Fake News Detection Using Deep Learning Model

Thesis Submitted In Partial Fulfilment of the Requirements for the Degree of

MASTER OF TECHNOLOGY

in

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Submitted by

Satyendra Yadav
(23/SWE/17)

"Under the Supervision of"
Dr. Rahul
(Assistant Professor, SE, DTU)

Department of Software Engineering
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-110042, India

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DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi – 110042

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Place: Delhi — Satyendra Yadav
Date: — (23/SWE/17)

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DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi – 110042

DECLARATION

I, Satyendra Yadav, Roll No's – 23/SWE/17 students of M.Tech (Software Engineering), hereby certify that the work which is being presented in the thesis entitled "**Fake News Detection Using Deep Learning Model**" in partial fulfilment of the requirements for the award of degree of Master of Technology, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from Jan 2025 to May 2025 under the supervision of Dr. Rahul.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

Satyendra Yadav

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

24.6.2025

Signature of External Examiner **Signature of Supervisor**

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DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
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CERTIFICATE

This is to confirm that Satyendra Yadav (23/SWE/17) completed the project "**Fake News Detection Using Deep Learning Model**" under my guidance in partial fulfilment of the MASTER OF TECHNOLOGY degree in Software Engineering at DELHI TECHNOLOGICAL UNIVERSITY, NEW DELHI. To the best of my knowledge this work has not been submitted in part or full for any other Degree to this University or elsewhere.

Dr. Rahul

Assistant Professor

Department of Software Engineering

ABSTRACT

In essence, fake news detection uses machine learning, deep learning, and natural language processing algorithms to recognize and categorize news material as either true or fraudulent. The phrase "fake news" refers to purposefully false or misleading content that is disseminated through social media, certain websites, or messaging apps under the guise of news channels in an effort to sway public opinion, cause confusion, or make money. Examining the textual, linguistic, and contextual elements of news reports and social media articles to ascertain their veracity and authenticity is the primary objective of the fake news detection method.

This thesis suggests a deep learning model for efficient fake news detection that combines a gated recurrent unit, convolutional neural networks, and attention mechanisms.

The suggested CNN and GRU and Attention model combines the advantages of each element to overcome these drawbacks CNN effectively simulates the sequential nature of text, GRU identifies important phrases and local patterns, and the Attention mechanism draws attention to the most instructive portions of the input. This architecture improves classification's interpretability and accuracy. Experimental results using benchmark false news datasets demonstrate that the proposed model outperforms previous approaches in terms of precision, recall, and F1-score. This gives it a scalable and dependable way to identify bogus news in real time.

Demonstrates the efficacy of CNN-GRU-attention model in identifying fake news, providing a robust and comprehensible way to counteract the spread of false information. The creation of even more accurate and dependable systems for identifying fake news has advanced significantly thanks to the synergistic integration of deep learning techniques, supporting ongoing efforts to ensure the accuracy of data transmitted online.

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CNN: Convolution Neural Network

LSTM: Long Short Term Memory

GRU : Gated Recurrent Unit

AT : Attention Mechanism

DL: Deep Learning

ML: Machine Learning

PCA: Principal Component Analysis

Bi-LSTM : Bidirectional Long Short-Term Memory

BERT: Bidirectional Encoder Representations from Transformers

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW:

The growing incidence in fake news on online platforms threatens to seriously undermine public trust, democratic processes, and social well-being. Automatic detection of fake news is now a pressing research problem in natural language processing and machine learning.
The dissemination of false information on the internet has become one of the largest problems in the current information age. Spreading false information at high velocity not only endangers public trust but also impacts decision-making in various domains. As a result, efforts to create effective methods for detecting false news have been growing. When it comes to managing intricate text structures and contextual relationships, keyword matching, rule-based, and machine learning approaches have limitations. This thesis suggests a hybrid deep learning technique that combines CNN, GRU, and an attention mechanism in an effort to overcome the limitations and increase the precision and effectiveness of fake news identification. The deep learning model presented in this thesis improves the precision and dependability of fake news identification. LSTM, Bi-LSTM and CNN models have been used before in this field, but they are generally not effective at handling both local and distant text connections and the importance of various words. The model handles these difficulties by utilizing CNN for feature extraction in each area, GRU for handling order and Attention to focus on the important pieces of the text. Training on typical benchmark datasets, the model beats other models like traditional and deep learning ones. As a result of this work, a simple and effective method is now available for curbing misinformation and it can be put to use in social media, news verification and moderation.

1.2 Motivation

The combination of CNN, GRU and attention mechanism results f rom each one having special qualities helpful for sequential data processing. Thanks to their structure, CNNs can learn about parts of the image and how they relate which leads the model to produce important features. As a kind of RNN, GRUs may use significantly more information with less compute than LSTMs and can describe how information changes over time. With the help of this attention mechanism, a model may better focus on the important elements of the input sequence, producing activities that are easier to comprehend and more effective-especially when the sequence is lengthy or noisy using these two models together allows for more accurate, general and robust results on a wide range of sequential tasks. Model uses to enhance the accuracy of model

1.3 Objectives.

A major objective in detecting fake news is to develop a precise and reliable method for distinguishing real news from falsified content. Increased usage of social media and online news sources has led to the spread of fake news, which spreads swiftly and has a big influence on people's opinions and political outcomes. By creating a model that can decipher the language and context of news articles, this study seeks to solve the rising problem posed by fake news. The large number and tempo of content being generated every day makes it difficult for current manual fact-checking techniques to keep up. For the semi-automated identification of false news, machine learning and deep learning techniques such as CNN, LSTM, and Bi-LSTM are frequently employed.

The complex patterns of meaning, structure, and context included in news articles are too complex for these models to manage. The majority of current methods are only able to extract local patterns or search for sequential information; they are unable to identify significant pieces and appropriately highlight them in the text. This problem can be solved by developing a model that can detect local features, analyze how these features interact with one another and signal importance within the news content. We integrate CNN, GRU and Attention mechanisms to create a hybrid model that improves the accuracy, robustness and interpretability of fake news detection systems.

The specific objectives include:

1. The goal of this step is to clean and read in the text news data so that it can be used by deep neural networks.

2. To use each component's strengths in identifying and comprehending textual structures, we use a CNN, GRU, and Attention model in combination.The model is then assessed using F-1 score, recall, accuracy, and precision using standard datasets.

3. This analysis focuses on comparing it with LSTM, Bi-LSTM and baseline CNN and evaluating its ability to achieve better performance and generalization than these other models.

4. The aim is to enable the creation of automated tools that help social media platforms, news aggregators and users identify and prevent the dissemination of false information.

1.4 Background:

Digital media and social media have undergone a tremendous explosion in popularity over the past several years, transforming the ways we produce, share and consume information. However, the dissemination of fake news-erroneous or deceptive information presented as news reports-has been greatly accelerated by these new platforms. Fake news has the power to greatly sway public opinion, deceive voters in crucial elections, aid in the dissemination of misleading information in times of emergency, and spark unrest. Current human fact-checking techniques are unable to keep up with the volume and velocity of false information propagated online. High-tech AI systems have therefore been developed to swiftly and accurately detect bogus news. Rules and statistics served as the foundation for early attempts, but as ML and NLP techniques have advanced, more complex models have lately been put out. The developed models aim to detect false information by using methods that analyze language structure, evaluate source reliability and interpret the surrounding context. CNN, RNN, LSTM, and attention models are examples of DL advancements that have significantly enhanced the abilities required to analyze text and identify misleading material. Addressing the detrimental effects of false information has grown in importance, and this is the exact intersection of data science, computer science, and social responsibility.

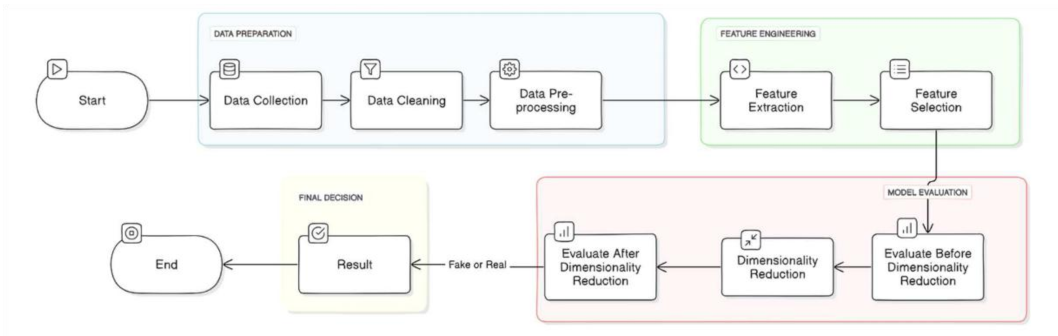

Fig 1.1: Process of fake news detection

A number of crucial phases of data preparation and analysis must be completed in order to assess the veracity of news. Initial processing entails clearing the data of punctuation, noise, and stopwords. Subsequently, the text data is segmented into individual words and padded to an identical length for all samples. Each word is then transformed into a series of vectors representing its semantic meaning. The deep model takes the preprocessed data as input and uses features extracted from the text as well as attention mechanisms to understand and identify the most relevant parts. The trained model is evaluated for its execution using accuracy, precision, true positive rate and F1-score to ensure optimal detection of fake news reports.

CHAPTER 2

LITERATURE SURVAY

This chapter discusses how ML and DL techniques are used in a large portion of the work done in the subject of false news identification. Multivariate feature selection combined with hybrid deep learning models is one way researchers integrate these methods to improve the precision and dependability of fake news detection systems. Finding the key characteristics that distinguish fake news from actual news can be accomplished with the use of chi-square, information gain, and correlation-based feature selection Sanida et al., 2024[1]. These methods have crucial benefits for reducing the amount of data needed to be processed, increasing the speed of models and improving their accuracy. A combination of network structures like CNNs, RNNs and Transformers is applied to network data to obtain contextual and linguistic representations of news articles Benaouda et al., 2024[2].

The introductions of deep learning models have enabled experts to identify fake news much more accurately than they were able to before. How accurate these models are largely depends on their ability to identify meaningful trends and features within large and intricate data. The performance of DL methods in identifying fake news improves significantly when different models are combined.. Ensembles of CNNs and LSTM have consistently achieved remarkable results in classification tasks related to fake news detection. CNNs excel in detecting specific phrases and textual cues that might signal deception, whereas LSTMs are particularly effective at taking into account the ordering of words and sentences in a piece of news to identify inconsistencies or logical incongruities. Word embeddings such as Fast Text or GloVe, introduce an important innovation in this approach. Alnabhan & Branco, 2024[3]. This methods represent words as numerical vectors, encoding those meaning and usage patterns in terms of how words relate to each other in different contexts. Word embeddings organize words in a common multidimensional space so that models can identify subtle differences and connections across word groups which plays a crucial part in detecting the language tricks used by fake news creators. The latest Transformer-style architectures such as BERT, XLNet and RoBERT a have demonstrated leading achievements in numerous natural language processing problems, including deception detection. Attention mechanisms underpin these architectures, enabling them to focus on specific text elements when formulating decisions. It makes a big difference in addressing shifts in language, convoluted sentence structures and the subtleties of meaning which are crucial for greater accuracy in identifying fake news. Transformer models may be able to effectively distinguish between substantive pieces of information and claims made later on in a news report, based on their understanding of interdependent relationships across long segments. This enriched comprehension enables them to outperform many earlier strategies and sophisticated neural networks built for tackling this delicate task. The majority of false news detection methods heavily rely on word embeddings Bhatia et al., 2023[4]. ML models can process and evaluate text data thanks to FastText and GloVe. They are designed to forecast using numerical data. . Word embeddings are more than just numbers assigned to each word. they represent how words are related to each other in meaning. Previous methods treat words as separate symbols rather than taking into consideration their meaning and surrounding words [5]. Word embeddings map words into a vector space in which similar meaning words are placed close to each other.

As a result, the model can determine that "true" is more similar to "authentic" than to false. Also Having this capacity is more important in fake news because understanding subtle language variations and identifying when words are being used deceptively helps improve the accuracy of differentiating real and fake news [6]. However, the complexity of recent deep learning approaches has spread excitement about the field in Explainable AI. XAI methods reveal how and why a model identifies certain news articles as authentic or fabricated. Techniques like LIME and LDA analyze the reasons behind a model's decision to classify an article as real or fraudulent Sharma et al., 2021 [8].

2.1 Related Work:

Various researchers have attempted to identify bogus news using various deep and machine learning techniques. Originally, manually created characteristics like word frequency and metadata were utilized with several classic models, such as SVM, Naive Bayes, and logistic regression. In order to automatically learn textual patterns and contextual features, deep learning models such as CNN, LSTM, and Bi-LSTM were later proposed. Whereas LSTM and Bi-LSTM handled sequential dependencies, CNN was able to extract local features. These models were integrated in later research to achieve better results. However, our suggested CNN-GRU-Attention model uses attention processes to improve accuracy and interpretability, but the majority of them were unable to highlight salient words.

2.2.1 Traditional Machine Learning Approaches:

The majority of early techniques for detecting false news relied on traditional ML models that process text input using specially designed features. Techniques like SVM, Logistic Regression, DT, and Naive Bayes have all been thoroughly studied and applied. To distinguish fake news from authentic information, conventional models have historically used hand-designed features such as sentiment scores, n-grams, bagof-words features, and TF-IDF vectors. The rich linguistic patterns and contextual dependencies of human language were not captured by these techniques, despite the fact that they provided a baseline and demonstrated the feasibility of automatic detection. For example, these models only process individual words and are unable to comprehend semantics or order beyond basic co-occurrence data. In addition, conventional models are susceptible to imbalanced datasets and the evolving nature of language, which can compromise their generalizability and accuracy over time. In spite of these constraints, conventional machine learning methods are still in high demand because they are simple, interpretable, and effective in resource-limited settings.

There are some advantage of traditional approaches.

- Simplicity and Interpretability
- Lower Computational Requirements
- Effective on Small to Medium Datasets

There are some disadvantage :

- Limited Contextual Understanding
- Manual Feature Engineering Dependency
- Difficulty Handling High-Dimensional Data
- Poor Handling of Sequential and Long-Range Dependencies:
- Limited Adaptability to Language Evolution

2.2.2 Hybrid And Ensemble Learning

Hybrid approaches are a promising direction in identifying fake news by combining the strengths ML and DL approach. Hybrid approaches leverage the interpretability and power of conventional feature-based models and the powerful feature extraction capability of neural networks. For example, some studies have combined TF-IDF vectors or hand-crafted linguistic features with CNN or LSTM models in order to improve input representation and classification accuracy. Other hybrid approaches utilize ensemble techniques, where multiple models such as CNN, LSTM, and conventional classifiers (e.g., SVM or AdaBoost) are trained separately, and their outputs are aggregated with voting or stacking strategies in order to reduce bias and variance. Examples of some of the most effective work include models such as PCA-AdaBoost, which uses dimensionality reduction to handle high-dimensional data, and K-means clustering with SVM classifiers for improved feature discrimination. Hybrid architectures are anticipated to perform better than single models by discovering multi-faceted properties of the data, such as local patterns, long-range dependencies, and global feature distributions. Although effective, optimal hybrid systems are a sensitive design due to careful tuning to balance model complexity and computational costs, and the danger of overfitting with small datasets.

There some advantage of hybrid deep learning model:

- Combines Strengths of Multiple Models:
- Improved Accuracy and Robustness
- Better Generalization on Unseen Data
- Reduced Model Bias and Variance
- Adaptability to Complex Patterns
- Support for Imbalanced Dataset

2.2.3 Deep Learning Approach:

As Deep learning developed, researchers began to investigate neural network architectures because of the strength to learn abstract and hierarchical representations from raw text automatically without feature engineering. Convolutional Neural Networks have been used to learn local text patterns and phrases frequently found in fabricated stories, with success in identifying stylistic patterns and nuance. Alternatively, RNN, specifically LSTM and BiLSTM networks, have featured prominently in modeling sequential data by tracing the history of words or phrases, thus comprehending context and sentence dependencies. Such models have excelled in spotting fake news by learning syntactic and semantic features. Further, the utilization of attention mechanisms allows models to selectively pay attention to the most relevant parts of the text, thereby improving interpretability and accuracy. However, deep learning models typically have big annotated datasets to learn on, as well as significant amounts of computational resources, which can be a barrier in real-time or low-resource environments. Further, although powerful, such models can be less interpretable compared to traditional machine learning methods.

Table 2.1: Models and Findings in Fake News Detection

Author	Year	Methodology	Findings/Gap
Jayakody& Halgamuge	2022	Fake news detection using federated learning and a decentralized deep learning model.	Enhances fake news detection by using a decentralized deep learning model with federated learning.

Ivancová et al.	2021	Deep learning techniques for Slovak language fake news detection.	Focuses on the detection of fake news in the Slovak language using deep learning models
Keya et al.	2021	DL-based fake news identification.	Utilizes deep learning techniques for fake news detection.
Polat & Cankurt	2023	Bi-LSTM with GloVe embedding	Classifies news datasets using a Bi-LSTM deep learning model.
Safdar& Wasim	2024	BERT and Bi-GRU	Find a research gap in utilizing user comments on platforms like Facebook and Instagram.
Bhatia& Manaskase-msak	2023	DNN; feature extraction (tweet content, published time, social graph)	find fake news sources (fake users) on Twitter.
Mohanta, Om & Swain	2024	Passive Aggressive Classifier (PAC) & Neural Network	Detect fake news using Neural Network

CHAPTER 3

METHODOLOGY

Fake news, reports, or rumors are fabricated with the intention of confuse and mislead and obscure people's views on certain societal issues. In the past, internet users were being impacted by the problem of bogus news spreading quickly. As a result, people started paying closer attention to this particular problem and taking it seriously. Utilizing current data through processes, methods, or models designed to differentiate between authentic and fake news or users is the goal of this key competition in the field of fake news detection and origin.

DL is a branch of machine learning that focuses on artificial neural networks and methods inspired by the structure and operation of the human brain. Without the need for manual feature extraction, it is designed to automatically discover patterns and representations in big datasets, especially unstructured data like text, images, and sound. Because deep learning has multiple layers of interconnected nodes (neurons), it is called "deep." Every layer gains the ability to transform the incoming data into representations that are more abstract and significant. In image recognition, for example, deeper layers may recognize complicated forms or objects, whereas earlier layers may recognize edges. NLP DL models are able to understand the context, syntax, and sentiment of a sentence. DL has enabled unprecedented breakthroughs in NLP, machine translation, image classification, speech recognition, and self-driving cars. Among the most popular deep learning models are CNN for visual tasks, RNN and GRU, LSTMs for sequential data, such text, and Transformers for more difficult NLP tasks. Machine learning (ML) is crucial for automatically identifying fake news since it enables algorithms to identify patterns in data and produce intelligent predictions.ML provides scalable and effective methods of detecting and eliminating fraudulent content in real-time, as the proliferation of false information on social media and online platforms becomes a serious problem in society.

3.1 Convolution Neural Network:

CNN are a subclass of DL algorithms designed especially to comprehend grid-structured input, such text or images. Although CNNs were initially developed for image recognition, they have also demonstrated remarkable proficiency in challenges involving natural language processing. This is particularly true for tasks like sentiment analysis, text classification, and fake news detection.

The fundamental concept of CNNs is that convolutional layers enable them to automatically learn the spatial hierarchies of features. In order to create feature maps, convolutional layers compute a number of filters (also known as kernels) and slide them across the input data. The filters are trained to identify particular patterns, such as edges in pictures or word co-occurrences (n-grams) in textBy doing so, CNNs are able to automatically identify local features that are crucial to identifying the meaning of the input. In sentence processing, a sentence is typically presented in the way of a matrix in which every row is the word embedding of a word in the sentence. The CNN applies 1D convolutions to this matrix to identify important local structures, such as important phrases or word co-occurrences, regardless of their exact positions in the sequence. This is then coming next a pooling layer that down samples the feature map and helps to retain the most important information, thus the model is computationally more efficient and less prone to overfit.

The typical layers in a Convolution Neural Network :

- Input Layer
- Convolution layer
- Max Pooling Layer
- Dense Layer
- Output Layer

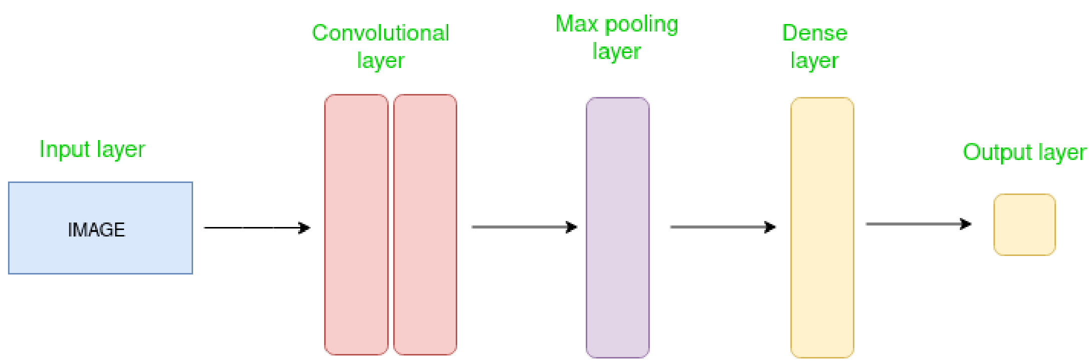

Figure 3.1: Convolution Neural Network

CNNs are efficient in that they are able to process big input data, learn position-invariant features, and have fewer parameters compared to fully connected networks. For fake news detection, CNNs are not able to identify discriminative patterns of text or linguistic features that are typically embedded in false or misleading content. However, while CNNs are excellent for identifying local patterns, they lack the ability to learn long-range dependencies in sequences and thus are typically employed alongside recurrent layers like GRU or LSTM in hybrid models

3.2 GRU: Gated Recurrent Unit

A RNN structure called a GRU is better adapted to handle sequential input and gets around some of the drawbacks of conventional RNNs. Understanding word sequence and context is crucial for handling natural language processing issues like detecting bogus news. By storing memory in between time steps and making decisions about what to remember or forget from prior knowledge, GRUs make it possible to comprehend such linkages.

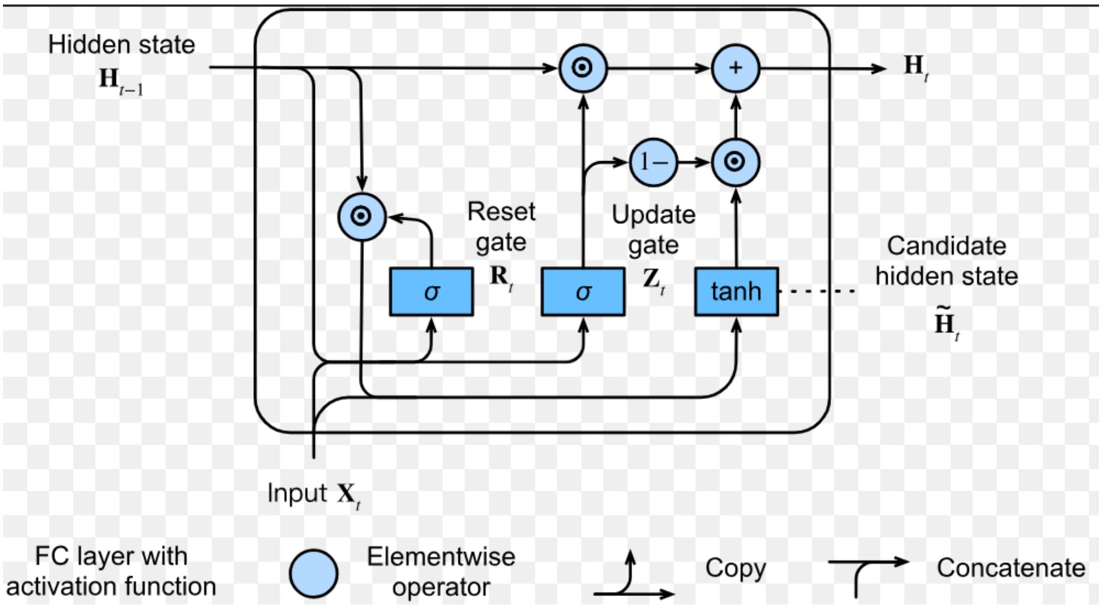

Figure 3.2: Gated Recurrent Unit

Classic RNNs are plagued by the vanishing gradient problem, which prevents learning very longstanding dependencies in sequences. GRUs, similar to LSTM networks, were created to address this challenge. GRUs are computationally less intensive than LSTMs since they have fewer gates and parameters, hence faster to train and simpler to implement with similar performance.

A Gated Recurrent Unit consists of two main gates:

1.Update Gate:-Calculate the proportion of previous data that has to be transmitted to the future. It supports the model's decision to accept or reject historical memory.

2. Reset Gate:- Controls the amount of past data to forget. It is useful when the model needs to forget its memory in order to learn new patterns.

These gates work together to allow GRUs to address dependencies in the input sequence adaptively, short or long. GRUs are particularly helpful in learning a sentence or document's information flow and how the meaning of a word or a phrase evolves dynamically with position and context in the detection of fake news.

3.3 Attention Mechanism:

Particularly in NLP, the AT is a useful component of contemporary deep learning architectures. It was developed to overcome the limitations of common sequence architectures, such as RNNs, GRUs, and LSTMs, in handling and utilizing data from lengthy input sequences. The general idea behind attention is to not consider all words or tokens equally, but to let the model pick out the most significant portions of the input when producing a prediction.

One word of input is processed at a time by typical sequence models, which aim to capture everything in the preceding concealed state.With longer input, though, important information is watered down or lost. Attention fixes this by putting weights on different parts of the many input sequence based on how salient they are for the current prediction task. These weights determine how much "attention" the model needs to pay to each token when generating the output.

3.4 Log Loss :

Log Loss, or Binary Cross-Entropy, is a estimate in how close a model's probabilities are to the true labels. It punishes higher-confidence incorrect predictions more than lower-confidence incorrect predictions. The measure is applied in probabilistic classifiers. Log loss reflects how confident and precise a model is at predicting the truth.

$$Log\,Loss = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1-y_i)\log(1-p_i)]$$

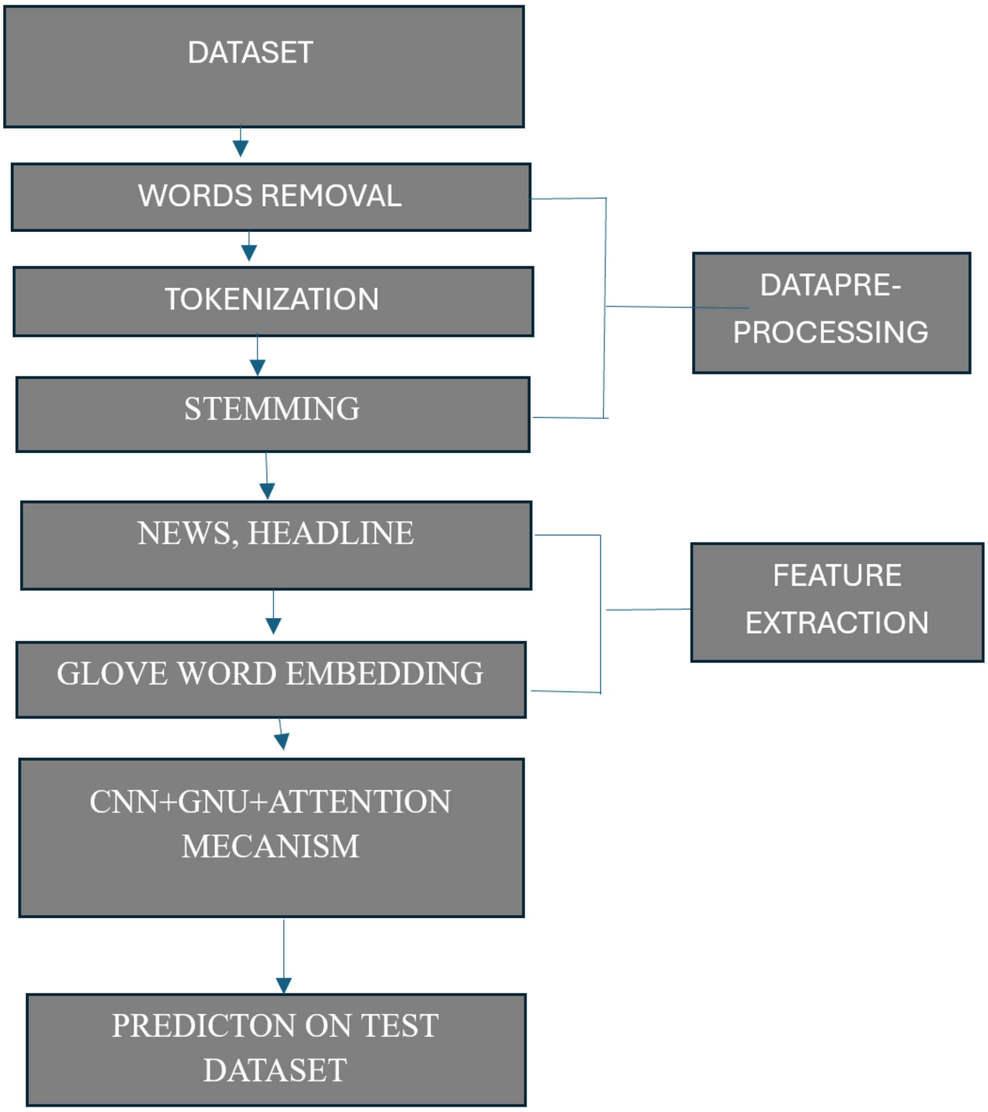

Fig 3.3: Architecture of Proposed System.

3.5 Proposed Model:

The proposed model by integrating CNN, GRU and attention mechanisms utilizes both short-term phrase models and long-term sentence contexts to effectively detect fake news. The CNN layer captures both semantic meaning and short-term patterns in the news text early on, allowing it to detect the deceiving linguistic signals. After initialization, these features are passed on to the GRU layer that captures long-term perspectives and analyzes relationships across different parts of the news text. An attention mechanism is used to help the model give more attention to the essential sections of the news text. A weighting system is applies to words and phrases to emphasize real information and suppress un important details. The robust design of the hybrid architecture combines CNN capabilities for extracting features, the sequential processing power of GRU and attention for improved interpretability and performance in detecting fake news**.**

3.5.1 Data Preprossing:

An essential step in every data analysis or ML endeavor is data preprocessing. It prepares and cleans raw data so that algorithms may process it efficiently and rapidly.. Data preprocessing usually starts with missing values handled either by excluding incomplete records or imputing them with suitable values such as mean, median, or mode. Data may then be normalized or standardized to scale all features to the same scale, particularly when algorithms are sensitive to feature magnitudes. Categorical data is typically encoded by methods such as one-hot encoding or label encoding. Irrelevant or redundant features may also be excluded to decrease dimensionality and maximize model performance. Outliers are also identified and addressed to avoid biasing results. Data preprocessing usually improves data quality and ensures the model trained on top of it acts consistently and accurately.

3.5.2 ISOT DATASET

'ISOT' in ISOT dataset stands for "Information Security and Object Technology". The dataset contains more than 44,000 new articles entries, collected from 2016 to 2017. The data is a culmination of all the news that are flagged by Politifact.com as unreliable and are published by legitimate news sites.Each entry in the dataset has 4 key attributes: date, title, article_test, and label. ISOT lab has already cleaned and processed all the data, without removing mistakes that were already present in the original article [9]. The breakdown of the ISOT dataset can be given as follows:

Table 3.1 Data Distribution of News

News	Size (Number of articles)	*Subjects*	
Real-News	21417	**Type**	**Articles size**
		World-News	*10145*
		Politics-News	*11272*
Fake-News	23481	**Type**	**Articles size**
		Government-News	*1570*
		Middle-east	*778*
		US News	*783*
		left-news	*4459*
		politics	*6841*
		News	*9050*

3.5.3Embedding Layer:

The Embedding layer is a foundational layer of the deep learning model that embeds discrete input words into dense vector representations. The embedding is crucial in natural processing tasks like identifying fake news because it allows the model to learn semantic word relationships in a continuous vector space. In our model, a word is embedded as a 100-dimensional vector, enabling textual data to be represented in a numerical form that can be processed efficiently by DL architectures. The model may learn more complex patterns in the input data thanks to the embeddings, which capture word meaning in context and word syntactic patterns. All input sequences with lengths less than the specified maximum token count are padded with zeros to ensure uniform input dimensions for each input sequence. This is required for batch processing as well as to provide model stability during training following the embedding layer, we have introduced a Dropout layer for regularization to prevent overfitting. We use a specific dropout of 0.2, meaning that 20% of the neurons in the layer are randomly dropped in each of the training iterations. By forcing the network to acquire more stable representations, random neuron dropping aids in generalization and keeps the model

from becoming overly reliant on any one attribute. Therefore, by minimizing variance and overfitting, the dropout layer plays a crucial role in the model's ability to generalize to new data.
In combination with the dropout layer, the embedding layer forms the core element of the model's input pipeline that converts raw text data into dense-feature information vectors and is also robust under regularization.

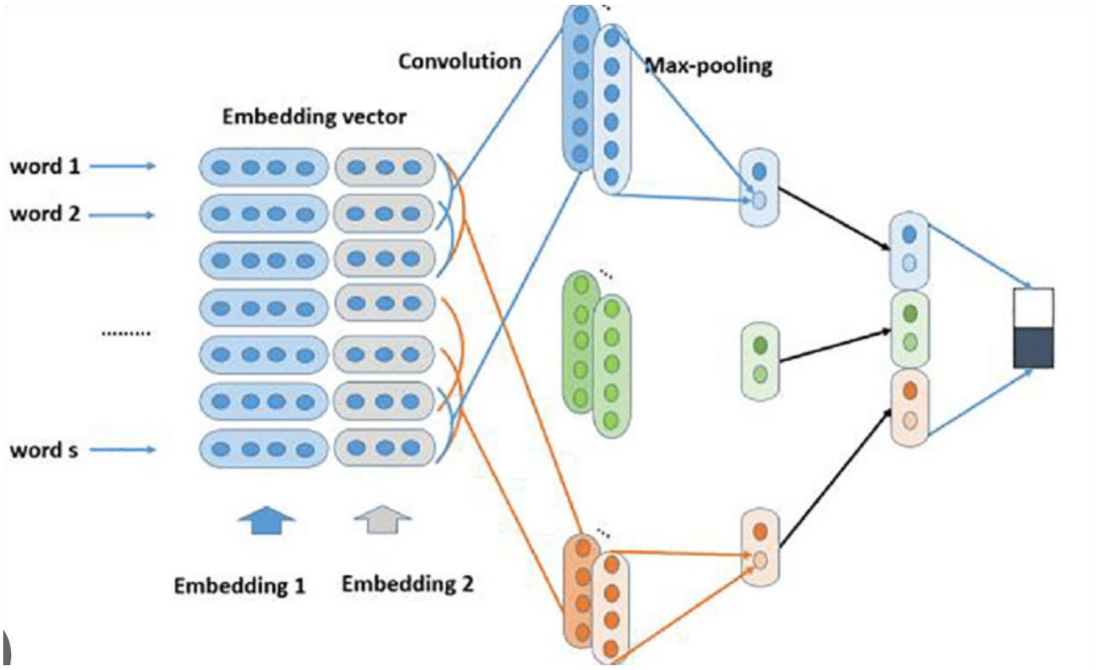

Fig 3.4: Embedding Layer

3.5.4 Convolution and Max-Pooling Layer:

In our model, we employ a simple but effective Convolutional Neural Network (CNN) architecture with two convolutional blocks. Each block consists of a also 1-dimensional in the max-pooling layer or the 1-dimensional convolutional layer (Conv1D) and which collectively are designed to extract and summarize the most significant features from the input text data. These convolutional blocks play a critical role in identifying local patterns, e.g., particular word combinations, n-grams, or phrase structures that are generally symptomatic of fake or real news content. We use 32 filters of size 5 in the first convolutional layer. They scan the input word embeddings and find a high-level pattern in brief text passages. The model can learn a wide variety of information from different perspectives thanks to the presence of several filters. In order to enable the network to identify more abstract, subtle elements at a deeper level of the model, we configured the second convolutional layer with 64

filters and a size 3 kernel. The primary benefit of CNNs is their ability to extract features from several layers.
In order to give the model non-linearity and enable it to learn more complex features, We apply the ReLU activation function to the output of every convolutional neuron. After ReLU sets all negative values to zero, positive values stay the same. By doing this, vanishing gradient issues are avoided, and the model learns more quickly. By promoting sparsity, it also makes it possible for the learnt features to be clear and sharp.

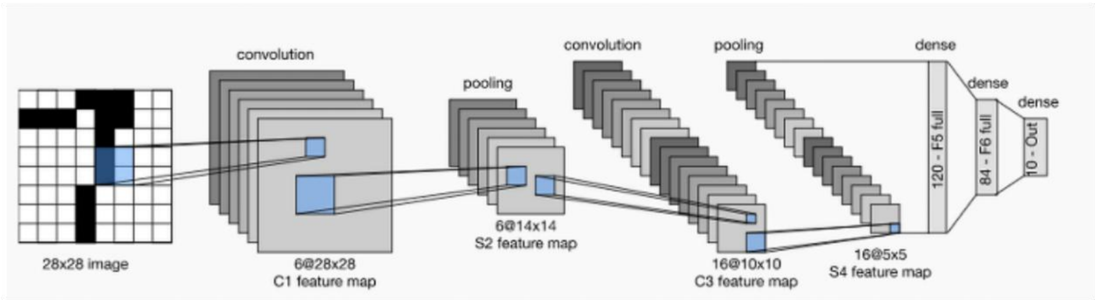

Figure 3.5: Convolution and Max-pooling

Following the ReLU and convolutional layer, we apply a 1-dimensional max-pooling layer 1-dimensional with pool size 2. Max-pooling decreases the dimension of the features map by taking the maximum value along each sub-region specified by the pool size. This not only decreases the computational cost but also preserves and the very important for features extracted by the filters. Max-pooling also provides translation invariance, i.e., the model becomes less dependent on the position of the features in the input sequence-a useful property if the text is of variable length.
The convolution and max-pooling layers combined enhance the ability of the model to learn discriminative text features automatically, reduce overfitting, and improve generalization to identify fake news.

3.5.5 GRU Layer

A GRU layer follows the convolution blocks. We used GRU because it helped us with our gradient fading and explosion gradient problems. It can also handle long sequential text data because to its recurring architecture. Because GRU requires less tensor operations than LSTM, it is simpler to train. We have trained our proposed model over 100 epochs. At the GRU layer, there is also 20% dropout and 20% recurrent dropout. We have kept the default values for more accuracy.

Layer (type)	Output Shape	Param #	Connected to
input_layer_2 (InputLayer)	(None, 200)	0	-
embedding_2 (Embedding)	(None, 200, 100)	1,000,100	input_layer_2[0][0]
conv1d_6 (Conv1D)	(None, 200, 128)	38,528	embedding_2[0][0]
conv1d_7 (Conv1D)	(None, 200, 128)	51,328	embedding_2[0][0]
conv1d_8 (Conv1D)	(None, 200, 128)	64,128	embedding_2[0][0]
max_pooling1d_6 (MaxPooling1D)	(None, 50, 128)	0	conv1d_6[0][0]
max_pooling1d_7 (MaxPooling1D)	(None, 50, 128)	0	conv1d_7[0][0]
max_pooling1d_8 (MaxPooling1D)	(None, 50, 128)	0	conv1d_8[0][0]
concatenate_2 (Concatenate)	(None, 50, 384)	0	max_pooling1d_6[0][0], max_pooling1d_7[0][0], max_pooling1d_8[0][0]
bidirectional_2 (Bidirectional)	(None, 50, 256)	394,752	concatenate_2[0][0]
attention_layer_2 (AttentionLayer)	(None, 256)	306	bidirectional_2[0][0]
dropout_2 (Dropout)	(None, 256)	0	attention_layer_2[0][…
dense_2 (Dense)	(None, 1)	257	dropout_2[0][0]

Table 3.2: Feature Classification

3.5.6 Attention Layer:

The AM acquires a context vector computing a weight sum of the input sequence's in hidden states. And The weight or more appropriately attention scores, are learned during the training process and are indicative of the words or phrases that have the most impact on the output. For example, in detecting fake news, the attention mechanism can help the model focus on words that elicit strong emotions, false claims, or repetitive patterns characteristic of deceptive content.The attention layer is typically placed above the GRU layer. The GRU maintains the sequence context very well, and the attention mechanism highlights the particular time steps (i.e., particular words or tokens) most relevant in performing the final classification. By visualizing the input elements that most influenced the decision-making process, this technique not only improves the model's performance but also its interpretability.

Generally, the attention model transformed models' sequential data processing to be more interpretable, efficient, and accurate, especially for complex tasks like the detection of fake news, machine translation, and question answering.

3.5.7 Dense Layer:

A dense layer, sometimes referred to as a completely connected layer, is the fundamental building block of deep models. Each neuron in the Dense layer is connected to every other neuron in the layer above it, allowing the network to learn abstract and high-level features from the data. Mathematically, it employs a linear translation followed by a non-linear activation function..Where-

- Output=f(Wt+k)
- W is the weight matrix
- Input vector is t,
- Bias is k
- f is the activation function (e.g., ReLU, and softmax or sigmoid function).

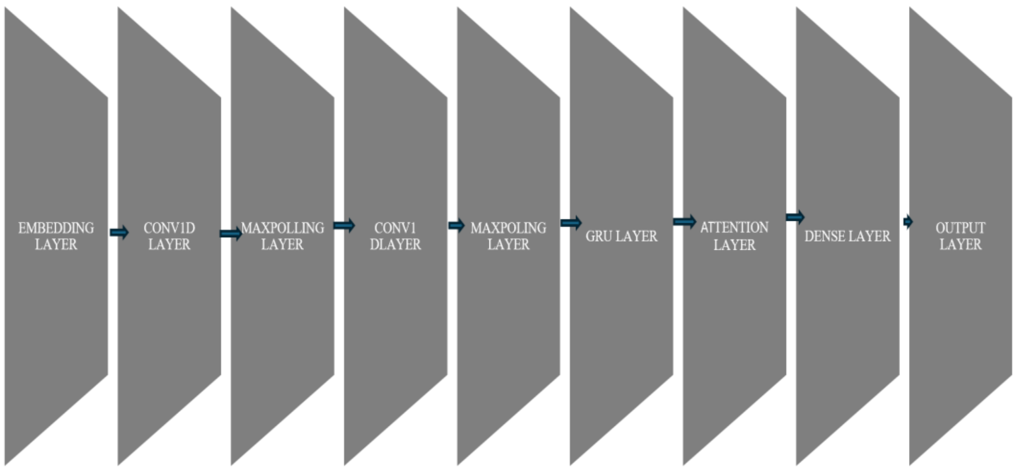

Figure 3.6: PROPOSED MODEL

CHAPTER 4

Result and Analysis

4.1 Configuration of Experimental Environment and Hyperparameter settings

In this section, detailed information on how the entire setup is implemented is provided. The sections have practical examples to help in understanding the data used in the new model. Also, Information on how hyperparameters were selected during training.

Dataset Collection: The explanation highlights the collection of data set used to train the model on various fake new detection. It is inclusive of various images depicting different types of fake news or true news as well as their conditions in the images; these have been carefully chosen with the intention of capturing many possible scenarios so as to ensure precise labeling which makes training more effective. I used the isot dataset for fake new detection.

Hyperparameter Selection: Optimal hyperparameters selection for model training would be discussed. The hyperparameters optimized were like learning rate and batch size; it also included tuning the number of epochs as well as fine-tuning other architecture-related ones. Explicitly, this part describes what specific values have been chosen in these hyperparameters 'set-up and provides insight into model precision as well as costs issues. Experimental Setup: We conducted experiments on a device with the hardware specifications mentioned here: - Processor: 13700H Intel i-7, Graphics: Intel Xeris 3.30 GHz speed - RAM: 8 GB

These hardware components enabled the model to carry out the complicated tasks in training and validating the deep learning algorithm. Selecting a high-speed graphics card such as NVIDIA GeForce RTX was essential in hastening the process of training due to the large volume and intricacy of the data set.

4.2 Evaluation Metrics:

This report utilize primary indicator namely, True positive rate , precision ,false and positive rate accuracy.

Accuracy, dependability, and robustness are evaluated using specific metrics in order to quantify the models' effectiveness in identifying fake news. The ones that we use the most frequently are F1-Score, Precision, Recall, and Accuracy. The model's overall correctness, or the number of accurate predictions, is captured by accuracy. However, in the case of imbalanced datasets—where both fake news and real news do not coexist in proportionate amounts-accuracy can be misleading.

1.Accuarcy:

Accuracy is the ratio of correct prediction of observations (True negative or True positive) to the number of observations. It is the simplest and most widely used measure. Accuracy can be misleading in the case of imbalanced datasets since it can give high values even if the model cannot identify minority class instances. When detecting fake news, if there is a dominance of more real news than fake news in the dataset, a classifier classifying all samples as real can potentially achieve high accuracy but fail.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Equation 4.1 Accuray

2.Precision:

It is calculates the number of corrected positive prediction observations among all observations predicted as all positive. This provides the answer to the question: "How many of the news articles predicted as fake are fake? " High precision indicates fewer false positives. This metric is relevant which is the cost of false positives is high in example, in detecting fake news, misidentifying real news as fake would injure credibility and trust, so high precision guarantees that only true fake content is targeted.

$$Precision = \frac{TP}{TP + FP}$$

Equation 4.2 Precision

3.True Positive Rate/Recall:

Recall calculates the ratio of actual positives (fake news) that were properly classified by the model. It informs us how accurately the model identifies all relevant instances. High recall in find fake news is important because failure to detect a fake news article (false negative) can lead to severe outcomes, like propagating misinformation. Recall therefore aids in assessing how many genuinely fake articles are trapped by the system irrespective of how many non-fake items it catches in error.

$$Recall = \frac{TP}{TP + FN}$$

Equation 4.3 True Positive Rate

4. AUC- ROC (Receiver Operating Characteristic Curve):

The ROC Curve is a visual display of a classifier's performance at all classification thresholds. It graphs the True Positive Rate (Recall) versus the False Positive Rate (FPR), indicating the balance between sensitivity and specificity. A better model has its curve closer to the top-left corner. In detecting fake news, ROC curves assist in displaying the performance across different thresholds, which is helpful in trading off between capturing fake news and producing false alarms.
The entire two-dimensional area under the ROC curve is computed by AUC. It provides a single scalar metric that summarizes the model's ability to distinguish across classes. A perfect model has an AUC of 1.0, while random guessing has an AUC of 0.5. Regardless of the threshold applied, a higher AUC in the detection of fake news suggests that the model can distinguish between fake and real news more successfully. It is very useful for comparing models and choosing the most suitable one.

4.3 Training Model Result

The goal of training a model for fake news is to allow this to develop the ability to discern discerning characteristics between real news and artificial information presented in texts. The model architecture combines CNN-based features, GRU layers for sequential processing and an Attention module that highlights the most important parts of each input. The data was cleaned, tokenized and then truncated to fit uniform input lengths before being fed into the model. Embedding the words into a 100-dimensional space conserved their underlying meaning. We trained the model using the Adam optimizer which is known to handle both sparse gradients and adjustable learning rates.
The categorical cross-entropy for loss function, which can also be used for binary classification problems ex. fake news identification, was utilized. Training was performed for more than 100 epochs using a batch size selected based on hardware capacity to strike a balance between speed and stability. Dropout layers used with a drop rate of 0.2 were used to stop overfitting

```
Training model...
Epoch 1/10
506/506 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step - accuracy: 0.9157 - loss: 0.3213 - precision_2: 0.9106 - recall_2: 0.9402
Epoch 1: val_accuracy improved from -inf to 0.99220, saving model to best_model.keras
506/506 ━━━━━━━━━━━━━━━━━━━━ 78s 140ms/step - accuracy: 0.9158 - loss: 0.3209 - precision_2: 0.9108 - recall_2: 0.9403 - val_accuracy: 0.9922 - val_loss: 0.0441 - val_precision_2: 0.9925 - val_re
call_2: 0.9925
Epoch 2/10
506/506 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step - accuracy: 0.9922 - loss: 0.0924 - precision_2: 0.9916 - recall_2: 0.9935
Epoch 2: val_accuracy did not improve from 0.99220
506/506 ━━━━━━━━━━━━━━━━━━━━ 70s 138ms/step - accuracy: 0.9922 - loss: 0.0924 - precision_2: 0.9916 - recall_2: 0.9935 - val_accuracy: 0.9908 - val_loss: 0.0434 - val_precision_2: 0.9984 - val_re
call_2: 0.9840
Epoch 3/10
506/506 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step - accuracy: 0.9970 - loss: 0.0152 - precision_2: 0.9981 - recall_2: 0.9962
Epoch 3: val_accuracy improved from 0.99220 to 0.99276, saving model to best_model.keras
506/506 ━━━━━━━━━━━━━━━━━━━━ 70s 139ms/step - accuracy: 0.9970 - loss: 0.0152 - precision_2: 0.9981 - recall_2: 0.9962 - val_accuracy: 0.9928 - val_loss: 0.0376 - val_precision_2: 0.9957 - val_re
call_2: 0.9904
Epoch 4/10
506/506 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step - accuracy: 0.9979 - loss: 0.0149 - precision_2: 0.9986 - recall_2: 0.9973
Epoch 4: val_accuracy improved from 0.99276 to 0.99415, saving model to best_model.keras
506/506 ━━━━━━━━━━━━━━━━━━━━ 70s 139ms/step - accuracy: 0.9979 - loss: 0.0149 - precision_2: 0.9986 - recall_2: 0.9973 - val_accuracy: 0.9942 - val_loss: 0.0245 - val_precision_2: 0.9947 - val_re
call_2: 0.9941
Epoch 5/10
506/506 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step - accuracy: 0.9996 - loss: 0.0061 - precision_2: 0.9997 - recall_2: 0.9995
Epoch 5: val_accuracy did not improve from 0.99415
506/506 ━━━━━━━━━━━━━━━━━━━━ 70s 139ms/step - accuracy: 0.9996 - loss: 0.0061 - precision_2: 0.9997 - recall_2: 0.9995 - val_accuracy: 0.9933 - val_loss: 0.0256 - val_precision_2: 0.9931 - val_re
call_2: 0.9941
Epoch 6/10
506/506 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step - accuracy: 0.9999 - loss: 0.0023 - precision_2: 0.9999 - recall_2: 1.0000
Epoch 6: val_accuracy did not improve from 0.99415
506/506 ━━━━━━━━━━━━━━━━━━━━ 70s 138ms/step - accuracy: 0.9999 - loss: 0.0023 - precision_2: 0.9999 - recall_2: 1.0000 - val_accuracy: 0.9922 - val_loss: 0.0278 - val_precision_2: 0.9910 - val_re
call_2: 0.9941
Epoch 7/10
506/506 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step - accuracy: 0.9943 - loss: 0.2722 - precision_2: 0.9925 - recall_2: 0.9966
Epoch 7: val_accuracy did not improve from 0.99415
506/506 ━━━━━━━━━━━━━━━━━━━━ 70s 138ms/step - accuracy: 0.9942 - loss: 0.2727 - precision_2: 0.9925 - recall_2: 0.9966 - val_accuracy: 0.9875 - val_loss: 0.0396 - val_precision_2: 0.9862 - val_re
call_2: 0.9899
Evaluating model...
281/281 ━━━━━━━━━━━━━━━━━━━━ 11s 35ms/step
Accuracy: 0.9947
Precision: 0.9932
Recall: 0.9966
F1 Score: 0.9949

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      4284
           1       0.99      1.00      0.99      4696

    accuracy                           0.99      8980
   macro avg       0.99      0.99      0.99      8980
weighted avg       0.99      0.99      0.99      8980
```

Figure 4.1: Train and Test score of Algorithm

4.4 Comparison Result

To verify the efficacy of our suggested CNN-GRU-Attention model, we compared its performance with other baseline and models utilized previously, including LSTM, and CNN-alone models. Performance was calculated used common parameters such as F1-score, recall and accuracy. The LSTM -CNN models showcased satisfactory sequential data processing capacity due to their memory cells but utilized more computational resources and took longer in training. The single-model CNN worked well to extract local features but was unable to achieve very longest-term dependencies in this text. However, our hybrid model not only extracted local and sequential patterns with CNN and GRU, respectively, but also utilized the attention mechanism to emphasize contextually important words, making the model more interpretable and accurate.

Model	Accuracy
CNN	98.92
LSTM+CNN	94.71
LSTM	97.9
CNN+GRU+ATTENTION	99.1

Table 4.1: Model Comparison

The training and testing phase forms an integral part of developing a successful fake news identification model. In our designed architecture, which incorporates CNN, GRU, and an Attention mechanism, To train the model, we used a labeled and unlabled dataset that will be everything about included both authentic and fraudulent news posts. The data were preprocessed, tokenized, and converted into fixed-length sequences using word embeddings before training. We employed a training-validation division, usually reserving training 80% of data and 20% for testing to enable the model to learn general trends while retaining a stable set for evaluation. The model was trained for 100 epochs with a suitable batch size and learning rate, and the optimization was performed using the Adam optimizer, which adjusts the learning rate during training for quicker convergence. We also used dropout and recurrent dropout layers to prevent overfitting and improve generalization. Model performance was monitored using validation accuracy and loss during training.

After training, we tested the model on blind data to evaluate its performance in practical use. The experimental results indicated that the CNN-GRU-Attention model possessed higher accuracy and generalization compared with traditional deep learning models and was effective in false news detection solely based on text content.

```
Sample prediction:
Text:
    Breaking: Scientists discover that drinking coffee makes you immortal,
    according to a new study that has not been peer-reviewed.
    Experts are shocked by this finding that contradicts all known medical knowledge.

Prediction: FAKE
Probability: 0.9913
Confidence: 0.9913
```

Figure 4.2: Classification of Real or Fake news

Table 4.2 Training and Validation Accuracy Loss, and Precision

Epoch	Train Accuracy	Train Loss	Train Precision	Val Accuracy	Val Precision
1	0.9158	0.3209	0.9108	0.9922	0.9925
2	0.9922	0.0924	0.9916	0.9908	0.9984
3	0.9970	0.0152	0.9981	0.9928	0.9957
4	0.9979	0.0149	0.9986	0.9942	0.9947
5	0.9996	0.0061	0.9997	0.9933	0.9931
6	0.9999	0.0023	0.9999	0.9922	0.9910
7	0.9942	0.2727	0.9925	0.9875	0.9862

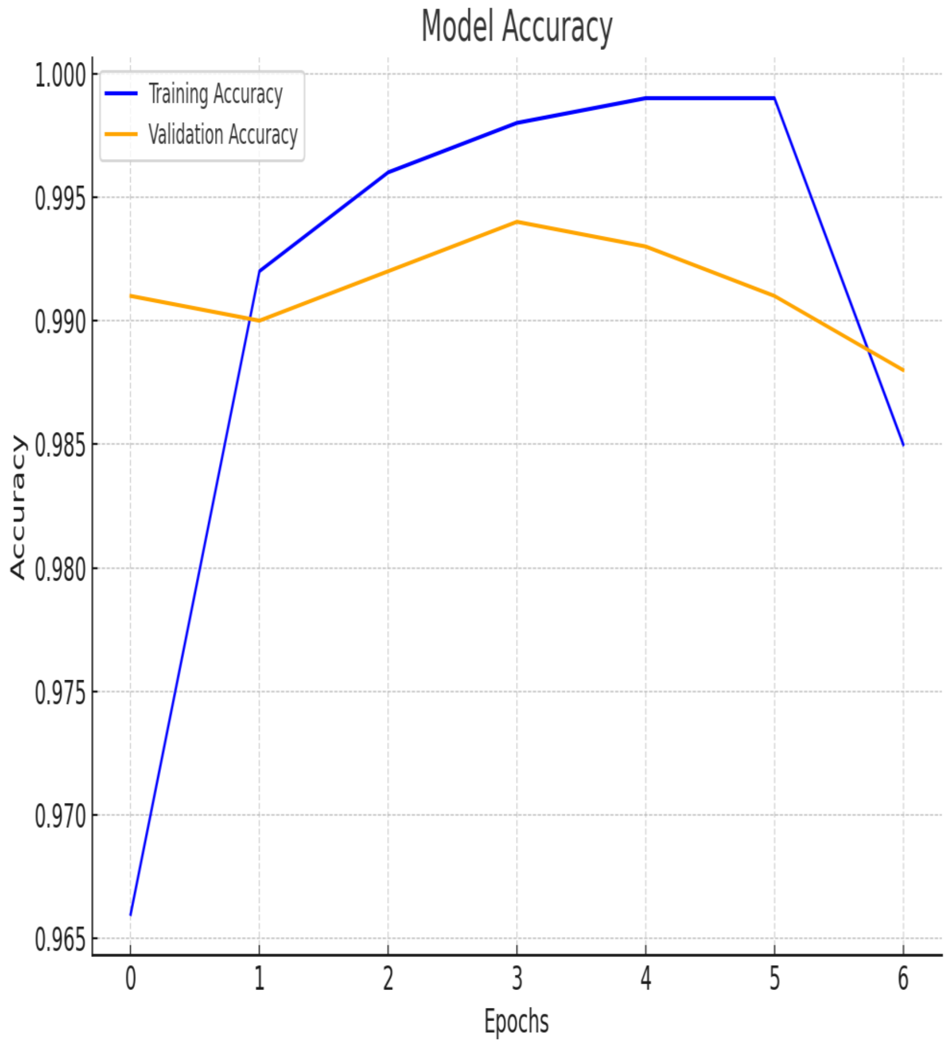

Figure 4.3. Training and validation Accuracy

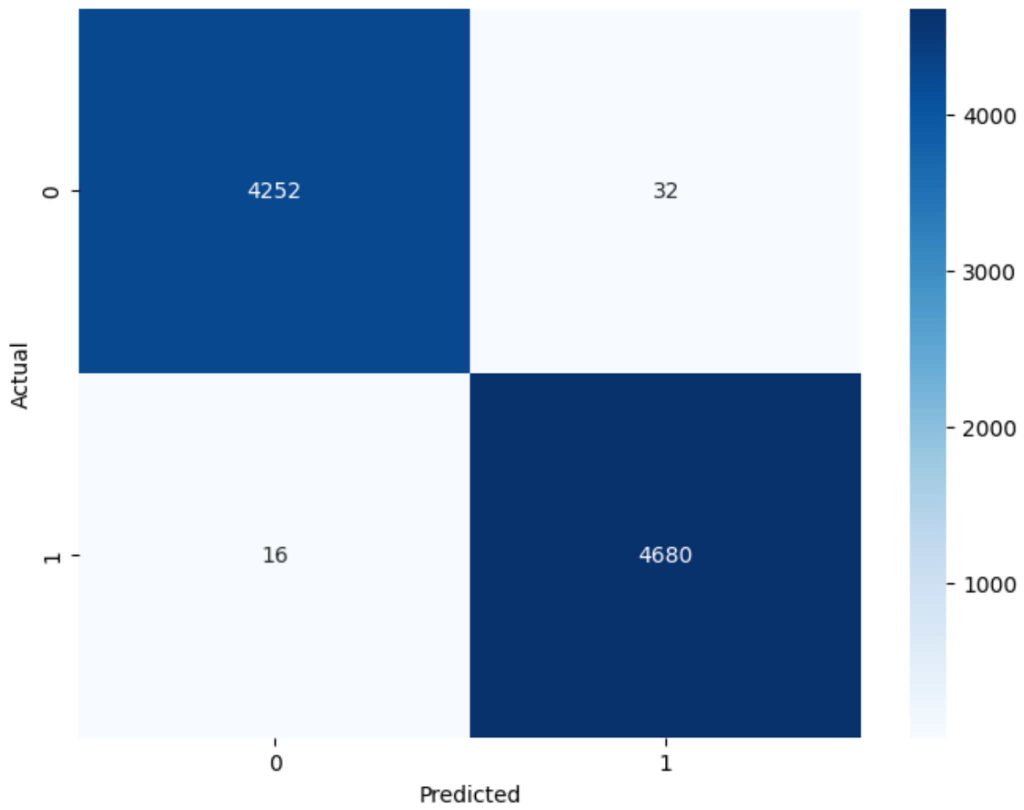

Figure 4.4: Confusion Matrix

F1 Score: F1 score is precision and TPR in harmony.
Precision: calculates the proportion of anticipated fake news stories that turn out to be phony.
Accuracy: calculates the percentage of authentic and fraudulent articles that were properly categorized out of all the predictions.

CHAPTER 5

CONCLUSION AND FUTURE WORK

This thesis, we formulated a DP architecture combining GRU, CNN, and the Attention Mechanism for this specific purpose of detecting fake news. Our method utilizes the strengths of each individual component: CNN for efficient local feature extraction, GRU for detecting sequential dependencies of text data, and attention for highlighting contextually significant words in the input. This integrated architecture allows the model to grasp both shallow patterns and deep contextual implications in news articles, thereby enabling a more accurate and robust separation of counterfeit and original content. In contrast to the previous methods, including common machine learning models and deep learning models composed of only LSTM, Bi-LSTM, or CNN, our intended model CNN-GRU-Attention shows better results in accuracy, generalization, and interpretability. LSTM and Bi-LSTM models have been successful in handling long-term dependencies but usually with additional computation costs. While stand-alone CNNs, being effective in detecting local features, are prone to overlook long-term semantic relations within textual data, our model overcomes such shortfalls by combining GRU's accuracy and contextual memory with the capabilities of attention to emphasize salient information in sequences and thus become more effective for practical applications where precision and scalability are essential.

The model was trained and evaluated with standard metrics and datasets, and it was able to perform well in detecting content that is misleading. The use of dropout layers and regularization also helped in preventing overfitting, so the model was able to generalize to new data well.Although the recommended model presents good performance, there are some directions for future improvement. One is that the model can be optimized by adding pre-trained word embeddings like GloVe, FastText, or transformer-based embeddings like BERT, which have the potential to offer more in-depth semantic meaning for words and phrases.

Another is that expanding the dataset with multilingual news articles would enable the model to work effectively in various linguistic contexts.Another line of future work is the integration of metadata and social context, like user behavior, sharing patterns, and source credibility, which can give more cues than textual content alone to fake news detection. Additionally, real-time fake news detection from streaming data (like Twitter or live news channels) is both a technical and computational challenge, for which model compression, online learning, and lightweight architectures are solutions.

Finally, beyond model explainability and interpretability, interpretability and explainability of model predictions are crucial in such sensitive domains as healthcare, politics, and finance. Future studies may involve integrating explainable AI (XAI) frameworks to provide transparency into why the model has made a specific decision, which would improve end-users and stakeholders regarding trust and usability.

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Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI-paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.