National University of Computer and Emerging Sciences

Fake News Detection Using Automatic Text Summarization

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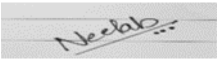
Signature: 

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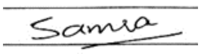
Signature: 

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Abstract

The growth of information and its widespread availability online has presented a challenge for readers in distinguishing between true and false information, leading to the propagation of fake news. The emergence of social media platforms and the ability to freely post content have only exacerbated this issue, with little to no oversight regarding the accuracy of the information shared. Our project aims to address this problem by detecting fake news and making it easily accessible to users. To achieve this goal, we will employ a range of Machine Learning and Deep Learning models, including the LSTM Encoder-Decoder with Attention mechanism, Pointer-Generator mechanism, Coverage mechanism, T5-base and T5-3B Transformer models, as well as Support Vector Machine and Convolutional Neural Network. These models will play a critical role in classifying true and false information accurately. Initially, we will explore an approach for abstractive text summarization using a Pointer-Generator mechanism and Coverage mechanism, with GloVe vectors as word embeddings. Additionally, we will utilize T5-3B Transformers for this purpose. After evaluating the results from both models, we will determine the best approach for abstractive text summarization. For Fake News Detection, we will utilize supervised machine learning algorithm, Support Vector Machine and supervised deep learning algorithm, Convolutional Neural Network. These models will help us distinguish news articles as legitimate or illegitimate. For the derivation of feature vectors of text articles, we will employ Term Frequency-Inverse Document Frequency and Count-Vectorizer. To accomplish our objectives, we will use two different datasets: one for summarization and another for fake news detection. We will use ROUGE score to analyze the effectiveness of the models used for summarization, while employing metrics such as Accuracy, Precision, Recall and F1-Score to evaluate the performance of the models used for fake news detection. Our aim is to achieve the highest accuracy and precision, while equating the effectiveness of various models in order to obtain optimal results.

Executive Summary

With the advancement in technology, the abundance of data is growing exponentially. Unfortunately, this surge in big data has also contributed to accelerate in the dissemination of fake news, which can be found on various platforms, including news articles and social media. Therefore, there is an urgent need to identify and address this issue.

This research project intends to address the problem of fake news via summarizing articles into plain English text with key points while also determining their authenticity. It is crucial for readers to know whether the articles they are reading are valid or not. Although existing work has focused on summarization and fake news detection as separate domains, there is still room for improvement in integrating both domains for more effective results.

There are several models that have been employed for summarizing text, such as LSTM, Transformers, and Pointer-Generator with Coverage mechanisms. These models can take single or multi-document input and generate summaries. Additionally, an Encoder-Decoder approach with an intra-decoder mechanism has been proposed for abstractive summarization.

In terms of fake news detection, there are three main approaches that can be used: content-based, context-based, and intervention-based. Recent studies have utilized neural networks, including RNN with LSTM or CNN, to achieve a high accuracy rate of up to 90%.

Our initial approach for abstractive text summarization involves using a combination of the Pointer-Generator mechanism and the Coverage mechanism, with the use of GloVe vectors for word embedding. We will also explore the suitability of the T5-3B Transformer model for text summarization and select the best model based on results.

We decide to use supervised machine learning algorithm like Support Vector Machine (SVM) and Convolutional Neural Network (CNN) to classify news articles as real or fake. For the derivation of feature vectors of text articles, we will be using Term Frequency-Inverse Document Frequency (TF-IDF) and Count-Vectorizer (CV).

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Chapter 1: Introduction

With the invention of the Internet and its ability to be used in daily activities, life has become easier. With the advancement of technology, this Internet is now in our hands (in the form of electronic gadgets). As time passes, every person, organization, individual and business is trying to digitize his stuff in order to make life easier for all. With this digitization, the traditional medium of receiving news and information is also affected. Nowadays, people prefer to read e-books, e-newspapers, and e-magazines and consume information online.

Due to the increased growth of information being readily available online, it has become difficult for readers to determine true from false, resulting in the transmission of fake news. The invention of social media and the freedom to post whatever and whenever, added a lot to it. Unfortunately, there is no check on what information is posted and its authenticity, therefore, a wide spread of fake news comes into place, whether done intentionally or unintentionally [1]. The current pandemic demonstrated that this fake information can be life-threatening. It is, therefore, crucial to detect fake news to inform people about authentic information online [2].

The first section of the project outlines the purpose and target audience of the research. The second chapter delineates the scope and primary objectives of the project. In the third chapter, a comprehensive literature review is presented. The fourth section elucidates the proposed methodology, while the fifth chapter explains our implementation along with test cases. The sixth chapter delineates our evaluation metrics and experimental findings. The seventh and final section of the project discusses our conclusions and offers ideas for future research.

1.1 Purpose of this Document

Previously, work has been organized to detect fake news on social media that doesn't have that much accuracy if the text is long. However, applying text summarization to detect misleading and biased information on the internet is still an area that needs to be explored. In general words, text summarization means creating concise and meaningful summaries of the source text. Creating concise and meaningful summaries for long articles is not an easy task and creating summaries while taking care that no important information is left behind is not a piece of cake [3].

In this work, we purposely detect fake news that is growing faster along with making this information easy for users to access. For this purpose, we decided to employ an initial approach for abstractive text summarization using a Pointer-Generator mechanism and Coverage mechanism, with GloVe vectors as word embeddings. We also decided to utilize T5-3B Transformers for this purpose. After evaluating the results from both models, we will determine the best approach for abstractive text summarization. We will use ROUGE-1, ROUGE-2, and ROUGE-L as our evaluation metrics to compare different algorithms used for summarization.

For the derivation of feature vectors of text articles, we will be using Term Frequency-Inverse Document Frequency (TF-IDF) and Count-Vectorizer (CV). Articles have been distinguished in two categories: fake and real, via application of supervised machine learning algorithms like Support Vector Machine (SVM) and Convolutional Neural Network (CNN). Evaluation metrics such as Accuracy, Precision, Recall and F1-Score are used to determine the authenticity of our results.

1.2 Intended Audience

Nowadays, many people read blogs and articles and even use social media. These people are mostly the general public and specifically office workers. All these platforms provide people with information. The information can be either fake or genuine. However, it is a difficult task for people to differentiate between them. All of them deserve to know what is true and what is false. Fake news also destroys the credibility of its reader. If based on fake news, the stance they are giving might damage their image. If they will know what is true and provide their opinion based on that information will help build the image.

We aim to help people who read blogs and articles and visit websites to get information. We will help people maintain their credibility and help them distinguish between true and false. With an increase in the amount of data, it became necessary to reveal which news is genuine and which is fake.

1.3 Definitions, Acronyms, and Abbreviations

1.3.1 Definitions

Text Summarization: It is a process of condensing content of the document so that it meets the needs of its user.

Extractive Summarization: It is one step simpler than the other kind. It means creating summaries of the source text by concatenating important (prominent) phrases from the text, chosen explicitly.

Abstractive Summarization: It creates meaning-based summaries of the source text. This gives results that are similar to the summarization approach of humans. This is why abstractive summarization is preferred.

Long Short-Term Memory: It is a neural network which grasps long-lasting dependencies from series prediction problems. It is a complex area of deep learning using machine translation, speech recognition, etc.

Transformers: Transformers are a type of deep learning model that do not rely on sequential processing of input data. Instead, they operate by utilizing attention mechanism to process the entire input in parallel.

Support Vector Machine: It is a supervised ML algorithm that is widely used for regression and classification problems. It works by finding an optimal hyper-plane that maximally divides different classes in the dataset.

Convolutional Neural Network: It is a deep learning model that works well for analyzing visual data such as images, videos and textual data without features. It is composed of multiple layers arranged in a specific order.

1.3.2 Acronyms, and Abbreviation

LSTM: Long Short-Term Memory

RNN: Recurrent Neural Networks

CNN: Convolutional Neural Networks

GloVe: Global Vector

BERT: Bi-directional Encoder Representations from Transformers

TF-IDF: Term Frequency-Inverse Document Frequency

CV: Count-Vectorizer

SVM: Support Vector Machine

Chapter 2: Project Vision

This chapter entails our project vision. Any good project is only as good as its vision. Entrepreneurs, businessmen, and project manager all put immense significance to it. We too aim to chalk out a solid vision where we define the goals and the scope of the project. Our plan was to be ambitious while setting realistic goals that we are capable of achieving.

2.1 Problem Domain Overview

Our project aims to detect fake news that is growing faster along with making this information easy for users to access. With the assistance of Deep Learning and Machine Learning models, such as LSTM Encoder-Decoder with Attention mechanism, Pointer Generator mechanism [4], Coverage mechanism, Transformers, BERT model, BART model [5], T5-3B model and many others, we classify true information from the false.

Typically, three approaches are available for fake news detection systems: content-based, context-based and intervention-based. However, content-based is the most commonly used approach. Content-based methods can be further characterized as linguistic, auditory and visual approaches. These methods are frequently based on knowledge or style.

Before beginning to classify the text, our project starts to do an abstractive summarization. For this we have decided to use LSTM Encoder-Decoder with Pointer-Generator Mechanism and T5-3B Transformers for text summarization and GloVe vector for word embedding to have better ROUGE score.

After summarization, our project will start running model for fake news detection. The model that we will be using is Support Vector Machine and Convolutional Neural Network. Our aim is to have better ROUGE score for Summarization and improved Accuracy, Precision, Recall, and F1-score for Fake News Detection.

A lot of work has already been done on fake news detection; many models have been used up till now which have a decent accuracy such as LSTM, Logistic Regression, Support Vector Machine which is why we are exploring several models. Already published work in this domain is majorly based upon summarization or upon fake news detection, but a few papers have been published that explores the two domains together.

2.2 Problem Statement

Various online tools that are available for summarization do not have that much accuracy and there are many fake news articles which the audience does not recognize. Our project will first summarize the article for the people who aren't interested in reading long articles or those who prefer reading simple words, then the fake news model will check the authenticity of the news.

2.3 Problem Elaboration

Many people aren’t interested in reading long articles worth thousands of words so they end up reading their summary. The community uses various online tools for summarization that do not have that much accuracy, hence, it results in a diminished user experience, as the summarized text might not reflect the correct context or point of view of the original article.

Due to an increased growth of information being readily available online, it has become difficult for the readers to determine true from the false, resulting in the broadcast of fake news. The discovery of social media and the freedom to post whatever and whenever, added a lot to it. Unfortunately, there is no check on what information is posted and its authenticity, therefore, a wide spread of fake news comes into place, whether done intentionally or unintentionally.

The recent pandemic of Covid-19 demonstrated that this fake information can be life-threatening. It is, therefore, crucial to detect fake news to inform people about authentic information online.

While original unaltered texts need to be checked for fake news, so does the summarized version of those texts. At the end of the day, it is the user experience we are trying to improve and while the user does read original unaltered texts, so do they read summarized versions of them.

2.4 Goals and Objectives

Fake News Detection is a classification problem with a variety of class numbers. This task is still unresolved, for which multiple techniques have opted. Transformer models like BERT, and BART are actively used in Fake News Detection. Moreover, XLM-ROBERTa is a multilingual model that applies when news appears in every language. DistilBART model is applied for text summarization through an extractive approach rather than an abstractive approach.

However, in this research, we will be working on Deep Learning and Machine Learning models, such as the LSTM Encoder-Decoder with Attention mechanism, Pointer-Generator mechanism, Coverage mechanism, as well as T5-base and T5-3B Transformer models for summarization and Support Vector Machine and Convolutional Neural Network for Fake News Detection. These models will play a critical role in summarizing text and classifying true and false information accurately.

Our objectives in this research are:

- Learn the best way to combine different news and social context elements for fake news identification.
- Understand the working of abstractive summarization techniques and use them to avoid the loss of information on long sequences.

The achievable goals, after using the datasets and applying the model are:

- To have the best ROUGE score for our summarization model.
- To have the best Accuracy, Precision, Recall, and F1-score for our fake news detection model.
- And the assessment of the opted model with other models.

2.5 Project Scope

Our project aims to investigate a given body of text and in turn detect any fake news found in them. This body of text can be of any medium including linguistic, visual or auditory but to keep things simple and not overcomplicate, we have decided to only focus on text-based content. Not only will this allow us to better explore the depth of the subject, but will also give us the opportunity to perfect a single functionality. Before we run the text through the algorithm of fake news detection, we will first employ abstractive summarizations in order which will serve two purposes, one to prevent the loss of further potentially crucial information and second to transform the text into clearer and simpler words.

Our ultimate target is to have the most accurate and precise results after applying an opted model. Moreover, ROUGE score and accuracy will be the key evaluation metrics against which our model will be compared to various other models present in the community. This will allow us to measure quantifiably how good our model is in detecting fake news using text representation.

2.6 Sustainable Development Goal (SDG)

2.6.1 Quality Education

Quality education is one of the bedrocks upon which any society builds itself. Newspapers play a significant role in print media since they provide the most recent information on a variety of topics. Our team recognizes the significance it has and one of the reasons for pursuing this topic in our research was its contribution to education. To elaborate, one of the functions of our project is summarizing longer texts such as a newspaper article. We believe that with video media on the rise, print media is being outdated because of the time taken, lack of imagination from the reader and the logistical challenge. However, those who still value print media know it's worth but sometimes even they can't appreciate it on a busy schedule. And any summarization tools online do not completely represent the correct view-point of these texts and/or do not go through the trouble of checking for accuracy of facts. With fake news on the rise, checking for accuracy has been more important now more than ever. Our research however will be working on not only summarizing longer newspaper article-like texts but also checking them for incorrect information. This directly and indirectly improves user experience and allows print media audiences to enjoy their reading without any challenge.

2.6.2 Industry, Innovation and Infrastructure

Over two decades, we have seen a massive innovative modification in everything we do, from communication to our studying tools, great minds innovating has made it all possible. While researching for which topic to pursue for our thesis, our checkpoint was, can this change people's lives, can it further improve user experience and has it ever been done before? We thus arrived at the topic we are researching on because the industry has never seen any publication that first converts texts into summaries and then audits them for fake news detection. The idea is simple yet complex, but in the end can change the ways people read news, improve their experience and has never been done before. What our project is doing is we are integrating these two methods to have a good accuracy and a better result. Industry needs this as this will reduce user's time.

Chapter 3: Literature Review / Related Work

This section will include detailed literature review of text summarization and fake news detection sequentially. Also, a summary table is provided at the end that shows results of each paper.

3.1 Definitions, Acronyms, and Abbreviations

Text summarization is the process of condensing a long document to a shorter version that contains main information from the original text. Abstractive and Extractive Summarization are two main domains of summarization. Both of these works differently but their task is to generate a summary of input containing all the key points from the text. Extractive summarization is creation of summaries of the source text using explicitly selecting key (prominent) phrases from the text. However, abstractive summarization produces meaning-based summaries of the original text.

For text summarization purposes, the data available needs to be filtered using pre-processing techniques. Number of pre-processing techniques were mentioned. PoS is one of the most important techniques. In this technique, tagging tokens are tagged into verbs, nouns or adjectives, etc.

The two categories of artificial neural networks mentioned in this document are: Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN). In RNN the connection can be created using a cycle, which allows the output of nodes to affect the subsequent input nodes. However, CNN is a DL algorithm that takes image input and applies biases and weights to the image's characteristics. Later, it is able to distinguish one from another.

RBM stands for Restricted Boltzmann Machine. It is a stochastic neural network where each neuron has arbitrary performance when stimulated. It learns probability distributions over the set of input. Long Short-Term Memory (LSTM) is a neural network which grasps long-lasting dependencies from series prediction problems. MMR stands for Maximal Marginal Relevance is an algorithm that considers the similarity of keywords with the text document, along with the similarity of selected words.

Moreover, many evaluation metrics were seen including ROUGE 1, ROUGE 2, ROUGE 3, ROUGE-L, Recall, RF classifier. RF classifier stands for Random Forest Classifier. It is a type of meta estimator. On subsamples of the dataset, it fits a number of decision trees. It employs an averaging function to control over-fitting and increase forecast accuracy.

Some abbreviations and acronyms used in the text are as follows:

C-BiLSTM: Convolutional- Bidirectional Long Short-Term Memory

CNN: Convolutional Neural Networks

LSTM: Long Short-Term Memory

MMR: Maximal Marginal Relevance

PoS: Part-of-Speech

RBM: Restricted Boltzmann Machine

RNN: Recurrent Neural Networks

RF: Random Forest

3.2 Detailed Literature Review

The following sections describe the detailed literature survey of previous researches.

3.2.1 Related Research Work 1 – Text Summarization

3.2.1.1 Summary of the research item

In the current period, data is rapidly growing trillions of online documents in the form of articles, blogs, web pages, etc. Summarization is a crucial part of Fake News Detection. Bundles of information available in these articles and text summarization make sorting and extracting information easier.

Text summarization is the process of concising a long document to a shorter version that contains main information from the original text. Abstractive and extractive summarization are the two basic categories into which text summarization is typically divided.

Creating summaries of the source text using explicitly selected key (prominent) phrases from the text is known as extractive summarization. On the other hand, meaning-based summaries of the original text are produced by abstractive summarization. This kind of summarization produces outcomes that are more similar to how humans summarize information [3].

Pre-processing is a necessary step in the summarization process. Document briefing, removing all unwanted words, and giving a proper structure requires various pre-processing techniques. Document Segmentation which divides the document into paragraphs. Paragraph segmentation divides each paragraph into sentences. Further word normalization breaks each sentence into words and normalizes those words using a lemma or stem words. Stop word Filtering removes high-scored stop words. Lastly, PoS tagging tokens are tagged into verbs, nouns or adjectives, etc. [6].

Extractive summarization produces a summary by choosing sentences in the original text. These sentences are only the critical and desired information from the document available.

Moreover, RBM is a stochastic neural network where each neuron has arbitrary performance when stimulated. Four different features were used for the feature extraction phase. The characteristic scores are applied to the RBM in which its rules optimize. After various levels of processing, a summary is generated. With an increase in the information available, it has become impossible for a human to remember every detail. Deep Learning algorithms are also playing their roles, making this task easy. Restricted Boltzmann Machine is used to obtain top most features from the texts [7].

Abstractive summarization generates new sentences. It is either rephrasing or using words that were not in the original document. Pointer-generator, a hybrid model, during training and testing phase chooses whether to duplicate words from the provided source text by pointing or construct a new word using a predefined vocabulary [8]. It is a first step towards multi-sentence abstractive summarization. The proposed mechanism of pointer generator, produces summary by combining abstractive and extractive approach in cascade.

An end-to-end approach has been introduced for abstractive summarization. It uses key attention mechanisms based on the encoder-decoder network and learning objectives (Intra decoder attention mechanism) to address repeating phase issues. This model gets the input sequence using a bi-directional LSTM encoder and output with a single LSTM decoder [9].

BERT, the Oracle, three codes enabling position and one code enabling position were used to automate the summarizes. However, the evaluation shows that the proposed framework (semantic-related sub-aspects condition code) achieved the most reasonable summaries [10].

The structured-based summarization approach marks the main aspects of the text, scores them based on representation, and selects the topmost k sentences to produce the summary of the text given. In a structure-based model, topic representation can be done using the main approaches mentioned are topic words, Bayesian topic models, frequency-driven methods, latent semantic analysis. All these approaches are used for single or multi-document summarization [11].

3.2.1.2 Critical analysis of the research item

RBM successfully discovered latent factors by extracting a hierarchical representation of the data with limited variation. This innovative approach yielded an average precision of 0.7 and an average recall value of 0.63, surpassing the performance of existing methods [6].

Multi-document summarization system developed using RBM along with 4 phases of feature extraction, considered recall, precision and f-measure as evaluation metrics. The maximum recall of an existing approach is 0.72 while for the proposed one it is around 0.62. ROUGE 1,2,3, L were used in the proposed mechanism of the pointer generator model in comparison with LexRank and MMR. It produced the highest scores of R1, R2, R3, RL 0.43013, 0.08056, 0.02526, and 0.33260 respectively. Multiple news articles can be summarized one at a time, producing multiple summaries for a single topic. In order to remove this redundancy, the second phase of solution performed extractive summarization on produced summaries [7].

Coverage mechanism reduces the repetition of information during the summarization process. Moreover, Pointer-generator model with attention and coverage mechanism generates high accuracies and overwhelms the issues found in abstractive text summarization [8].

Intra-decoder attention allows models to make structured and reliable predictions while avoiding the repetition of same information which may be generated step away. Moreover, it does not make any assumptions about the type of decoder RNN. This increases the ROUGE-1 score along with ground truth summary [9].

The proposed framework (semantic-related sub-aspects condition code) reduces a longstanding problem, position bias. It preserves the comparable performance with other models [10].

3.2.1.3 Relationship to the proposed research work

A lot of work has been done on fake news detection; many models have been used up till now which have a normal accuracy such as Long Short-Term Memory (LSTM). We have explored several models for word embedding including GloVe. We will be using the LSTM encoder-decoder mechanism along with Transformer models to generate the summary of the news which is an input to the system.

3.2.2 Related Research Work 2 – Fake News Detection

3.2.2.1 Summary of the research item

Typically, three approaches are available for fake news systems: content-based, context-based, and intervention-based approach. [12] But, content-based is the most commonly used approach. It can be further categorized into linguistic, auditory and visual approaches. These are either knowledge-based or style-based approaches [13].

Since fake news aims to spread false and misleading information, a knowledge-based approach focuses on checking the veracity of claims using external sources. On the contrary, style-based approach aims to identify fake news by identifying exploiters in writing style [14]. Linguistic approaches are often classified by deep learning concepts of Attention-based networks and Long Short-Term Memory (LSTM) architecture [15].

A major drawback of context-based approaches is that they might miss valuable context information. Hence, a context-based approach comes into place, which focuses on secondary information such as dissemination networks [16] and user engagements [17] to detect fake news. This can be done using propagation, temporal [18] and stance analysis [19]. Stance-based approaches, therefore, focus on user's viewpoints from relevant post contents to check the authenticity of news. In a propagation-based approach, credibility scores are assigned to each social media post, user and news article. The veracity of news is then computed by examining the credibility scores of particular users or news articles.

Contextual information is so far the best approach for fake news detection but it is often not available or partially available. With this drawback, intervention-based approaches are considered. These approaches tend to dynamically interpret real time dissemination data. They work by injecting true news into social media platforms [20] and user intervention [21]. Although, they give best results but they are least commonly used because of their complexity and difficulty to evaluate.

3.2.2.2 Critical analysis of the research item

The work in [3] uses sequence-to-sequence encoder decoder as its baseline model to evaluate fake news detection. The RNN encoder and RNN decoder make up the sequence-to-sequence architecture. The RNN encoder takes the input sequence token by token as a single-layer bidirectional Long-short-term Memory (LSTM) unit and creates a series of hidden states that encode the input. The RNN decoder, which is a single-layer unidirectional LSTM, creates the hidden states of the decoder sequentially, resulting in the output sequence that serves as the summary.

The baseline model was then modified by calculating attention weights which assists the decoder determine which source words to focus on in order to create the next word. This model was dropped due to its drawbacks as it can't handle out of vocabulary words and can reproduce factual details incorrectly. Also, it is unable to replicate source words as well as maintain long term statistics in the decoder state. After this model, other models were considered which include coverage mechanism, pointer generator mechanism, and transformers. This work uses CNN-DailyMail dataset which is split into 92% training, 4.2% development and 3.8% testing. Recall, Precision and Accuracy were used as its evaluation metrics.

The work in [22] uses different deep learning techniques for fake news detection. The results are clearly evident as SVM and Neural Networks (Logistic Regression) gives 90.90% accuracy while Naïve Bayes provides 96.08% accuracy [23].

The work in [24] uses a supervised learning model for detecting fake news. The implementation recommends including new features to train various classifiers, which improves the accuracy rate for detecting fake news. 2282 US election-related news stories were used in the experiment. The outcomes demonstrate that the RF classifier has an accuracy rate of 85%. To test the accuracy of deep learning algorithms with enhanced fake news predictions, the authors, however, employed a very small dataset and did not use supervised learning models on huge datasets.

The work in [25] another use of deep neural networks for the early detection of fake news. During the process, input is employed as feedback from status-sensitive audience, and a classifier trained on unlabeled and positive data reaps the benefits of five-fold cross-validation. The experiment employed two distinct datasets, Twitter and Weibo. The proposed architecture attained an accuracy rate of 90% within 5 minutes timeframe of the news delivery. However, the author faced limitations in the intended task because of the use of small dataset.

3.2.2.3 Relationship to the proposed research work

Previously, work has been done to identify fake news but there is little or no work that focuses on the integration of text summarization and fake news detection. Our main aim is to integrate the both and check the authenticity of news. Precisely, our work will first compute a summary of the news article and will then use this summary in a fake news detection model to identify true from the false.

3.3 Literature Review Summary Table

During the course of our exploration, we studied many of the existing papers that have been published and found that various methods and techniques were used in them. You'll find the names and references of those papers against the methods and techniques that were used in them. Table 1 presents the state-of-the-art methods.

Table 1: Existing state-of-the-art research studies
This table contains detailed analysis of the existing research studies for Fake News Detection and Text Summarization

No.	Name, Reference	Method	Output
1.	Neural Abstractive Text Summarization and Fake News Detection [3]	LSTM Encoder Decoder with Attention Mechanism, Pointer Generator Mechanism, Coverage Mechanism, Transformers	**F1-Macro:** 35.68 **Recall:** 44.07 **Precision:** 31.95
2.	Abstractive Review Summarization based on Improved Attention Mechanism with Pointer Generator Network Model [4]	Pointer Generator + Improved attention mechanism + Coverage mechanism	**ROUGE-1:** 41.2 **ROUGE-2:** 22.4 **ROUGE-L:** 37.1
3.	Extractive Summarization using Deep Learning [6]	RBM with pre-processing of text	**Average of** **Precision:** 0.7 **Recall:** 0.63
4.	Conditional Neural Generation using Sub-Aspect Functions for Extractive News Summarization [7]	Model with Control codes	**Code [1,0,0]** **R-1 F1:** 34.81 **R-2 F1:** 6.23 **R-2 Recall:** 6.34
5.	An Approach for Text Summarization Using Deep Learning Algorithm [8]	RBM with document pre-processing	**F-measure values:** **Doc1:** 0.49 **Doc2:** 0.469 **Doc3:** 0.520

6.	A Deep Reinforced Model for Abstractive Summarization [9]	Maximum-likelihood + Reinforcement Learning with intra-decoder attention	**R-1:** 42.94 **R-2:** 26.02
7.	Deep Learning Architecture for Multi-document Summarization as a Cascade of Abstractive and Extractive Summarization Approaches [11]	Pointer Generator along with Abstractive and Extractive Summarization Cascading	**R1:** 0.43013 **R2:** 0.08056 **R3:** 0.02526 **RL:** 0.33260
8.	Applying Automatic Text Summarization for Fake News Detection [13]	BERT	**Accuracy:** 0.453 **Precision:** 0.424 **F1-Macro:** 0.395 **Recall:** 0.402
9.	Hierarchical Propagation Networks for Fake News Detection: Investigation and Exploitation [16]	Hierarchical Propagation Network Feature vector	**Accuracy:** 0.861 **Precision:** 0.854 **F1-Macro:** 0.862 **Recall:** 0.869
10.	dEFEND: Explainable Fake News Detection [17]	dEFEND	**Accuracy:** 0.904 **Precision:** 0.902 **F1-Macro:** 0.956 **Recall:** 0.928

3.4 Conclusion

We have seen techniques of text summarization and Fake News Detection. The integration of text summarization and Fake News is less than the work done separately. Mainly used summarization techniques are Abstractive and Extractive summarization. LSTM encoder-decoder, pointer generator, RBM, and many other frameworks are used for the summarization of the document. Furthermore, for Fake News detection different approaches were seen.

Chapter 4: Proposed Approach and Methodology

In our work, we considered Sequence-to-Sequence Encoder-Decoder architecture with Pointer Generator Mechanism and T5-3B Transformers as our model for text summarization purposes. The models employed for Fake News Detection are Support Vector Machine and Convolutional Neural Network.

4.1 Text Summarization

For the purpose of Text Summarization, we are using CNN-DailyMail Dataset. We will apply preprocessing techniques on the dataset being used in this research like removing unwanted characters and symbols. The preprocessed and cleaned data will be tokenized and padded. Later, word embedding will be done using gloVe Vector. Afterward, the data will be passed onto our baseline model which is LSTM Encoder-Decoder using the Attention Mechanism.

4.1.1 Dataset

We are using CNN-DailyMail dataset[1] for Text Summarization. This dataset contains news from two separate datasets: CNN and DailyMail.

4.1.1.1 CNN

This dataset is designed for text summarization. It contains the documents from the news articles of CNN. There are 92,579 documents. The dataset supports both extractive and abstractive summarization. It has two data fields; article and highlights.

Table 2: Samples from CNN Dataset

This table contains some of the samples from CNN dataset. This dataset has two data fields; article and highlight

Article	Highlights
….hours after announcing that he believes military action against Syrian targets is the right step to take over the alleged use of chemical weapons .\n\nThe proposed legislation from Obama asks Congress to approve the use of military force….	Syrian official : Obama climbed to the top of the tree , `` does n't know how to get down '', Obama sends a letter to the heads of the House and Senate, Obama to seek congressional approval on military action against Syria, Aim is to determine whether CW were used , not by whom , says U.N. spokesman
…Police arrested another teen Thursday , the sixth suspect jailed in connection with the gang rape of a 15-year-old girl on a northern California high school campus…	Another arrest made in gang rape outside California school, Investigators say up to 20 people took part or stood and watched the assault, Four suspects appeared in court Thursday ; three wore bulletproof vests
…pushing relations back one giant step .\n\n\n\n\n\n\nColombian Gen. Freddy Padilla , the armed forces chief whose arrest is sought , canceled a	Ecuadorian judge issues an arrest warrant for head of Colombian armed forces, Colombian Gen. Freddy Padilla cancels trip to Ecuador for fear of arrest, Tensions between neighbors

[1] https://github.com/abisee/cnn-dailymail

meeting scheduled for Friday with Ecuadorian..	stem from FARC rebels taking refuge in Ecuador

4.1.1.2 Daily Mail

This dataset is designed for text summarization. It contains the documents from the news articles of Daily Mail. There are 219,506 documents. It supports both extractive and abstractive summarization. This dataset has two data fields; article and highlights.

Table 3: Samples from DailyMail Dataset

This table contains some of the samples from DailyMail dataset. This dataset has two data fields; article and highlight

Article	Highlights
….A city trader who conned millions of pounds from wealthy investors was yesterday ordered to pay back Â£1.\n\nNicholas Levene, 48, was jailed for 13 years last November after he admitted orchestrating a lucrative Ponzi scheme which raked in Â£316million.\n\nHe used the money to finance his own lavish lifestyle with private jets, super yachts and round-the-world trips.\n\nMust pay Â£.…..	Nicholas Levene must pay the nominal sum because he is bankrupt, He used the money for private jets, super yachts, a Â£150,000-a-year box at Ascot and to host Â£10,000-a-day pheasant shoots, The city trader spent Â£588,000 on his son's Bar Mitzvah hiring girl band The Saturday's, He tricked some of Britain's most successful businessmen including Stagecoach boss Sir Brian Souter.
…Sky to fend off fierce competition from Frank Warrenâ€™s BoxNation.\n\nFloyd Mayweather's hotly-anticipated bout with Manny Pacquiao will be shown on Sky Sports\n\nPacquiao headed for the playground after working out in Los Angeles previously\n\nThe price for the fight has been set at Â£19.95 until midnight of Friday May …	Sky has been in fierce competition with Frank Warren's BoxNation, The broadcaster has won the right to show the $300m (Â£200m) bout, Sky has set the price for Floyd Mayweather vs Manny Pacquiao at Â£19.95, The mega-fight takes place at the MGM Grand in Las Vegas on May 2, Read how Jeff Powell broke the news of Sky's dealÂ.
…the device on charge for just ten minutes before she noticed flames and thick black smoke billowing from the vehicle.\n\nNo one was inside at the time, but the back seat was completely melted and the mother-of-two was horrified at the thought she and her family could have been injured…	Kim Taylor, 54, left the device plugged in on back seat of Ford Mondeo, But she returned minutes later to see smoke billowing from the vehicle, She says the device exploded and burned a huge hole in her car seat, Manufacturers say e-cigarettes must be used with the correct adapters, The incident is the latest in a spate of fires attributed to e-cigarettes.

4.1.2 Proposed Methodology

4.1.2.1 Pre-processing

The dataset we are using is unclean and has a variety of unwanted symbols and characters in it. So, the dataset is cleaned by removing all unwanted symbols and characters.

4.1.2.2 Tokenization

To tokenize words, we are applying the Keras[2] tokenizer. Following the creation of the tokenizer, we fit it to the training data and then apply it to fit the testing data as well.

Padding is required since each sentence in the text does not contain the same amounts of words. We may also choose the maximum amounts of words for each phrase, and if the sentence is longer than that, we can eliminate certain words.

4.1.2.3 Word Embedding

What are word embeddings? To understand this phenomenon, let's think about each word as a real-valued vector in a predefined vector space. This means that each word is mapped to a single vector where each vector value is learned to resemble a neural network [26].

If we take a step back and see, word embeddings are text representations where similar meaning words have similar representation. This approach then becomes one of the breakthroughs that have happened in this space of deep learning on challenging natural language processing problems.

The most crucial part of the approach is to use a densely diffused representation for each word embedded. Many models are used for word embedding. For experimentation purposes, we have used "GloVe". GloVe is an unsupervised learning approach for constructing vector representations of words [27]. Annotation global word-word co-occurrence statistics are used for training, and the resultant representations highlight some of the word vector space's intriguing linear substructures.

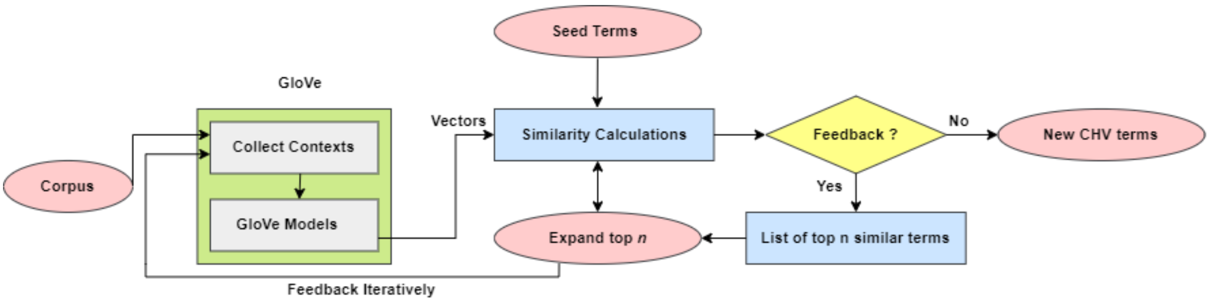

Figure 1: The architecture of gloVe for word embedding
This figure represents the architecture for gloVe used for word embedding

4.1.3 Deep Learning Models

Following deep learning models are used for text summarization:

4.1.3.1 Seq-to-Seq Encoder-Decoder with Pointer-Generator Mechanism

This technique involves the use of Sequence-to-Sequence Encoder-Decoder along with Attention Mechanism, Pointer-Generator Mechanism, Coverage Mechanism.

4.1.3.1.1 Sequence-to-Sequence Encoder-Decoder with Attention Mechanism

LSTM encoder-decoder is an RNN that is intended to deal with sequence-to-sequence problems. Generally, for an input sequence, sequence prediction includes the prediction of the succeeding value in a real-valued progression. This sequence is usually designed as a sequence

[2] https://keras.io/api/keras_nlp/tokenizers/tokenizer/

of a single input to single output or multiple input time steps to a single output step. The Encoder-Decoder LSTM is composed of two models:

One model is for understanding the input sequence and encrypting it to a fixed-length vector. A variable-length source is mapped onto the fixed-length vector. This fixed-length vector has the summarized information of the data. The input sequence is summarized into the thought vectors which are passed onto the decoder.

However, the second model is for the decoding of the fixed-length vector which is generated by the first model, and predicting the output sequence. The second model is initialized with the final stages of the first model. Using these states this model generates the output sequence. The behavior of the decoder is different at the time of training of the data and inference procedure. The LSTM reads the data in one sequence one by one. If 'K' is the length of the input sequence, then the LSTM reads it in 'K' steps.

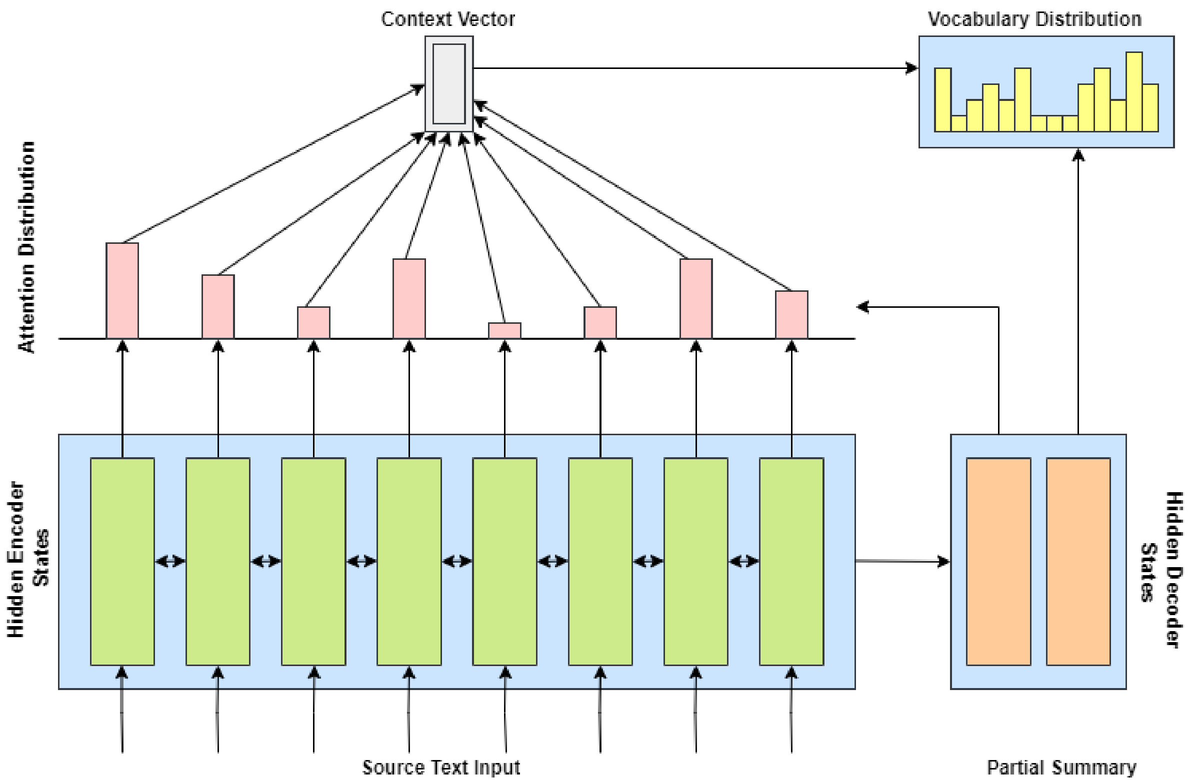

Figure 2: Sequence-to-Sequence Encoder-Decoder with Attention Mechanism
This figure represents a seq2seq Encoder Decoder with attention mechanism. It yields an input string and produces a set of hidden encoder states

The drawback of this mechanism is that it has no ability to extract strong contextual information and relation from long and lengthy semantic sentences. There comes the use of attention-based mechanisms. It provides the weighted and signified information from encoder to decoder. This frees the existing encoder-decoder technique from the fixed and short-length representation of the information by keeping the output of the encoder, the first model. From every step of the input, sequence, and training model to learn and give selected attention to elements. Later relating them to the output. Due to these few selective elements in the input, the output sequence becomes conditional. These conditionals are those which got attention and are used for training and predicting the desired result. In nutshell, the context vector is selectively filtered for each and every output time step. The attention distribution is computed using a likelihood distribution across the terms in the source text, which assists the decoder in determining which terms should be concatenated while creating the subsequent words. This can be computed using,

$$e_i^t = v^T \tanh\left(W_h h_i + W_{S_t} + b_{attn}\right) \qquad (1)$$

and,

$$a^t = softmax\,(e^t)$$

where the parameters v, W_h, Ws_t, b_{attn} are learnable. The model computes attention weights at each step. Attention weights mean the amount of attention that should be paid to the terms in the source text. $\mathbf{a}^{\mathbf{t}}$ is used to compute the weighted sum of hidden states of encoder h^*_t.

$$h_t^* = \sum_i a_i^t h_i$$

Pvocab is calculated,

$$P_{vocab} = softmax\,(V'\,(V\,[s_t, h_t^*] + b) + b')$$

Then, using vocabulary distribution loss of timestep is calculated:

$$loss_t = -\log P\,(w_t^*)$$

Overall loss for whole sequence is,

$$loss = \frac{1}{T}\sum_{t=0}^{T} loss_t$$

4.1.3.1.2 Pointer-Generator Mechanism

A Pointer-Generator Mechanism is a hybrid network that decides whether to produce new words from predetermined vocabulary set or replicate words from the source text via pointing, during training and testing.

In our baseline model, we only computed attention and vocabulary distribution, as shown in Figure 1. However, in Pointer Generator Mechanism, we also calculated generation probability P_{gen} which is a scalar value between 0 and 1. Generation probability of each timestep is calculated using the formula:

$$P_{gen} = \sigma\,(w_{h^*}^T h_t^* + w_s^T s_t + w_x^T x_t + b_{ptr})$$

Here, s^t represents the decoder state, x^t symbolizes the decoder input and h^t characterizes the context vector. This generation probability P_{gen} is acts as a soft switch to choose between whether to produce a new word from the predefined vocabulary set or copying it from the source text by selecting from the attention distribution. To make our prediction, we obtain final distribution by combining the vocabulary distribution and attention distribution through a weighted summation. The final distribution of a word P_{final} is computed using the equation:

$$P_{final}(w) = P_{gen} P_{vocab}(w) + \left(1 - P_{gen}\right) \sum_{i:\, w_i = w} a_i$$

Here, P_{final} is the final probability distribution, P_{gen} is the generation probability, P_{vocab} is the vocabulary distribution used for creating the word and a is the attention distribution used for pointing to the word in the source text. Based on this equation, we can say that the likelihood of generating a word w is equal to the generation probability P_{gen} multiplied by the likelihood of creating it from the predefined vocabulary P_{vocab} plus replication likelihood multiplied by the likelihood of directing to it in the source text.

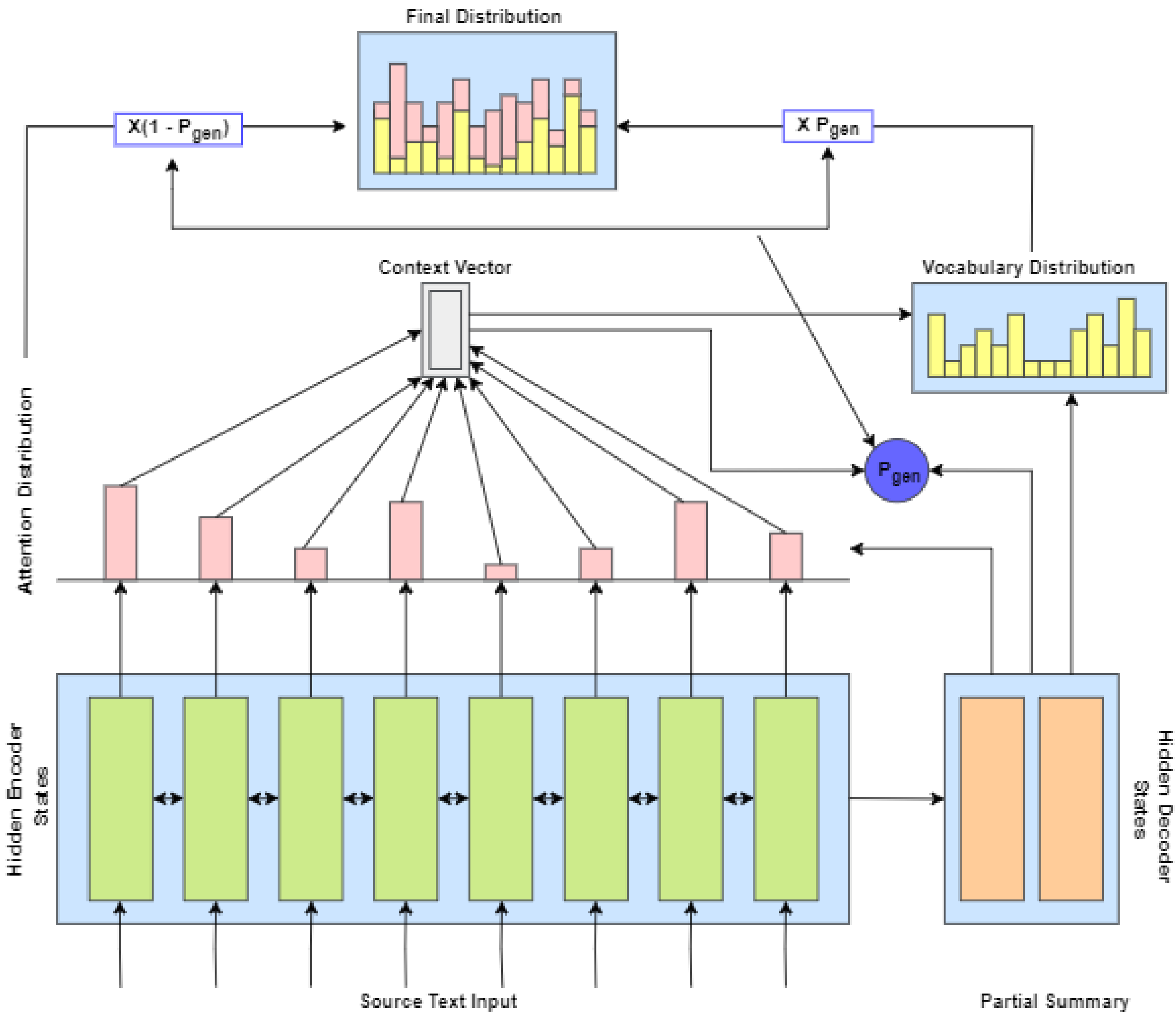

Figure 3: LSTM Encoder-Decoder with Attention and Pointer-Generator Mechanism
This figure represents a seq2seq Encoder Decoder with Attention Mechanism and Pointer-Generator Mechanism. It decides whether to create words from vocabulary or point towards the words in the source text.

If w does not appear in the source document, then attention distribution is zero. Similarly, if w is an out-of-vocabulary word, then $P_{vocab}(w)$ is zero. Our model's input is a single document or article, and its output is a collection of a few lines that effectively summarize the content of the input material in a meaningful manner.

As compared to the attention mechanism, the Pointer Generator mechanism makes it possible to handle unseen words by enabling the model to copy out of vocabulary words while employing a limited vocabulary, resulting in less computation and storage space. It also makes copying words from the source text easier by assigning appropriately high attention weights to the relevant words. This model is also quicker to train since it takes lesser training repetitions to attain the same outcomes.

4.1.3.1.3 Coverage Mechanism

All the Sequence-to-Sequence Encoder-Decoder mechanisms have a common issue of repetition during text summarization. In order to overcome this drawback, a coverage mechanism is used. It keeps track of the coverage vector at each iteration. On each timestep, the coverage vector c^t is calculated as a summation of all the attention distributions $a^{t'}$ over preceding decoder time steps as:

$$c^t = \sum_{t'=0}^{t-1} a^{t'}$$

Coverage vector, which is a component of the attention mechanism, demonstrates the amount of coverage that words in the source text have acquired from the attention mechanism. The model avoids redundancy by not heeding attention to words already used in the summarization process because coverage vector is continuously maintained and it shows cumulative attention. This coverage vector also helps us to calculate attention, thus equation (1) can be modified as:

$$e_i^t = v^T \tanh\left(W_h h_i + W_{S_t} + w_c c_i^t + b_{attn}\right)$$

This communicates the current timestep of the attention mechanism about the prior attention information collected in coverage vector c^t, preventing recurrent attention to the same source words. The coverage loss hinders any similarity between the new attention distribution and the coverage vector c^t as:

$$covloss_t = \sum_i min\,(a_i^t\,, c_i^t)$$

Finally, the overall loss becomes:

$$loss = \frac{1}{T}\sum_{t=0}^{T}(loss_t + covloss_t)$$

4.1.3.2 Transformers

Transformers are a type of deep learning model that do not rely on sequential processing of input data. Instead, they utilize an attention mechanism to process the entire input sequence in parallel. This enables transformers to apprehend dependencies between various segments of the progression and produce more accurate outputs.

Transformers consist of an encoder and a decoder, both of which are composed of multiple layers. The encoder analyzes the input sequence and generates a sequence of feature vectors, while the decoder takes these feature vectors as input and generates the output sequence. The decoder is trained during training to predict the accurate output sequence provided the input sequence.

4.1.3.2.1 T5-base Transformer

T5-base is a variant of the T5 (Text-to-Text Transfer Transformer) model, which is a popular transformer-based language model. The T5-base model comprises of an encoder-decoder structure, where the input is first passed through the encoder and then the decoder generates the output. The encoder is a stack of 12 transformer blocks, while the decoder is a stack of 12 transformer blocks with an additional cross-attention mechanism between the encoder and decoder.

Each transformer block is composed of two sub-layers, a feed-forward neural network and a self-attention mechanism. The self-attention mechanism enables the model to concentrate on various parts of the input sequence, while the feed-forward neural network analyzes the output of the self-attention mechanism.

The T5-base architecture employs a text-to-text technique, where the input and output are both text sequences. This means that the model is trained to perform various NLP tasks by converting the input to a fixed-length vector representation and then using the decoder to generate the output sequence.

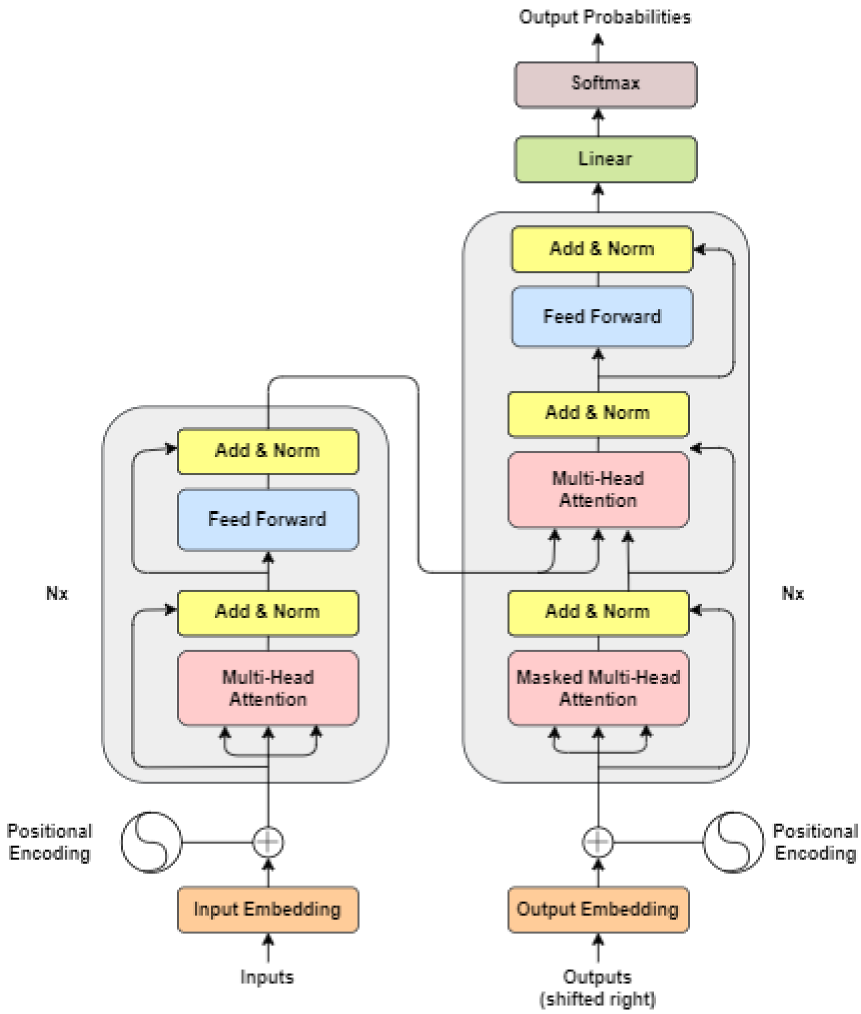

Figure 4: The architecture of Transformers

This figure represents the general architecture of Transformers which can be improved for a specific model

The T5-base model is trained using a transformer-based architecture, which is a deep neural network that uses self-attention mechanisms to process the input sequence of tokens. The model is trained on a diverse set of tasks, such as machine translation, summarization, and question-answering, using a simple yet effective training objective called “pre-training through denoising autoencoding”. This objective involves randomly masking some tokens in the input sequence and asking the model to predict the masked tokens.

Once the T5-base model is pre-trained, it can be fine-tuned on specific downstream tasks using supervised learning. For example, it can be fine-tuned on a summarization task by training it on a dataset of article-summary pairs, where the input is an article and the output is a summary of the article. During fine-tuning, the model adjusts its parameters to better predict the outputs based on the input data.

4.1.3.2.2 T5-3B Transformer

The T5-3B transformer is a type of transformer architecture used in natural language processing tasks. It is based on the T5 (Text-to-Text Transfer Transformer) model, which was introduced by Google AI.

The T5-3B transformer is an even larger version of the original T5 model, with 3 billion parameters. It consists of 32 layers of transformer blocks, with each block containing multiple self-attention layers and feedforward layers. The model is trained on massive amounts of data using a technique called unsupervised pre-training, where the model learns to generate text from text by predicting missing words or sentences.

The T5-3B transformer has achieved state-of-the-art results on a wide range of NLP benchmarks, including language understanding, language generation, and question answering tasks. Its large size and computational requirements make it suitable for use in high-performance computing environments, such as cloud computing platforms and supercomputers.

4.2 Fake News Detection

We have distinguished between fake and real news articles by utilizing supervised machine and deep learning algorithms Convolutional Neural Network and Support Vector Machine. Feature extraction techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) and Count-Vectorizer (CV) are employed to extract feature vectors from the textual content of the articles. Their efficacy is evaluated based on their ability to predict the labels of testing samples after learning from the training data utilizing these feature extraction techniques. Different supervised machine learning models are widely utilized for the classification of textual data as real or fake.

4.2.1 Dataset

We are using the Github dataset for Fake News Detection, which contains news from two separate datasets - Fake News and True News. Additionally, we will be utilizing the Kaggle dataset for conducting different experiments.

4.2.1.1 Fake News & True News

This dataset is designed for Fake News Detection. This dataset contains the documents from the news articles of Fake News [3]and True News[4]. There are 44900 news combined. This dataset has four data title, text, subject and date.

Table 4: Samples from Github Dataset

This table contains some of the samples from Github dataset. This dataset has four data fields; title, text, subject and date

[3] https://github.com/akshaysharmajs/Fake-News-Detection/blob/main/jupyter_main/Fake.zip

[4] https://github.com/akshaysharmajs/Fake-News-Detection/blob/main/jupyter_main/True.zip

Title	Text	Subject	Date
Drunk Bragging Trump Staffer Started Russian Collusion Investigation	… according to four current and former American and foreign officials with direct knowledge of the Australians role. Papadopoulos pleaded guilty to lying to the F.B.I. …	News	December 31, 2017
Sunnistan: US and Allied 'Safe Zone' Plan to Take Territorial Booty in Northern Syria	…Who could blame them? After all, it worked in Libya in late 2011.Fast forward to 2016, having failed to overthrow Assad and implode the nation-state of Syria…	Middle-east	January 15, 2016
10 U.S. Navy Sailors Held by Iranian Military – Signs of a Neocon Political Stunt	…According to NBC News, U.S. State Department is in touch with Tehran officials and the Iranians recognize that the U.S. Navy straying off course was a mistake, and that the sailors will be released within hours. …	Middle-east	January 12, 2016
U.S. might ban laptops on all flights into and out of the country	…at a limited number of airports, requiring people to remove additional items from carry-on bags for separate screenings. Asked whether the government would expand such meas…	politicsNews	May 28, 2017
As U.S. budget fight looms, Republicans flip their fiscal script	… That will be followed by a weekend of strategy sessions for Trump and Republican leaders on Jan. 6 and 7, the White House said. Trump was also scheduled to meet…	politicsNews	December 31, 2017

4.2.2 Proposed Methodology

4.2.2.1 Preprocessing

The dataset we are using is unclean and has a variety of unwanted symbols and characters in it. So, the dataset is cleaned by removing all unwanted symbols and characters. Furthermore, we have removed punctuations within the dataset and stopwords, which were downloaded from nltk library.

4.2.2.2 Tokenization

To tokenize words, we are applying the Keras[5] tokenizer. Following the creation of the tokenizer, we fit it to the training data and then apply it to fit the testing data as well.

[5] https://keras.io/api/keras_nlp/tokenizers/tokenizer/

Padding is required since each sentence in the text does not contains the same amount of words. We may also choose the maximum number of words for each phrase, and if the sentence is longer than that, we can eliminate certain words.

4.2.3 Deep Learning Models

4.2.3.1 Convolutional Neural Network

Convolutional Neural Network, usually abbreviated as CNN, is a deep learning model that works well for analyzing visual data such as images, videos and textual data without features. The structure and functionality of CNN is quite similar to the visual cortex in human brain.

CNN is composed of multiple layers arranged in a specific order. These layers include input layer, convolutional layers, activation function, pooling layers, fully connected layers, hidden layer and output layers but the main layers of CNN are convolutional layers, pooling layers, and fully connected layers.

Input layer represents raw input data, usually in the form of images. Convolutional layers learn feature representations from the input data. Each convolutional layer produces feature maps that represents various features and patterns in the input data. The number of filters in the layer correlates to the depth of the feature maps. After each convolutional layer, activation function, such as ReLU (Rectified Linear Unit) is applied to feature maps. Pooling layers reduces spatial dimensions of the feature maps by preserving the important information and discarding other details. Most commonly used pooling function is max pooling which selects maximum value specified in the pooling frame.

After pooling layers, fully connected layers come into place. They are composed of neurons which are fully connected to the previous layer. They classify input data by taking high level features from previous layers and learn to predict based on the specified task. Flatten layer is usually placed between the convolutional, pooling or fully connected layers. It reshapes feature maps into vectors, making them able to be connected to fully connected layers. The output layer produces the final predictions of the CNN model based on the specified task.

4.2.3.2 Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning model that is actively used for classification and regression problems. It is particularly used for pattern recognition, image analysis, and text classification.

SVMs work by locating the hyperplane in the feature space that best splits the data into different categories. The hyperplane is selected, such that the margin is maximum and classification error is minimum. Margin is the distance between the hyperplane and the Support Vectors. Support Vectors are the extreme points, which are closest to the margin of the hyperplane.

In the case of linearly separable data, the hyperplane can be found directly by solving an optimization problem called the ‘primal problem’ or ‘dual problem’. Numerical optimization techniques such as gradient-descent and quadratic programming are typically employed to solve this optimization problem. For non-linearly separable data, SVMs map the original feature space to a higher dimensional where the data becomes linearly separable. It allows SVMs to classify non-linearly separable data.

In addition to the classification task, SVMs can be used for regression problems by fitting a hyperplane that approximates the association between the input features and the output variable. This is done by minimizing a cost function that penalizes deviations from the desired output.

SVMs have several advantages as compared to other machine learning algorithms used for fake news detection, such as the ability to handle high-dimensional data, robustness to the outliers, being effective with small training datasets, having a strong theoretical foundation, and being able to handle non-linear decision boundaries. Despite its advantages, SVMs can pose a challenge in terms of its usage. They can be computationally expensive and are suspectable to the changes in the choice of hyperparameters.

4.2.3.3 TF-IDF Transformer

TF-IDF is a widely used natural language processing technique for text analysis, specifically for feature extraction. It is used for extracting features from the text. It is used to determine the significance of words or terms in a document by measuring their relevance to the overall corpus of documents. A term is a word that is normalized to its case, morphology or spellings.

TF-IDF is based on two components: Term Frequency (TF) and Inverse Document Frequency (IDF). Term Frequency refers to the frequency of a term in a respective document. It is calculated as:

$$\boldsymbol{TF\ (term) = \frac{Number\ of\ times\ a\ term\ appears\ in\ the\ document}{Total\ number\ of\ terms\ in\ the\ document}}$$

IDF is the Inverse Document Frequency. It measures the importance of a term across the whole corpus of manuscripts. It is calculated as:

$$\boldsymbol{IDF\ (term) = \log_{10} \frac{Total\ number\ of\ documents}{Number\ of\ documents\ containing\ the\ term}}$$

TF-IDF is a powerful technique for text analysis, as it can help identify the most important words or terms in a document or corpus of documents. The TF-IDF score for a term is calculated by the product of the TF and IDF values for that term. Terms that occur rarely in the entire corpus will have a high IDF and the terms that occur frequently in the document will have high TF.

$$\boldsymbol{TFIDF\ (term) = TF(term) * IDF(term)}$$

4.2.3.4 Count Vectorizer

For machines, it is difficult to understand words and even characters. To understand such data it is necessary to convert textual data into numbers. Here comes the concept of count vectorizer. Count Vectorizer is a popular feature extraction approach. It involves the conversion of textual data into numerical vectors, where every unique word is represented by a unique integer.

Count Vectorizer works by counting the frequency of each word in a given text document and creating a table where rows represent a document and each column represents a unique word. The value in each cell of the table is the number of times that word occurs in that particular document.

Chapter 5: Implementation and Test Cases

We will provide the implementation details of our project in this chapter. It contains detail about our implementation methodology for both Text Summarization and Fake News Detection.

5.1 Implementation

Our project is dependent on two main things: testing the summarization of each article in the dataset and then using these summarized articles for Fake News Detection.

5.1.1 Abstractive Text Summarization

For Text Summarization, we are using CNN-Daily Mail Dataset. Finalizing the model for abstractive summarization is done using comparative analysis. To determine which model is more suitable for abstractive summarization, we did a comparison between; LSTM encoder-decoder with Pointer Generator mechanism and Transformers.

For **LSTM encoder-decoder with Pointer Generator mechanism**, we will apply different pre-processing techniques on the dataset being used in this research; removing stopwords, unwanted characters, and symbols, and normalizing and standardizing data. The pre-processed and cleaned data will be tokenized and padded. Word embedding will be done using gloVe Vector and the data will be passed onto our baseline model which is LSTM Encoder-Decoder using the Attention Mechanism which uses attention weights to encode and decode hidden words. The output is then passed on to the Pointer Generator Mechanism which decides whether to generate new words or point words in the source text for summarization. The summarized text is then passed as input to the Coverage Mechanism which removes repetitive words and produces the final summarized text.

For **Transformers** we utilized **T5-3B Transformer Model**, we will apply pre-processing techniques on the dataset; removing, stopwords, unwanted characters, and symbols, and normalizing and standardizing data. Our model is also fine-tuned on 1k entries of the dataset to generate better results. The pre-processed and cleaned data is tokenized and padded and passed onto our baseline model which is T5-3B Transformer.

On the analysis of both models, Transformers have been concluded as an efficient and better way to generate abstractive text summarization.

5.1.2 Fake News Detection

In the non-integrated phase of Fake News Detection, the articles in two different files are labelled as fake and real. These articles are processed using various techniques; removing, stopwords, unwanted characters, and symbols. The whole processed and cleaned dataset is used and passed to the SVM model to find the accuracy for the classification of articles in two main categories.

However, in the integrated part, the generated result of the Text Summarization part is saved in an output file and later labelled as fake or real. These summaries are passed into the second phase of the project which is Fake News Detection. The summarized articles are pre-processed using various techniques; removing, stopwords, unwanted characters, and symbols. The updated summaries are normalized and passed to SVM and CNN models for classification of fake and real News. The accuracy deduced from these models will decide which model is efficient for Fake News Detection.

5.2 Test case Design and description

As our project is research based, so it does not have traditional test cases. Therefore, no such conditions should be fulfilled in order to perform Abstractive Summarization and Fake News Detection. Thus, we have provided a sample test case of each methodology according to its evaluation results.

5.2.1 Text Summarization

5.2.1.1 Using LSTM Encoder Decoder with Pointer Generator Mechanism

5.2.1.1.1 Test Case No. 1

Original Text	michael jackson, the show stopping singer whose best selling albums including off the wall, thriller and bad and electrifying stage presence made him one of the most popular artists of all time, died thursday, has confirmed. he was 50. he collapsed at his residence in the holmby hills section of los angeles, california, about noon pacific time, suffering cardiac arrest, according to brother randy jackson. he died at ucla medical center. as news of his death spread, stunned fans began to react and remember one of the most remarkable careers in music.
Predicted Summary	to electrifying
Evaluation Results	**Rouge-1:** 0.3448 **Rouge-2:** 0.1428 **Rouge-L:** 0.3448

5.2.1.1.2 Test Case No. 2

Original Text	president barack obama appeared on nbc is meet the press on sunday , talking about the fiscal cliff negotiations and priorities for his administration in his second term . the president told host david gregory that he was optimistic something will be worked out to keep tax rates from rising on tuesday but … the question is how do we do that in a way that but the most pressing quandary is the fiscal cliff . it is going to be very hard for the economy to sustain its current growth trends if suddenly we have a huge bite taken of the average american is paycheck , he said .
Predicted Summary	to priorities

	priorities priorities priorities priorities priorities priorities priorities priorities priorities priorities priorities priorities priorities priorities priorities
Evaluation Results	**Rouge-1:** 0.2153 **Rouge-2:** 0.0634 **Rouge-L:** 0.2153

5.2.1.1.3 Test Case No. 3

Original Text	president robert mugabe is zanu pf party dismissed monday a confidential cable released by wikileaks that claims the zimbabwean leader has cancer . wikileaks claimed friday that reserve bank of zimbabwe governor gideon gono had told the former u.s. ambassador christopher dell during a private meeting in 2006 … appeared to be deteriorating mentally and losing his capacity to balance factional interests , dell wrote in his report after meeting gono who has repeatedly denied claims of having an affair with grace . she grace wanted him mugabe to step down . gono did not answer several calls made to him by .
Predicted Summary	to gideon
Evaluation Results	**Rouge-1:** 0.1454 **Rouge-2:** 0.0000 **Rouge-L:** 0.1454

5.2.1.1.4 Test Case No. 4

Original Text	three french journalists charged in an alleged plot to kidnap african children for adoption in europe arrived in paris on sunday , hours after french president nicolas sarkozy held emergency talks in chad . but 14 other people remained in custody in the african nation , some facing serious charges that could send them to jail … told le parisien on sunday that workers from zoe is ark had visited his village three times . they never said they would take away our children , he told the newspaper . e mail to a friend is nic robertson and al goodman contributed to this report .
Predicted Summary	to french
Evaluation Results	**Rouge-1:** 0.1034 **Rouge-2:** 0.0000 **Rouge-L:** 0.1034

5.2.1.1.5 Test Case No. 5

Original Text	the u.s. military held a day of reflection on friday for troops in japan after allegations that two u.s. service members committed sexual assaults on the southern island of okinawa . protestors in okinawa express anger at … have continued despite years of promises to prevent them . the u.s. military bases in okinawa and japan are not welcome , watanabe said . they do not protect the safety of the local community . it is more danger for the community . e mail to a friend is kyung lah contributed to this report .
Predicted Summary	to a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a a
Evaluation Results	**Rouge-1:** 0.001 **Rouge-2:** 0.0000 **Rouge-L:** 0.001

5.2.1.2 Using T5 - 3B Transformers

5.2.1.2.1 Test Case No. 1

Input Text	Barcelona's Argentina striker Lionel Messi will be out of action for six weeks after tearing a muscle in his left leg during Tuesday night's 1-0 Champions League victory over Celtic. Messi is helped off the pitch after injuring his left thigh during Tuesday's 1-0 victory over Celtic. The Catalan club confirmed on Wednesday that Messi will miss both legs of Barcelona's Champions League quarterfinal encounter. … Rijkaard also has other options to replace Messi on the right flank in the shape of Portuguese international Deco or teenage Mexican winger Giovanni Dos Santos.
Expected Summary	Barcelona striker Lionel Messi is ruled out for six weeks with a thigh injury. The Argentine sustained the injury in Tuesday night's 1-0 victory over Celtic. It is third time in the last three years that Messi has suffered the same injury.
Generated Summary	Barcelona striker Lionel Messi will be out of action for six weeks after tearing a muscle in his left leg. the 27-year-old suffered the injury during Tuesday's 1-0 Champions League victory over Celtic. it is the third time in the last three years that he has had the same injury.
Evaluation Results	**Rouge-1:** 0.7142 **Rouge-2:** 0.4583 **Rouge-L:** 0.6734

5.2.1.2.2 Test Case No. 2

Input Text	Two U.S. Air Force F-15s escorted two Russian Bear long-range bombers out of an air exclusion zone off the coast of Alaska,

	U.S. military officials said Wednesday. Two U.S. Air Force F-15s were dispatched to meet the Russian bombers. U.S. radar picked up the Russian turbo-prop Tupolev-95 planes about 500 miles off the Alaska coast. … A ministry official described the flights as standard operating procedure for air force training. Meanwhile, U.S. military officials say the incidents are not a concern. They say it's the Russian military flexing its ability and presence.
Expected Summary	U.S. radar picks up the Russian planes about 500 miles off the Alaska coast. The Russians entered an air exclusion zone. They are escorted out of the area without incident. Russian planes last came near the U.S. coastline in February.
Generated Summary	U.S. radar picked up the Russian planes about 500 miles off the Alaska coast. the bombers were escorted out of the area without incident, the officials said. four Russian aircraft flew near the aircraft carrier USS Nimitz in february.
Evaluation Results	**Rouge-1:** 0.6829 **Rouge-2:** 0.575 **Rouge-L:** 0.6829

5.2.1.2.3 Test Case No. 3

Input Text	Josephs and Marys in search of a room at the inn this Christmas are being made an offer they can't refuse. Mary and Joseph ride a donkey to Bethlehem in a performance of the Nativity story near Guildford, England. … I think people like the fact that it resonates with the Nativity story at a time when the actual meaning of Christmas often becomes forgotten in festive overkill," she said. Couples can register their names at a special e-mail address set up by Travelodge, which has hotels across the Britain, Ireland and Spain, Ahmed said.
Expected Summary	Couples who share names with the couple from the Nativity story get free room. Almost 30 Josephs and Marys have signed up for the free night's stay. Couples have to bring proof of identity. They also have to prove that they are in a long-term relationship.
Generated Summary	a British hotel chain is offering free accommodation to couples who share their first names with the couple from the Christian Nativity story. Almost 30 Josephs and Marys have already signed up for the free night's stay at the Travelodge. the offer is good at any one of the chain’s 322 hotels in the United Kingdom.
Evaluation Results	**Rouge-1:** 0.5660 **Rouge-2:** 0.3846 **Rouge-L:** 0.5094

5.2.1.2.4 Test Case No. 4

Input Text	Rock group R.E.M. debuted a song from its upcoming album Wednesday on CNN's "Anderson Cooper 360°" program. R.E.M. singer Michael Stipe says the band was honored to be involved with the "Planet in Peril" project. … which is scheduled to be released next year. The band also is releasing a live CD/DVD on Tuesday with 22-tracks recorded at a 2005 concert in Dublin, Ireland.
Expected Summary	R.E.M. song "Until the Day Is Done" debuts on CNN. Song also to be used in documentary "Planet in Peril" Song will be on R.E.M.'s upcoming album. Band releasing live CD/DVD next week.
Generated Summary	"Until the Day Is Done" premiered on CNN's "Anderson Cooper 360°" the song also will appear in "Planet in Peril," a four-hour CNN documentary. the documentary will air on October 23 and 24 at 9 p.m. ET.
Evaluation Results	**Rouge-1:** 0.4556 **Rouge-2:** 0.2077 **Rouge-L:** 0.4050

5.2.1.2.5 Test Case No. 5

Input Text	U.S. Secretary of Defense Robert Gates flew into Iraq on Monday to oversee a change of command of American forces. Robert Gates is greeted Monday at Baghdad … The Interior Ministry said at least 30 people were killed and 45 wounded; the U.S. said 31 were killed and 40 were wounded. CNN's Jomana Karadsheh and Mohammed Jamjoom contributed to this report.
Expected Summary	Defense Secretary Robert Gates says U.S. troops in midst of "mission transition". Gen. Ray Odierno taking over command in Iraq from Gen. David Petraeus. Odierno expected to set stage for eventual U.S. withdrawal.
Generated Summary	Gen. Ray Odierno will take over command of U.S. forces in Iraq on Tuesday. he will replace Gen David petraeus, who will become chief of u.s. central command. "I have never seen a working relationship like this," Gates said of the two men. three bombings in Baghdad and one in diyala province on the eve of gates' arrival.
Evaluation Results	**Rouge-1:** 0.3789 **Rouge-2:** 0.1935 **Rouge-L:** 0.2736

5.2.1.2.6 Test Case No. 6

Input Text	The Beijing Olympics has lost one of its major attractions after Maria Sharapova pulled out of the tennis tournament with a shoulder injury. Sharapova has treatment for a shoulder injury … Mary Pierce. Meanwhile, Vera Zvonareva will replace Sharapova in the Russian team for Beijing, spokesman Vladimir Kamelzon has confirmed.
Expected Summary	Maria Sharapova withdraws from the Bejing Olympics due to a shoulder injury. Russian star aggravated the injury in three-set win at Rogers Cup Wednesday. Sharapova now a serious doubt for the final grand slam at Flushing Meadows.
Generated Summary	Maria Sharapova has pulled out of the Beijing Olympics with a shoulder injury. the 21-year-old Russian world number three was playing in the WTA tournament in Montreal if she sustained the injury in that match. "The timing is so unfortunate and this makes me more sad than anything else," she said.
Evaluation Results	**Rouge-1:** 0.2857 **Rouge-2:** 0.1123 **Rouge-L:** 0.2637

5.2.1.2.7 Test Case No. 7

Input Text	They wore feathers. They wore fancy hats. And of course, they wore fur. Never mind the human -- the dog in haute couture was the fashionistas' focus during Pet Fashion Week. … Booths at the annual event features couture clothing, jewelry and other accessories for the well-dressed doggie -- all part of the $40 billion pet industry.
Expected Summary	Dogs ruled in New York during Pet Fashion Week. Dazzling couture designs trotted down the runway. Upscale pet accessories, apparel, and lifestyle items on display. Design awards encourage pushing the envelope in style.
Generated Summary	NEW YORK wore fur. Fashion Week New York. E-mail to a friend
Evaluation Results	**Rouge-1:** 0.1739 **Rouge-2:** 0.0909 **Rouge-L:** 0.1739

5.2.1.2.8 Test Case No. 8

Input Text	Some Christian congregations, particularly in lower income, urban areas, are turning to an unlikely source for help -- the Church of Scientology. Rev, Charles Kennedy uses Scientology founder L. Ron Hubbard's book during a Friday night sermon. Scientologists do not worship God, much less Jesus Christ. … "I think that they truly believe that this may help their communities, but in my opinion, they're naïve," Ross said. Scientologists, he added, "have their own agenda." The Church of Scientology would not grant CNN an interview, nor would its

	representatives answer questions about the Hubbard-based programs.
Expected Summary	Christian pastors borrow ideas from Scientology to preach temperate lifestyle. Critics say Scientology is a cult, always looking for recruits. Pastor in Houston, Texas, claims 70 percent success rate with addicts.
Generated Summary	"I'm a Pentecostal Scientologist, that's what I am," she said. "We're not going to go to church, but we'll be in church," Kennedy added. McLaughlin, meanwhile,
Evaluation Results	**Rouge-1:** 0.0983 **Rouge-2:** 0.0000 **Rouge-L:** 0.0655

5.3 Test Metrics

5.3.1 Abstractive Text Summarization

5.3.1.1 LSTM Encoder Decoder with Pointer Generator Mechanism

Metric	Results
Size of Test Data Set	10 k
Training Loss	6.2168
Validation Loss	6.2418
Number of Epochs	14
Evaluation Results	**ROUGE 1:** 0.171 **ROUGE 2:** 0.069 **ROUGE L:** 0.171

5.3.1.2 T5-3B Transformers

Metric	Results
Fine Tune Data Set	1%
Evaluation Results	**ROUGE 1:** 0.352 **ROUGE 2:** 0.137 **ROUGE L:** 0.241

5.3.2 Fake News Detection

5.3.2.1 Support Vector Mechanism

Metric	Results
Size of Total Data Set	6 k
Size of Train Data Set	3600
Size of Test Data Set	2400
Size of Validation Data Set	0.2 %
Value of C	0.2222
Model Kernel	Sigmoid
Vector N-gram Range	[(1,1) , (1,2)]

Evaluation Results	**Accuracy:** 0.75
True	**Precision:** 0.99 **Recall:** 0.24 **F1-Score:** 0.39
Fake	**Precision:** 0.73 **Recall:** 1.00 **F1-Score:** 0.84

5.3.2.2 Convolutional Neural Network

Metric	Results
Size of Total Data Set	73,205
Size of Train Data Set	51,244
Size of Test Data Set	21,961
Size of Validation Data Set	0.4 %
Learning Rate	0.8
Activation Function	Sigmoid
No. of epochs	10
Evaluation Results	**Accuracy:** 0.92
True	**Precision:** 0.94 **Recall:** 0.89 **F1-Score:** 0.91
Fake	**Precision:** 0.91 **Recall:** 0.95 **F1-Score:** 0.93

Chapter 6: Experimental Results and Discussion

We will be explaining the experimental setup of our model including System specifications, Turing Parameters e.g. epochs and optimizer. Along with experimental results, we will be explaining the evaluation metrics we are employing in our project.

6.1 Evaluation Metrics

Summarization has proved to be a tough problem because the system has to understand the context of the text. The general metrics we are using for the evaluation of text summarization model is ROUGE score while Accuracy is used to measure the effectiveness of Fake News Detection Model.

6.1.1 Accuracy

Accuracy is a metric used to evaluate the performance of a deep learning model. It evaluates the model as the ratio of correct predictions over total predictions. In other words, accuracy measures how often the model correctly predicts the correct output for a given input.

Mathematically, accuracy can be defined as:

$$\boldsymbol{Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}}$$

6.1.2 Precision

Precision is a statistical metric that quantifies the ratio of correctly predicted positive cases to all the cases that are predicted as positive. In other words, it evaluates the accuracy of positive predictions. Mathematically,

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

6.1.3 Recall

Recall is a statistical metric that measures the proportion of correctly predicted positive cases out of all the actual positive cases. In other words, it measures the ability of a model to identify all positive instances.

Mathematically, it can be defined as:

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

6.1.4 F1-Score

The F1 score combines both precision and recall to assess the overall effectiveness of a binary classification model. It is the harmonic mean of precision and recall, and provides a single score that reflects both metrics. Mathematically,

$$\boldsymbol{F1\ score\ = \frac{2\ *(precision\ *\ recall)}{precision\ +\ recall}}$$

6.1.5 ROUGE

ROUGE stands for Recall-Oriented Understudy for Gisting Evaluation. For the evaluation of the goodness of the induced summary, we use a common metric ROUGE in Text Summarization. It operates by comparing an automatically generated translation or summary with a collection of reference summaries. It acts by comparing the n-gram overlapping among the reference and generated summary. It is a zero-centric function.

Given an n-gram length n, the ROUGE-N metric between a single-referenced document ref and candidate document c is

$$\boldsymbol{ROUGE-N_{single}(c,ref)} = \frac{\sum_{r_i \in ref} \sum_{n-gram \in r_i} \boldsymbol{Count(n-gram, c)}}{\sum_{r_i \in ref} \boldsymbol{numNgrams(r_i)}}$$

where the elements *ri* are sentences in the reference document, *c* is the candidate document, *ref* is the reference document and *Count(n-grams, c)* is the number of times of n-grams in the specified reference sentence *ri*.

6.1.5.1 ROUGE-1

It is used for the overlapping of unigrams (for each word) between the system and the suggested summary.

6.1.5.2 ROUGE-2

ROUGE-2 is used for the bigram overlapping amongst the suggested and system summary.

6.1.5.3 ROUGE-L

ROUGE-L is concerned with the statistics centered on the longest common subsequence (LCS). It automatically selects the longest coinciding in sequence n-grams while it accounts for sentence-level structure correspondences. This metric is quite flexible but has a liability that all the n-grams must be successive [10].

The ROUGE-L metric between a candidate document c and a single reference document ref is given by F-score measure.

$$\boldsymbol{ROUGE-L_{single}(c,ref)} = \frac{\boldsymbol{(1+\beta^2)R_{lcs}(c,ref)P_{lcs}(c,ref)}}{\boldsymbol{R_{lcs}(c,ref)+\beta^2 P_{lcs}(c,ref)}}$$

6.2 Experimental Setup

We performed our experiments on the Google Collaboratory which offers 12GB GPU and 12GB CPU RAM. We could train our models for more than 1 hour. Which was the reason we had to lessen our dataset and also, trained our models to a limited number of epochs.

We have used Adam Optimizer from Keras as an optimizer in our code. It is a stochastic gradient descent approach that integrates adaptive evaluations of first and second order moments during the optimization process.

Moreover, the activation function used in our code is Hyperbolic Tangent. It is essential for our model to use a single-layer network with biased inputs. The output received is also weighted using a hyperbolic tangent (tanh) transfer function. Furthermore, a softmax activation function is used to standardized alignment scores after getting the weighted outputs.

6.3 Results

The results extracted from the model which contains multiple layers for generating summary are shown.

6.3.1 Text Summarization Model Results

This section contains experimental results of our text summarization model, Sequence-to-Sequence Encoder Decoder with Pointer Generator Mechanism and T5-3B Transformers.

Table 5: Text Summarization Model Results
This table shows the results of text summarization model which is Sequence-to-Sequence Encoder Decoder with Pointer Generator Mechanism and T5-3B Transformers

Models	ROUGE-1	ROUGE-2	ROUGE-L
Seq-to-seq + attention mechanism	0.160	0.065	0.158
Seq-to-seq + attention + pointer generator + coverage mechanism	0.216	0.081	0.213
T5-3B Transformers	0.352	0.137	0.241

6.3.1.1 Train Loss Vs. Epoch

Train loss measures how our model fits the datasets while epoch refers to the number of iterations dataset makes around the algorithm. In our case, we took 14 iterations. Train loss during epoch is showed in Figure 4.

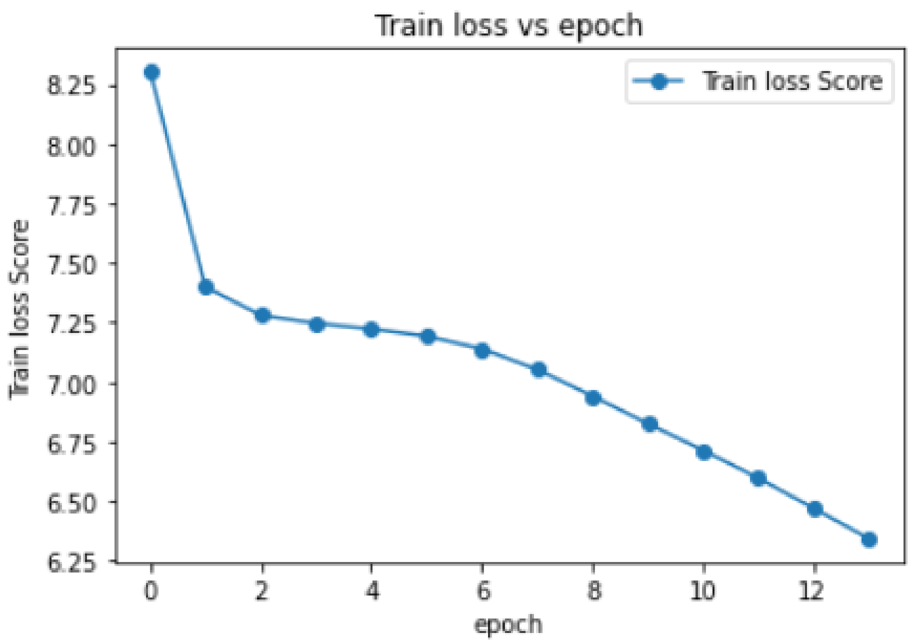

Figure 5: Train Loss Curve for Summarization
This graph shows Train Loss Curve Vs Epoch

6.3.1.2 Test Loss Vs. Epoch

Test loss refers to the loss over the testing data at the end off each epoch. It is considered as the lower, the better. Test loss during epoch is showed in figure 5.

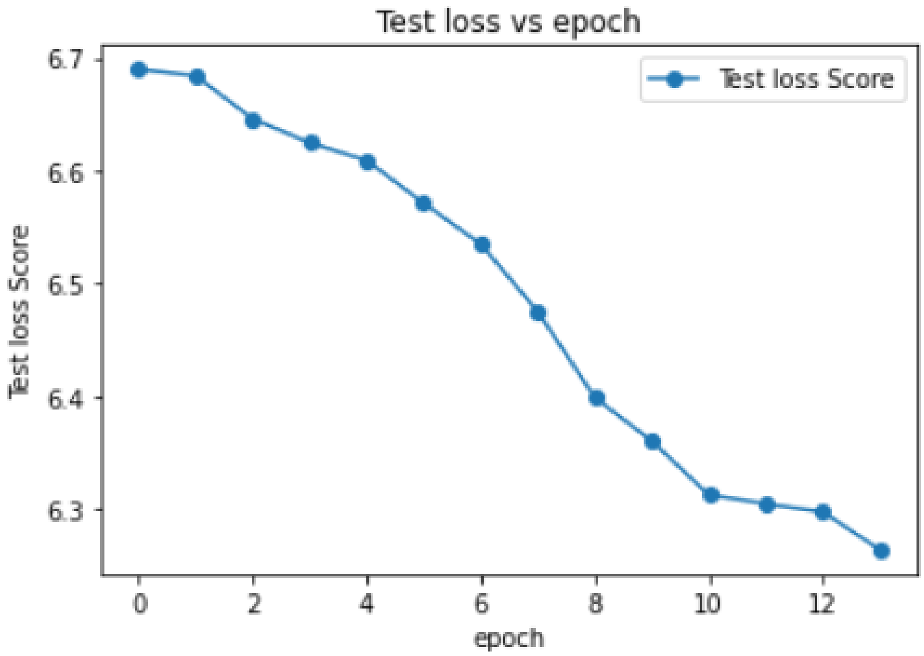

Figure 6: Test Loss Curve for Summarization
This graph shows Test Loss Curve Vs Epoch

6.3.2 Fake News Model Results

This section contains experimental results of Fake News Detection model, which involves Support Vector Machine (SVM) and Convolutional Neural Network (CNN).

Table 6: Fake News Detection Model Results
This table shows the results of fake news detection model which is Support Vector Machine (SVM) and Convolutional Neural Network (CNN)

Models	Labels	Precision	Recall	F1-Score	Accuracy
Support Vector Machine	**Fake**	0.73	1.00	0.84	75 %
	True	0.99	0.24	0.39	
Convolutional Neural Network	**Fake**	0.91	0.95	0.93	92 %
	True	0.94	0.89	0.91	

6.3.2.1 Support Vector Machine

The Support Vector Classifier (SVC) model was trained using the sigmoid activation function and a C value of 0.0222. The overall accuracy of the model on the test data was found to be 0.853, indicating that it correctly classified approximately 85.3% of the instances in the dataset.

The precision for the "fake" class was 0.82, indicating that when the model predicted an instance as "fake," it was correct around 82% of the time. The recall for the "fake" class was

1.00, suggesting that the model correctly identified all instances of the "fake" class. On the other hand, for the "true" class, the precision was 1.00, implying that when the model predicted an instance as "true," it was correct 100% of the time. However, the recall for the "true" class was 0.56, indicating that the model missed some instances of the "true" class.

Overall, the model achieved good performance with a high accuracy. However, it exhibited better performance for the "fake" class than the "true" class, as reflected in the precision and recall scores. Confusion matrix results of Fake News Detection model using Support Vector Machine (SVM) shown in figure 7.

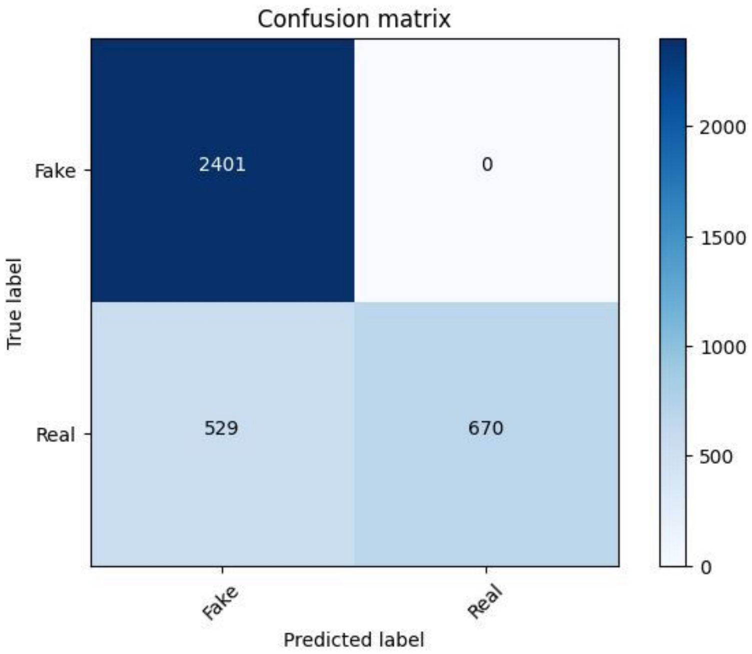

Figure 7: Confusion Matrix for SVM
This show confusion matrix of SVM without normalization

6.3.2.2 Convolutional Neural Network

The sequential model consists of an embedding layer followed by a 1-dimensional convolutional layer with 8 filters and a kernel size of 3. This is followed by a global max pooling layer to extract the most important features. The model then includes a dense layer with 64 units and ReLU activation function. To prevent overfitting, a dropout layer with a rate of 0.8 is applied. Finally, a dense layer with a single unit and sigmoid activation function is used for binary classification.

The model achieved an overall accuracy of 0.91 on the test data, indicating that it correctly classified around 91% of the instances. The precision for class 0 (label 0) was 0.91, implying that when the model predicted an instance as class 0, it was correct approximately 91% of the time. The recall for class 0 was 0.92, indicating that the model correctly identified 92% of the instances of class 0.

Similarly, for class 1 (label 1), the precision was 0.91, suggesting that when the model predicted an instance as class 1, it was correct approximately 91% of the time. The recall for class 1 was 0.90, indicating that the model correctly identified 90% of the instances of class 1.

Overall, the model demonstrated strong performance with high accuracy, precision, and recall scores for both classes, indicating its ability to effectively classify instances into their respective classes.

6.3.2.2.1 Loss Curve

The loss curve for Convolutional Neural Network is displayed in the Figure 7.

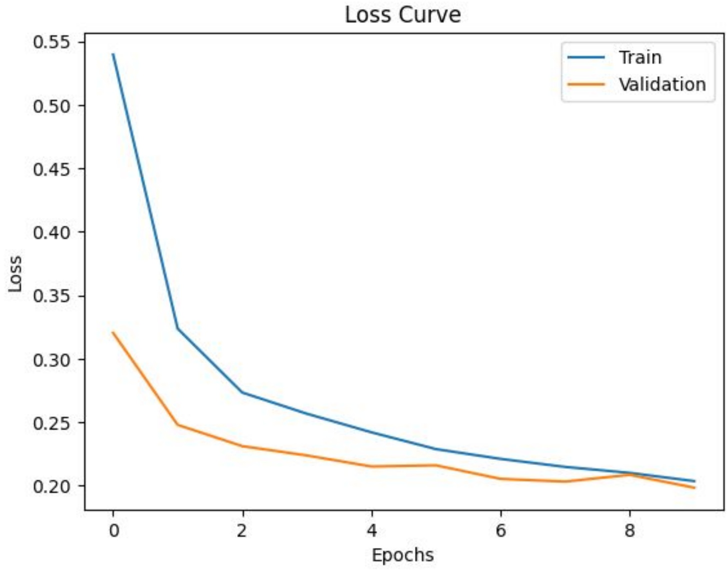

Figure 8: Loss curve for Fake News Detection
This figure shows the loss curve for Fake News Detection using Convolutional Neural Network (CNN)

6.3.2.2.2 Learning Curve

This figure shows learning curve for Fake News Detection using Convolution Neural Network (CNN).

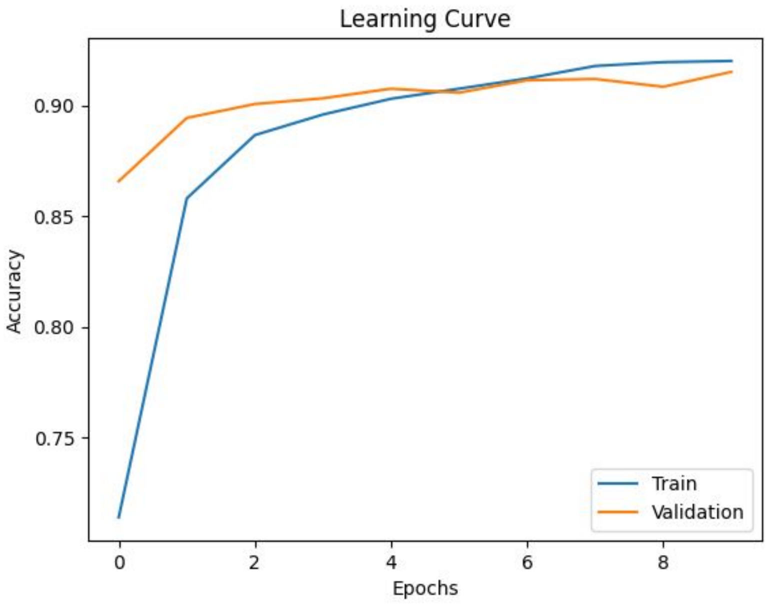

Figure 9: Learning Curve for Fake News Detection
This figure shows the learning curve for Fake News Detection using Convolutional Neural Network (CNN)

Chapter 7: Conclusion and Future Work

7.1 Conclusion

The work done so far has induced an output, however, there is still room for improvement. The first model which we opted for Abstractive Text Summarization consists of an encoder-decoder architecture that uses a fixed-length context vector to encode the input sequence. The encoder's output is used by an attention model to generate a context vector for each input time step. Precise tags are used to indicate when to start and stop producing new predictions during training. The measurements of how closely each encoded input complements the existing decoder output are computed by the alignment model. It uses a hyperbolic tangent function to weight the produced output. A softmax function is used to standardize the alignment scores, and a new attended context vector is achieved by multiplying each annotation with the annotation weights. The resulting attended context vector is the weighted mean of the scores and annotations and is used to decode the current output time step according to the encoder-decoder model.

The second model consists of Transformers. Transformers are a specific type of deep learning model that uses an attention mechanism to process the entire input sequence in parallel, enabling them to encapsulate dependencies among various parts of the sequence and produce more accurate outputs. T5 is a text-to-text Transfer Transformer Model and T5-base is a variation of it. T5-base is a widely used transformer-based linguistic model which employs a text-to-text technique and consists of an encoder-decoder structure. It is trained using a transformer-based architecture and can be fine-tuned on certain downstream tasks using supervised learning. However, its major drawback is that it splits text after getting the required number of tokens, which leads to the loss of a significant amount of data. To overcome this issue, the T5-3B transformer, an even larger version of the original T5 model with 3 billion parameters, has been introduced. This model has accomplished state-of-the-art results on a variety of NLP benchmarks and represents the cutting edge of NLP research.

Furthermore, we obtained a dataset from GitHub and utilized supervised machine learning algorithm, Support Vector Machine (SVM) and Convolutional Neural Network (CNN) to distinguish between authentic and fabricated news articles. For the derivation of feature vectors of text articles, we will be using Term Frequency-Inverse Document Frequency (TF-IDF) and Count-Vectorizer (CV).

7.2 Future Work

The high precision we have achieved so far in our text summarization task was made possible by utilizing an LSTM encoder-decoder model with attention and coverage techniques. This approach was effective in addressing issues with repetition and the use of uncommon words in abstractive text summaries. Although we attempted to improve the model performance by adding a pointer-generator model, the results were not up to our expectations. Therefore, we utilized a transformer model, which provided better results. In our fake news detection task, we employed various machine learning classifiers such as support vector machine (SVM) and convolutional neural network (CNN) as well as TF-IDF transformer and count vectorizer for feature extraction. The accuracy of our model was very good. As part of our future work, we will try to improve our results for convolutional neural network model and we will integrate both the models (Text Summarization and Fake News Detection). Once the integration is complete, we will evaluate the results to determine which models require further improvement. We will analyze the performance of the integrated system on the basis of accuracy and rogue score and identify any areas where the system could be further optimized.

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