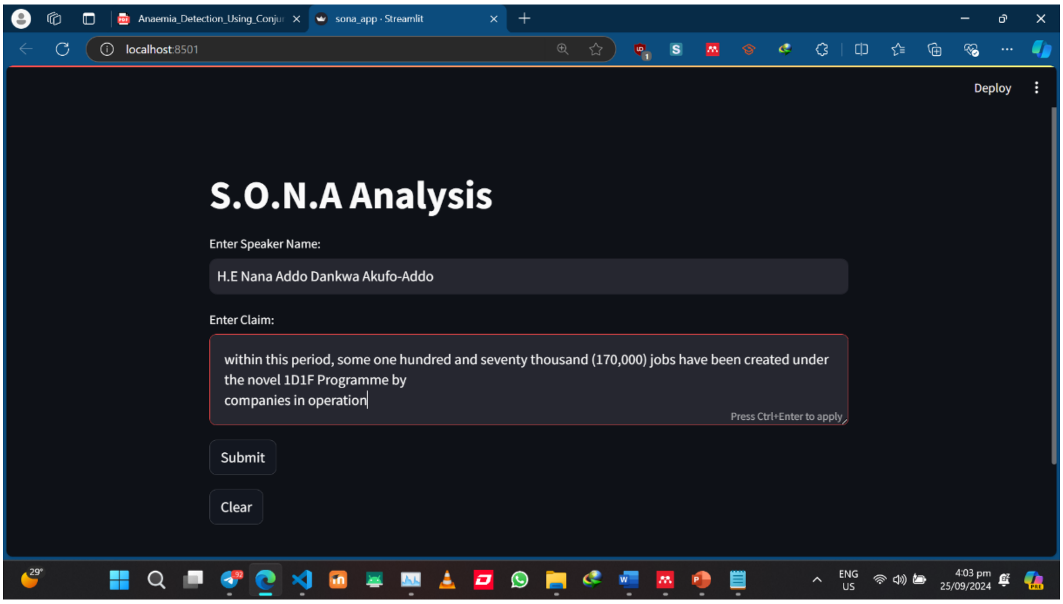


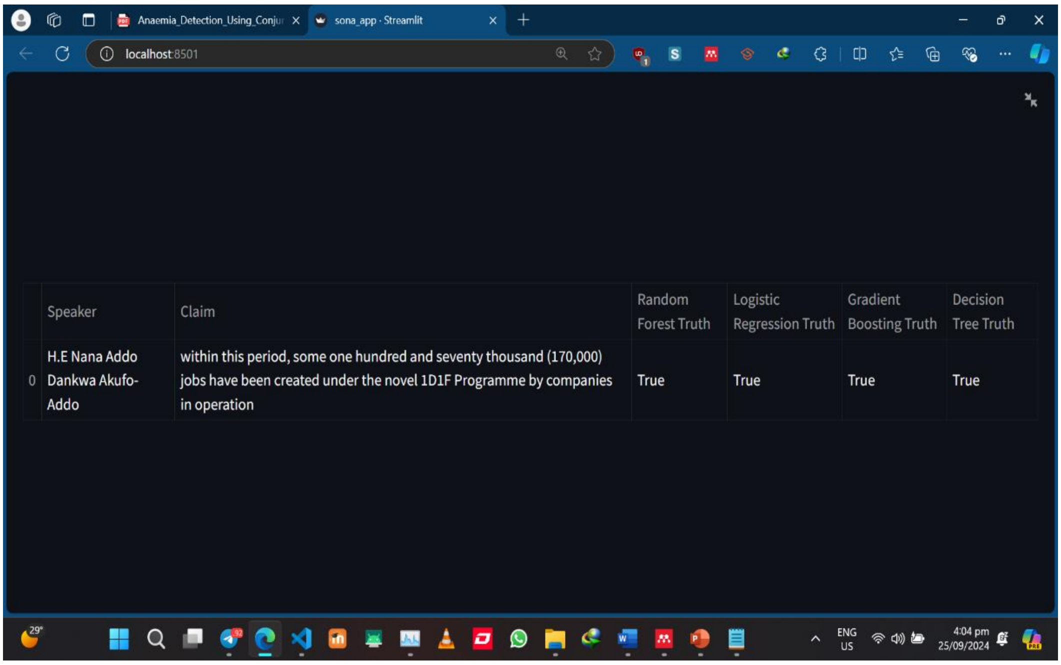


4.4 Using the interface

1. Open source file of the app in any IDE of choice
2. Locate the terminal and run “streamlit run sona_app.py”
3. Input speaker name
4. Input Claim
5. Wait for results
6. Redo or clear
7. Exit







4.5 Conclusion

In summary, while all models achieved high training accuracy, their performance on the test set varied significantly, particularly in recall for false claims. This highlights the importance of addressing class imbalance and employing strategies such as data augmentation, resampling techniques, or using different evaluation metrics to ensure robust model performance across all classes.

Chapter 5 SUMMARY AND CONCLUSION

Introduction

This chapter presents a comprehensive discussion of the results from our text classification model, comparing its performance with similar projects and explaining its strengths and weaknesses. We also highlight the limitations of our research, propose future improvements, and conclude with a summary of our research study.

5.1 Discussion of Results

Our text classification model, designed to classify claims from presidential speeches as either true or false, was trained and evaluated using three different algorithms: Random Forest, Logistic Regression, and Decision Tree. The dataset used for this analysis was highly imbalanced, with 2,489 true claims and only 120 false claims. This imbalance posed significant challenges to the model's ability to accurately identify false claims.

The precision for false claims on the test set was 8%, while the precision for true claims was 95%, confirming the model's bias towards predicting true claims. Despite the high overall accuracy, the imbalance in the dataset caused the model to be less effective in identifying false claims, leading to potential issues in real-world applications where detecting false claims is critical.

Logistic Regression Model

The Logistic Regression model also performed well on the training set, with an accuracy of 96.93%. However, like the Random Forest model, it struggled to accurately classify false claims. On the test set, the Logistic Regression model's accuracy dropped, and its recall for false claims was similarly low, indicating that it too was affected by the imbalance in the dataset.

Comparison with Similar Projects

Compared to other classification models in similar projects, our model excels in accuracy for true claims but falls short in identifying false claims. The imbalance in our dataset is a major factor contributing to this discrepancy. Similar projects that addressed imbalanced datasets through techniques such as oversampling or synthetic data generation showed better performance in identifying minority classes

Strengths and Weaknesses

One of the key strengths of our model is its high accuracy in identifying true claims, which makes it highly reliable when the goal is to verify true statements. However, the primary weakness of the model is its poor performance in detecting false claims. This limitation could lead to false claims going unnoticed, which is a significant concern in the context of fact-checking systems.

5.2 Future Works/Recommendations

To improve the performance of our model, especially in identifying false claims, we propose several future enhancements:

1. **Addressing Dataset Imbalance**: The most critical issue in our current model is the imbalance in the dataset. We recommend exploring techniques like Synthetic Minority Over-sampling Technique (SMOTE) or Class Weight Adjustment to give more importance to the minority class (false claims). These techniques would help the model better distinguish between true and false claims.

2. **Advanced Model Architectures**: In future iterations, we could explore more advanced machine learning models, such as **Deep Learning models** like Recurrent Neural Networks (RNNs) or Transformer-based models (e.g., BERT), which are known for handling textual data and imbalanced classes more effectively.

3.**Feature Engineering**: Further feature engineering, such as including the **context of the claim** or identifying **claim patterns based on the speaker**, could help improve the model's performance. These additional features may help the model better differentiate between true and false claims.

4.**Cross-Validation and Hyperparameter Tuning**: More comprehensive hyperparameter tuning and the use of cross-validation techniques will help optimize the performance of the model and ensure its robustness across different datasets.

5.**Deployment and User Feedback**: Once the model is fine-tuned, deploying the model for real-world use and collecting user feedback will be critical. This feedback can provide insights into the model's performance outside the controlled environment of our study and highlight areas for further improvement.

5.3 Conclusion

To end it all, our study highlights the strengths and weaknesses of a text classification model designed to evaluate claims from presidential SONA speeches. While the model demonstrates high accuracy in identifying true claims, it fails significantly with false claims due to the imbalanced dataset, marked by huge difference between the number of true (2,489) and false (120) claims. This imbalance has led to a model biased towards predicting true claims, resulting in a precision of only 8% for false claims, which raises concerns regarding the reliability of the model in real-world applications.

Despite these challenges, our findings provide valuable insights into the potential of various machine learning algorithms, including Random Forest, Gradient boosting, Logistic Regression, and Decision Tree, in the context of text classification. The performance of these models, particularly in identifying true claims, shows their reliability for certain operations, although their limitations must not be overlooked, especially regarding the detection of misleading or false information.

As we look to the future, addressing the dataset imbalance will be crucial for enhancing the model's capability to accurately classify false claims. Implementing techniques like SMOTE, exploring advanced architectures such as RNNs and Transformer-based models, and conducting thorough feature engineering will collectively strengthen the model's performance. Moreover, iterative improvements through hyperparameter tuning, cross-validation, and real-world deployment will be essential steps in refining our approach.

Ultimately, our research highlights the significance of continuous improvement in text classification models, particularly in the context of fact-checking and misinformation detection. By adopting the proposed enhancements and remaining responsive to user feedback, we aim to develop a more robust and reliable system that can effectively contribute to the critical task of verifying claims in political discourse.

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