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HYBRID DEEP LEARNING MODEL FOR AUTOMATIC FAKE NEWS DETECTION

Othman Araf Hanshal HANSHAL

Doctor of Philosophy

Supervisor

Prof. Dr. Osman Nuri UÇAN

İstanbul, 2022

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The dissertation titled HYBRID DEEP LEARNING MODEL FOR AUTOMATIC FAKE NEWS DETECTION prepared by OTHMAN ARAF HANSHAL HANSHAL and submitted on 23/12/2022 has been **accepted unanimously** for the degree of PhD in Electrical and Computer Engineering.

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Prof. Dr. Osman Nuri UÇAN

the Supervisor

Thesis Defense Committee Members:

Prof. Dr. Osman Nuri UÇAN	Department of Electrical and Electronic Engineering, Altınbaş University	__________________
Prof. Dr. Hasan Hüseyin BALIK	Department of Computer Engineering, Yıldız Technical University	__________________
Assoc. Prof. Dr. Adil Deniz DURU	Department of Trainer Education Marmara University	__________________
Asst. Prof. Dr. Abdullahi Abdu IBRAHIM	Department of Computer Engineering, Altınbaş University	__________________
Asst. Prof. Dr. Oğuz ATA	Department of Software Engineering, Altınbaş University	__________________

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Othman Araf Hanshal HANSHAL

Signature

DEDICATION

For the love of Allah, my Maker and my Master; in honor of my wonderful advisor, Prof. Dr. Osman Nuri Uçan (May Allah bless and give him); and in gratitude to Iraq, my mother.

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First and foremost, I want to give my deep appreciation to my advisor, Prof. Dr. Osman Nuri Uçan, for his unwavering encouragement, inspiration, and guidance during my PhD studies and research. All through the process of researching and writing this thesis, his advice was invaluable. The guidance and support I received from my adviser and mentor during my PhD studies was invaluable.

ABSTRACT

HYBRID DEEP LEARNING MODEL FOR AUTOMATIC FAKE NEWS DETECTION

Hanshal, Othman Araf Hanshal

Ph.D., Electrical and Computer Engineering, Altınbaş University,

Supervisor: Prof. Dr. Osman Nuri UÇAN

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With the fast advancement in digital news, fake news has already caused grave threats to the public's actual judgment and credibility, in specific, with the wide use of social networking platforms, which provide a rich environment for the generation and dissemination of fake news. To cope with these challenges, several techniques were proposed to detect fake news, but still, there is an urgent need to propose an improved detection technique that provides a high level of detection performance in an automatic manner. Therefore, this article proposes a hybrid-improved deep learning model for automatic fake news detection. The proposed model adopts automatic data augmentation method, called Auxiliary Classifier Generative Adversarial Networks, to artificially synthesize new fake news samples, and then, hybridize the Convolutional Neural Network with the Recurrent Neural Networks to detect the fake news efficiently. The proposed model shows superior results against the state-of-the-art models as it provides 93.87% accuracy, 10.39% recall, 93.12%% precision in detecting the fake news using Buzzfeed, FakeNewsNet and FakeNewsChallenges datasets.

Keywords: Automatic Data Augmentation, Auxiliary Classifier Generative Adversarial Networks, Convolutional Neural Network, Digital News, Fake News, Recurrent Neural Networks.

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ABBREVIATIONS

ACGAN	:	Auxiliary Classifier Generative Adversarial Network
AI	:	Artificial Intelligence
CGAN	:	Conditional Generative Adversarial Network
CNN	:	Convolutional Neural Networks
DL	:	Deep learning
LSTM	:	Long Short-Term Memory
NLP	:	Natural Language Processing
PCA	:	Principal Component Analysis
RNN	:	Recurrent Neural Networks
ACGAN	:	Auxiliary Classifier Generative Adversarial Network

1. INTRODUCTION

1.1 OVERVIEW

Recent technical advancements and the proliferation of the Internet have significantly altered social connections. People are using digital platforms to get information to the public on a regular basis. On various via social networks sites, Persons also discuss their individual interests., interests and viewpoints the internet has various benefits, including quick information dissemination, low cost, and simple access to data. Due to these benefits, many individuals prefer using social media to find news rather than traditional news outlets like television or newspapers. As a result, traditional news sources are being quickly replaced by social media news. Social media offers numerous benefits, however when compared to traditional news sources, online social media news is unreliable. But occasionally, Social networking content might be changed to serve other purposes. such webpages can be found in many other nations, including Macedonia, Romania, Russia, the UK and USA [1]. The spread of social media networking has, for the time being, drastically altered how consumers gather data. Recent Pew Research Center survey results show., about (68%) adult Americans at least occasionally obtain news through social media networking [2].

1.2 BACKGROUND

1.2.1 Fake News

Fake media is misinformation that has been deliberately spread through mainstream communications and social internet. Headlines that is false spreads very quickly. This is demonstrated by the fact that, after a misleading news site is taken down, another one quickly replaces it. Furthermore, misinformation can easily meld with credible news due to how quickly it spreads, making it difficult to distinguish between the two.

Websites offer articles that anyone can purchase., The misleading news has spread so away from its original origin by the end of each day. that it can no longer be distinguished from reliable information. This happens when people share them with others and then re-share them from other sources [3].

An huge amount of information online creation every day technology-based era. However, an enormous volume of the data that has the World wide web was inundated is false information, which is created to draw viewers, influence people's opinions and decisions [4]–[5], raise clickthrough income [6], and have an impact on significant events like political elections [7]. Spreading intentionally misleading information leads to reader confusion. It is now very easy to obtain and disseminate information via social media platforms, making it difficult and nontrivial to recognize based only on the news's source. For instance, some studies show and social media bots to disseminate incorrect news. A study found that 64% of US individuals believed that false news has greatly confused people regarding the veracity of reported events [8]. Additionally, a large-scale cascade of incorrect information has effects that are getting worse in the business, marketing, and stock-share sectors. For instance, after a false rumor about Barack Obama being hurt in an explosion propagated on twitter in 2013 [7], 130 billion dollars in stock value were lost. Fake news has been charged with being the main contributor to the rise in during the partisan fighting and political polarization 2016 US presidential campaign, as well as influencing the outcome [9],[10]. As a result, rumors and false information spread widely and swiftly [3].

Figure (1.1) shows an example of bogus news that has been circulated on social media.

Figure 1.1: Sample of incorrect news

1.3 RESEARCH MOTIVATION

The detection of false information has attracted the interest of academics in the natural language processing and artificial intelligent sectors from all around the globe as one of the most current topics. Thus, a vast amount of study has been done based on suggested benchmark results as well as content- or context-based news elements. Even though false news detection has received a lot of attention in the academic community, there isn't enough context-based news data to show a meaningful improvement in performance. Technically speaking, it is difficult to create suitable hand-engineered news features [11] that can tell whether certain news is authentic or untrue. Deep learning-based detection offers an advantage over traditional feature-based techniques in that it can classify and differentiate the best feature set for a problem on its own, without the requirement for hand-crafting features.

Fake news is now posing serious dangers to the public's credibility and actual judgment, especially in light of the widespread usage of social networking sites that offer a fertile environment for its creation. As an illustration, in the 2016 Presidential campaign, a significant amount of false information about the candidates was created and disseminated on various social media platforms [12]. Facebook users posted bogus news in favor of Donald Trump more than 30 million times, while users shared fake news stories in favor of Hillary Clinton more than 41 million different ways [1]. The public persona of candidates has been completely destroyed by the vast amount of widely disseminated false information, which has therefore obscured the judgment of the electorate. In order to prevent the rapid spread of fake news, it is crucial to identify it quickly, especially on social media networking sites.

Fake news and traditional bogus data/information, however, differ significantly. In order to achieve the objective of incorrect news the audience, the fake news is purposefully altered by its creators. For instance, news about the same subject released by various creators is entirely comparable in most material,but damaging Fake media carriers distribute news items. in objective statements. Despite their small percentage, these dubious materials are enough to taint the news and render it harmfully false. Additionally, consumers have a prophylactic mentality by nature when it comes to traditional bad content, like spam [13], making them less susceptible to deception. However, when it comes to news, people frequently actively seek, obtain, send, and share without being on guard for accurate information. Additionally, because there are so many well-organized messages, spam is frequently easier to avoid or detect; nevertheless, as news is a time-sensitive topic, it has been very difficult to identify fake news. It's not always possible to clearly identify fake news using the evidence obtained about previous news. The detecting process becomes more difficult and sophisticated due to these characteristics of fake news. Additionally, a sizable amount of false and unbelievable information is produced by numerous users and disseminated through the social networking site ([14],[15],[16],[17].

In terms of the 3Vs depicted in Figure 1.2, it also produced a potential malevolent danger to various communities and had a profoundly detrimental impact on end-users via multiple advertisements, electronic purchasing, and/or social messaging in terms of 3Vs drawn in Figure (1.2)

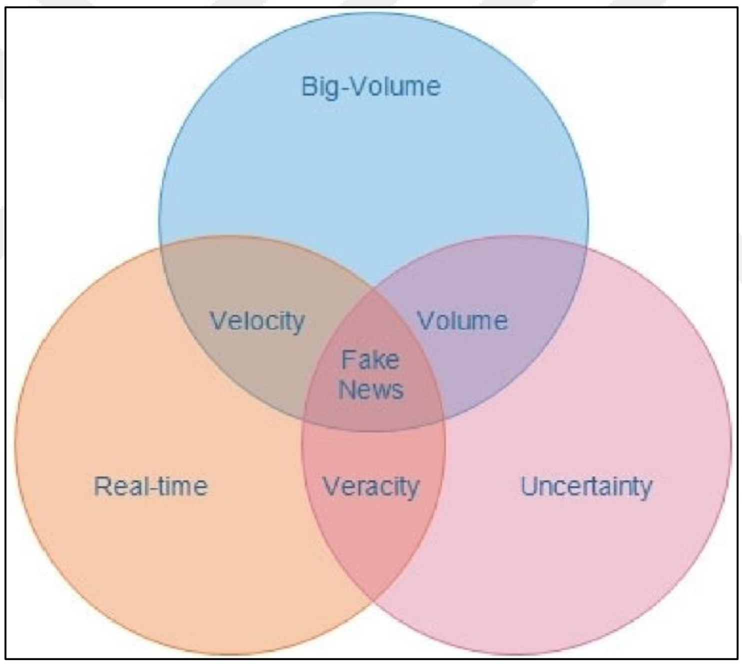

Figure 1.2: Fake news in terms of 3Vs [17].

1.4 RESEARCH PROBLEM

For the time being, a number of methods for spotting fake news have been put forth. These methods may be loosely divided into two groups: I detection based on classical learning ([18]; [19]; [20]); and (ii) detection based on deep learning models ([21], [22], [23]). The classifier is trained using the attributes that were generally taken from news items for the first category. In contrast hand, deep learning-based detection had offered an increased efficiency in recognize false information because of its strong ability to autonomously learn relevant formulations. But a lot of labeled data is needed in order to train deep learning models effectively (i.e., News should be classified as either true or false.). Cost-wise and in terms of time, the production cost of this classified data is high. Furthermore, skilled annotators who are sufficiently knowledgeable about the news may be able to produce accurate and precise labeling. Additionally, the news stories' dynamic nature degrades the quality of the currently labeled data because it is so frequently updated. Additionally, some of these news samples can quickly become out of date and may not accurately reflect the news articles on now trending themes. Thus, in order to maintain the standard of the labeled sample and the commentators would need to constantly label breaking news, which is an impractical operation. The difficulty of accurately classifying fake news must be mastered in order to fully harness the power of deep learning technologies in detecting it.

1.5 RESEARCH OBJECTIVES

The major objective of this study is to enhance the mixed deep learning approach for false information identification. To accomplish the core purpose, the following goals have been established:

a. To examine whether deep learning is preferable to machine learning models for identifying false information.

b. To modify the faster information augmentation technique known as Auxiliary Classifier Generative Adversarial Networks (ACGAN) in order to fictitiously create fresh sampling of false information.

c. To effectively detect bogus news, merge the convolutional Nerual networks' work with Recurrent Neural Networks.

d. To assess the effectiveness of the suggested methodology by contrasting it with cutting-edge methods.

1.6 THESIS ORGANIZATION

A overview of several techniques for the optimization methods utilized in the thesis is included in Chapter 2 of the way this thesis has been constructed. In Chapter 3, methodology is described, along with examples of the techniques and model analysis. The proposed algorithm's output has also been presented for a current proposal in Chapter 4 and has been examined under a variety of circumstances. Chapter 5 then addresses the conclusions and the potential research directions moving forward.

2. LITERATURE REVIEW

2.1 INTROUDCTION

The recent advancement in technology and the widespread use of the internet have had a significant impact on social interaction. People now share their personal interests, activities, and opinions on a variety of social media platforms, and social media has grown in popularity as a source of information for people. The method of obtaining information from web is like a double-edged sword: on the one hand, it's user-friendly, less time-consuming, easily communicable, and socially relevant news with the ability to get multiple perspectives on a single news article and updated every minute with the rapid development of artificial intelligence. Many experiments are continuously being conducted to address problems that were never considered within the context of computer science. [24] In the age of technology, enormous amounts of news are creation online every day, yet an incredible quantity of that information is incorrect news that is created to lure the public and influence their opinions

[12], propagation of false information necessitates the development of computer algorithms to identify it. Users are encouraged to reveal different types of fake news by using fake news detecting tools. Based on previous experiences with true or fake news, we can determine if the news is reliable or fraudulent.

2.2 RESEARCH BAGROUND

2.2.1 Digital News

Digital news portals are currently among Internet consumers' most essential news sources. However, how it is written is influenced by the content's direction. Utilizing deceptive writing is one method of reporting news. Such a style of writing has produced a lot of unfavorable effects, including political turmoil, slander, and a negative view of the company, its employees, and the nation. It is crucial for readers to select news sources that are reporting favorably and to ignore those that use deceptive writing techniques to further their personal interests or harm the community.

The objective of this study is to organize and analyze the data veracity research literature so that it may be used to the profile of a digital news portal. Classifying and defining data authenticity is the method employed in this paper; conducting a thorough examination of the literature is the conduct. Journal and conference proceedings are included.

The findings include goals for data veracity, topical structure, research trends with publications, and framework veracity model validation. This essay offers an exhaustive analysis of the research on measuring the data validity of digital news portals.

2.2.2 Fake News and its Impact

Social media is a platform for rapidly generating and spreading data. Millions of individuals use browser services every second, creating huge amounts of information in the process. however, the reliability of contents flowing on the web of internet differs from traditional news sources like news stations and newspapers is disputed due to independence of free speech. The number of users has dramatically increased recently, it has been observed. [25], who use via digital networking and online platforms to access news and information The preferences of people are being influenced by social media material. Following the "2016 US presidential elections," the term "fake news" has gained widespread usage.

Digital networks has advantages and disadvantages for news consumption. On the one hand, people utilize social media to discover and absorb news because it is free, simple to use, and information is spread quickly. On the other hand, it encourages the mass spreading of "incorrect information," which is poor news that intentionally contains deceptive information. Misinformation being widely disseminated could have highly negative repercussions on society and people [26].

Fake news has existed for a very long time—basically since the start of existence widespread news distribution. The word "fake news" has no accepted definition, nevertheless. As a result, before providing our standard for misleading media which will be employed for the duration of this study, we first analyze and contrast various commonly used definitions of incorrect information in the current literature. Articles of news that are deliberately and demonstrably untrue and may deceive readers are considered fake news [1].

2.2.3 Various Fake News Categories

The categorization of incorrect news, also known as information pollution, which can be found in photographs, blogs, messages, tales, and breaking news, has a variety of formats that are not mutually exclusive while yet possessing some heterogeneity that places them in a certain category.

In Figure (2.1) a Venn diagram is used to show how different information pollution formats are categorized. The effects of false content on the internet are categorized and summarized in Table 1. Although each category has certain distinguishing traits throughout the research, we have frequently used the terminologies interchangeably to present a comprehensive Synergy of digital communication platform information pollution.

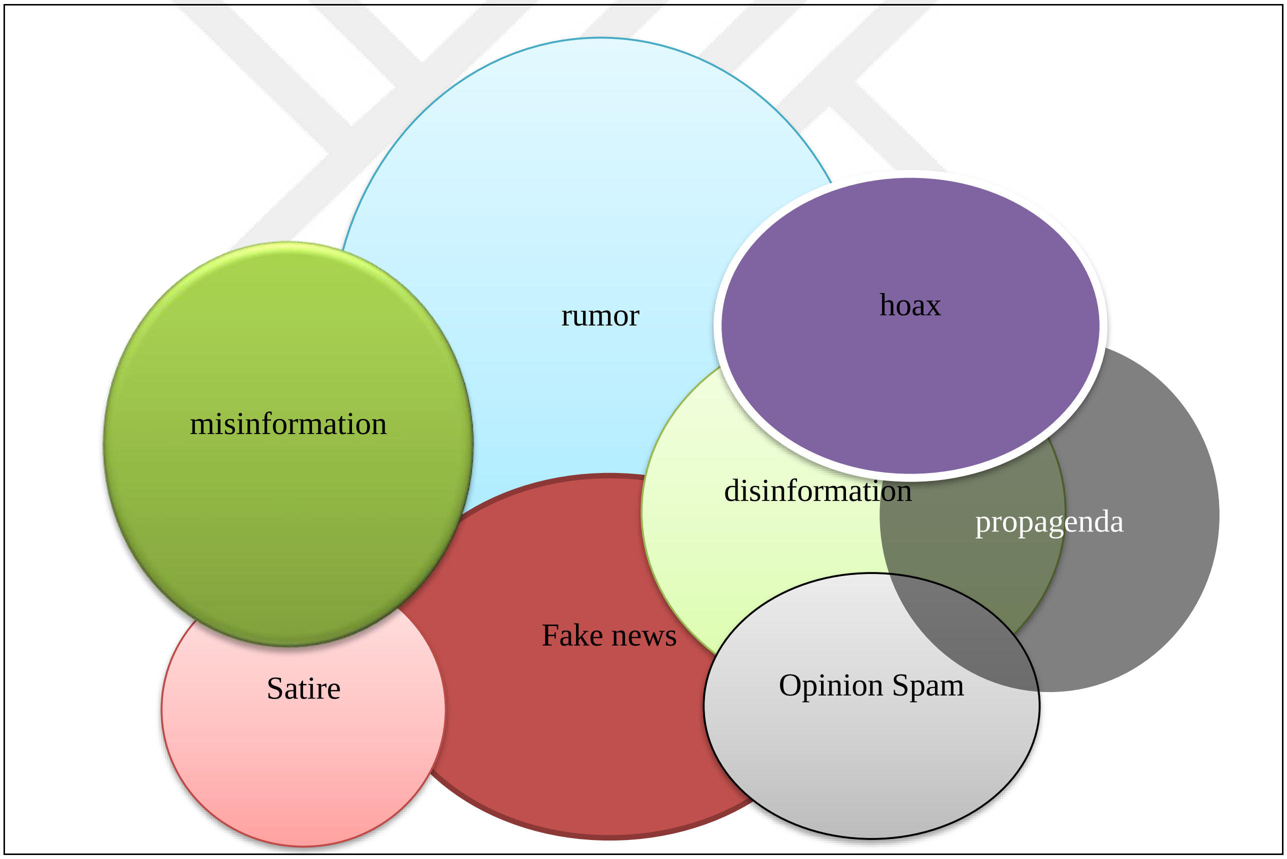

Figure 2.1: Venn diagram of false information on social media

Table 2.1: Categorization of False information

Category	Definition	impact
Rumor	Unverified data that may turn out to be genuine but is not guaranteed to be so.	Facts that are uncertain and unclear
Fake news	False information is frequently disseminated online or through news sources under the premise of being news in an effort to profit politically or financially, get more readers, or sway public opinion.	to harm a group, organization, or individual, or to achieve financial or political benefit
misinformation	spreading information that is unintentionally inaccurate due to negligence, cognitive bias, or an honest mistake	Less damaging but incorrect fact interpretation can cause significant effect
Disinformation	material that is purposefully misleading and has a predetermined goal	to advance a viewpoint, a concept, monetary gain, or to damage the reputation of a rival
Clickbait	the purposeful use of deceptive headings to entice users to click on a specific webpage	To generate cash via advertising, to start phishing assaults
Hoax	Joke, prank, humor, or other malicious deceit is often employed to disguise the reality as a fictitious story.	The perception of falsehood as reality and the truth.
Satire/parody	articles with a strong comedy and irony element that have no malicious purpose yet have the capacity to fool. Satire news articles can be found on websites like Satire Wire and The Onion.	The goal is enjoyable, but it can also have negative implications.
Opinion Spam	fake or purposefully skewed comments or reviews about goods and services	unreliable consumer feedback
Propaganda	Information that is unfairly biased and deceitful and is disseminated in specific communities in accordance with a predetermined plan to further a certain point of view or political agenda	Political/financial profit

2.2.4 Natural Language Processing

Even if the linked world has a lot of natural language text and it contains a lot of knowledge, it is becoming more difficult for humans to disseminate it and discover the wisdom or knowledge in it.

precisely, within any predetermined time limits. The automated NLP is designed to carry out this duty as precisely and effectively as a human would (for a limited of amount text). so far, NLP applications, NLP components, and the English grammar that machines need. Along with it, it covers specific subjects such probabilistic parsing, ambiguities and their resolution, information extraction, discourse analysis, natural language question-answering, commonsense interfaces, commonsense thinking and reasoning, causal variety, and a variety of NLP tools [29].

By improving a better comprehension of the human language for linguistically based human-computer communication, natural language processing (NLP) contributes to the empowerment of intelligent machines.

The need and desire for automating semantic analysis using data-driven methodologies has increased as a result of recent advances in processing capacity and the appearance of vast amounts of linguistic data. Due to the substantial advancements made possible by the application of deep learning techniques in fields like Computer Vision, Automatic Speech Recognition, and particularly NLP, the use of data-driven strategies is now widespread. The various facets and applications of NLP that have benefited from deep learning are categorized and discussed in this survey. It discusses how deep learning techniques and models progress key NLP tasks and applications. We also assess and contrast other strategies [30].

2.2.5 Deep Learning

A group of machine learning techniques are together referred to as deep learning. It simply refers to networks with several layers in neural networks [27]. The primary goal of using this type of architecture is to learn a hierarchy of features, where each layer processes the input and provides a richer representation of the input data to the following layer (indeed, each added layer can increase exponentially the number of possible state representations of the network). It was influenced by nature since the mammal brain has a deep design that is particularly reminiscent of the mammal visual system [28].

2.2.6 Convolutional Neural Network

The convolutional neural network is one of the most significant networks in the field of deep learning Considering all the tremendous accomplishments CNN has done,

The use of CNNs in both research and commercial projects has grown significantly as a result of its benefits, including local connection, weight sharing, and down sampling dimensionality reduction. Its inspiration, classic networks, related functions, applications, and prospects, as well as its motivation. We briefly discuss CNN models. They provide us with some recommendations for creating innovative networks that are accurate and quick.

More particular, larger and deeper brain structures can learn more accurate representations than shallow ones. Additionally, leftover connections can be used to create very deep neural networks, increasing the. We introduce optimizers, hyperparameter selection, activation functions, loss functions, and optimizers for CNN. The results of experimental analysis lead to a number of conclusions. Convolutions offer a lot of advantages and are frequently utilized, but we believe there is room for improvement in terms of model size, security, and NAS. Convolution is also difficult to manage due to a number of issues, including poor crowded-scene outcomes, a lack of equivariance, and inadequate generalization capacity, hence numerous interesting directions are suggested [31]

2.2.7 Recurrent Neural Networks

Using Natural language Processing (NLP), computers can more intelligently analyze, comprehend, and extrapolate meaning from human language. The area of NLP has undergone a revolution thanks to recurrent neural networks (RNN). RNNs are applied sequentially to modeling units. RNNs have cyclic connections, which makes them more effective for modeling inputs of sequences than feed-forward neural networks. They have been effectively employed for applications like handwriting recognition, language modeling, machine translation, phonetic labeling of audio frames, and others that need sequence labeling and sequence prediction. This article provides an overview of the applications and handling of Natural Language Processing by RNNs [32].

From sequential and time-series data, recurrent neural networks (RNNs) are able to learn features and long-term dependencies. A directed cycle is formed by at least one connection between each non-linear unit in the RNNs' stack of non-linear units. A well-trained RNN may simulate any dynamical system; unfortunately, problems with long-term dependency learning hamper RNN training the most. For newbies and experts in the subject, we give an overview on RNNs and a number of recent developments in this paper. The principles, contemporary developments, and research difficulties are described [33] .

2.3 LITERATURE REVIEW

Because it could have a harmful impact on society and the nation, the proliferation of false information on social media . for example is a serious concern. There has previously been extensive research before it was discovered. This study studies the research on incorrect information recognize and investigates the top conventional supervised computer learning approach to develop a model of a product using machine learning models categorize disinformation as genuine or false [34].

In the modern era, everyone relies on a variety of internet tools for news because the internet is so widely utilized. As the use of social media sites like Facebook, Twitter, etc. has increased, news has quickly spread across millions of users in a short period of time. The spread of misleading information has a broad spectrum of effects, including the development of distorted views and the swaying of election outcomes in favor of particular politicians. Additionally, spammers profit from clickbait advertisements by using alluring news headlines. we want to perform binary categorization of various news articles that are available online using concepts from intelligent machines, natural language processing, and machine learning. We aim to provide users with the choice to classify news as authentic or fake and to confirm the reliability of the domain that is publishing the news [35].

The proliferation of false information, whether created by people or algorithms, has a harmful im pact on society and consumers on both a political and social
level. The rapid turnover of news in the online social era makes it difficult to determie its veracit y in a timely manner.
Therefore, it has become essential to have automated methods for spotting bogs news.
A mixed neural network design that merges the characteristics of CNN and LSTM has been deve loped to address the aforementioned problem [36].

The advancement of social media has made it possible for people to disseminate knowledge more easily, cheaply, and with fewer filters than ever before. This exacerbated the long-standing issue of fake news, which is now a serious worry because of the harm it causes to communities. To stop the emergence and spread of false information, automatic monitoring systems have been researched. These techniques rely on artificial intelligence and machine learning. Deep learning methods are now a viable option for identifying fake news because they have lately made substantial progress in difficult natural language processing problems. In order to categorize incorrect news, this research suggests a revolutionary deep-learning model that blends convolutional and recurrent neural networks. The model was successfully validated using datasets of false news (ISO and FA-KES) [37].

Due to the proliferation of information on the internet, it has grown more challenging for users to acquire accurate and trustworthy news in past few years. by integrating text mining techniques and trained artificial intelligence algorithms, bogus news in social networks can be detected. Separate studies on controlled artificial intelligence systems and text mining analyses have been done. The accuracy, recall, precision, and F-measure values of this integrated model have been tested on three separate real-world data sets. We have calculated the average performances of all supervised artificial intelligence systems across all assessment metrics across three data sets [38].

Analysis of socially relevant data is done for incorrect information recognize to determine whether it is true or not. We looked into a range of machine learning methods for this project, such as Naive Bayes, K nearest neighbors, Decision trees, Random forests, and Shallow CNN [39].

Twitter played a significant impact on the most significant political event of the year, the 2016 U.S. presidential vote. Online campaigns for candidates made considerable use of this channel of social media. Meanwhile, there have been many speculations on social networks, which may have had a significant impact on voters' choices.

In this essay, we provide a comprehensive study of rumors tweeted by supporters of Hillary Clinton and Donald Trump. By comparing rumor tweets with confirmed rumor articles, we are able to avoid the challenge of categorizing a huge number of tweets as training data and instead identify rumor tweets. We examine more than 8 million tweets gathered from the two candidates' followers. Our findings address a number of important questions about rumors in this vote, including which side of the followers submitted the most rumors, who posted these rumors, what kinds of rumors they posted, and when they posted them. We can better comprehend online rumor practices in American politics thanks to the insights provided in this research. [40]

The popular and scientific communities have both expressed interest in the subject of fake news. Such misleading news has the possibility of influencing public opinion, giving nefarious groups the chance to influence the results of public events like elections. Automatically identifying false information is a crucial yet difficult topic that is still little understood since the consequences are so high. However, there are three features of false news that are universally acknowledged: the language of an article, the user responses it obtains, and the original users endorsing it. The achievement and generality of the work that has already been done has been severely constrained by its heavy reliance on customizing solutions to a single characteristic. In this study, we provide a model that integrates all three traits for an automated prediction that is more precise. We specifically take into account the actions of both parties—users and articles—as well as the collective actions of users who spread false information. We suggest a model called CSI that is made up of three modules: Capture, Score, and Integrate. This model is driven by the three characteristics. Based on the response and message, the first module employs a recurrent neural network to catch the temporal pattern of user activity on a specific item.. In order to determine if an item is fraudulent or not, the third module integrates with the second module, which learns the resource characteristic based on user activity. [41]

The detection of false information is a crucial but tricky issue in natural language processing (NLP). In addition to resulting in a massive increase in information accessibility, the quick emergence of social media sites has also sped up the transmission of false information. Fake news's influence has grown as a result, occasionally affecting the offline world and jeopardizing public safety. Given the abundance of content online, automatic false information detection is an important NLP problem for all content creators, as it will save people time and effort in identifying and preventing the spread of misleading data [42].

2.4 RELATED WORK

a. The single model's failure to effectively identify bogus news pushed researchers to develop different techniques. There are a number of hybrid-based strategies that combine various models with dynamic processes. Due to the complexity and ambiguity of false news, hybrid detection techniques have emerged as an alternative to numerous traditional fake news detection strategies. [43].

b. Many studies have been conducted utilizing different DL models individually. However, hybrid models are desperately needed to improve the performance of individual models. Therefore, mixed DL has been seen as a developing method for a number of reasons over the last few decades.

c. A hybrid model generally performs better compared to a single model for binary classification [44]. The experiments of reveal that the reliability of hybrid models outperformed all tested models for classification models.

d. We use comparable methods for the creation of text since generative adversarial networks (GANs) have demonstrated significant success, particularly in the realistic generation of images. Using word embeddings, we provide a novel method to handle the discontinuous nature of text during training. In comparison to methods using other discrete gradient estimators, our method produces results that are competitive and independent of vocabulary size [45].

2.5 SUMMARY

Recognizing false news on various websites and social media platforms faster and more effectively, all of the papers in the literature review in this chapter still need to improve their methods and large datasets. This is because the algorithms and models for detecting fake news still need to be more accurate, recall, and precision, and because building large datasets requires more time, money, and effort, The dataset and the model must have sufficient data for training and classification in neural network algorithms because underfitting occurs when the dataset is small, and we need new methods to enhance the data to address this issue.

3. MATERIAL AND METHOD

3.1 PROPOSED MODEL

The following process will be used to accomplish the purpose of this research. The three primary steps of the technique are data preparation, (ii) Auxiliary Classifier Generative Adversarial Networks, and (iii) classifying using a mixed Convolutional neural network and recurrent neural network, as illustrated in Figure 3.1 above.

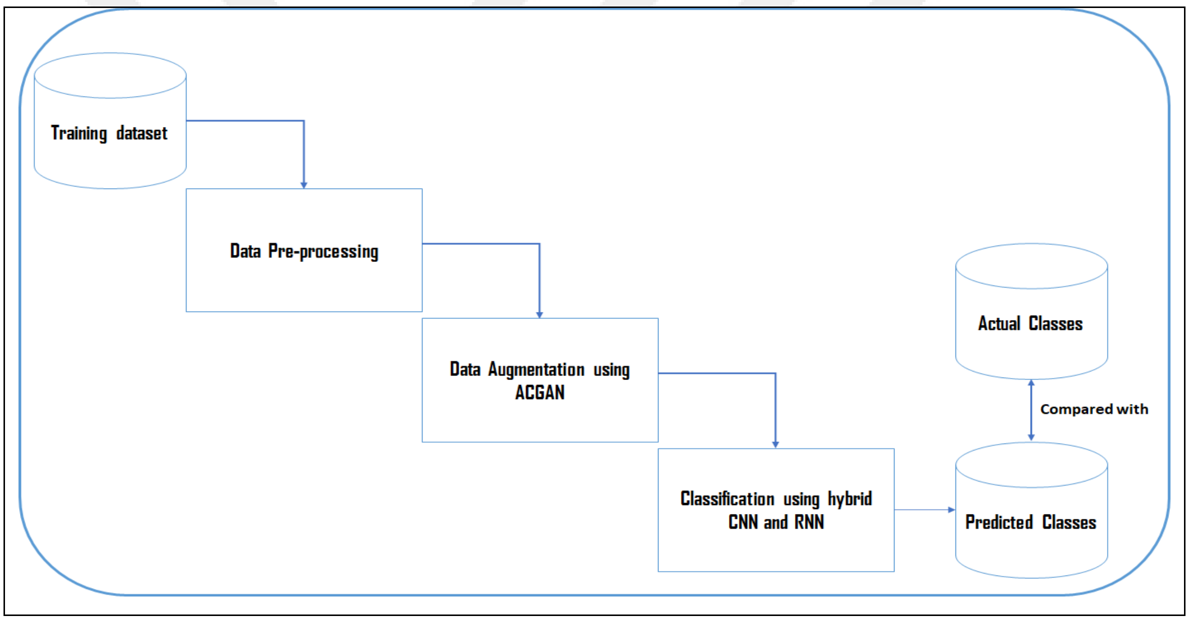

Figure 3.1: Research Methodology

3.2 PRE- PROCESSING

Data will be gathered from internet sites (such as Fake Newsnet, Buzzfeed, and Fake News Challenges) in the initial step to show the efficacy of false information modeling, as has been done in previous research [38-40]. These information will then be pre-processed because of their flexibility in data formats; as a result, preprocessing and encode them before to submitting them to the following stage.

The pre-processing steps are as illustrated in Figure (3.2)

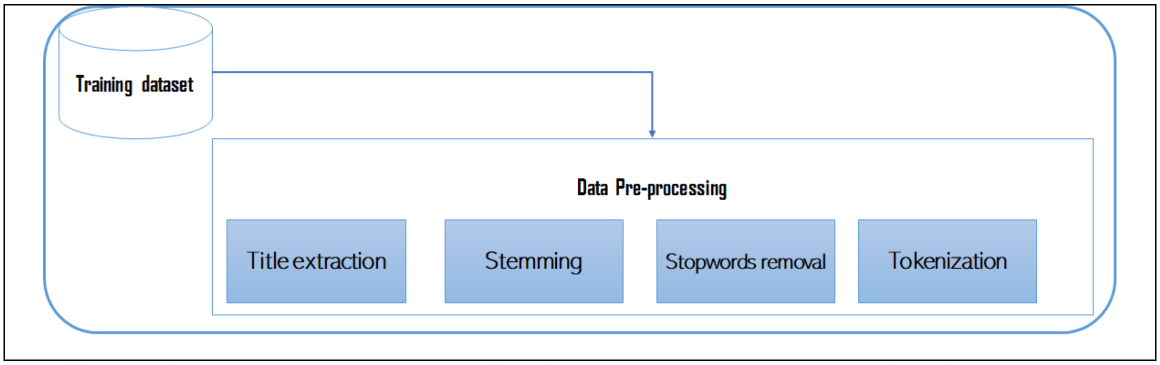

Figure 3.2: Pre-processing Steps.

All words are changed to lowercase, and any URLs are deleted, before beginning any of the labor-intensive pre-processing steps. A straightforward RegEx expression in Python can easily solve this work. Similar to URLs, abbreviations can have unforeseen consequences if used carelessly. To the rescue comes the Python library's Aptly package named contractions. When finding abbreviations, it breaks them apart into their root words. The next step is text normalization, which is the act of condensing multiple spellings or tenses of a single word. Text normalization techniques include stemming and lemmatization, with the former being the less complex. Simply removing a word's suffix will bring it back to its base, which is known as stemming. For instance, "walking," "walks," and "walked" are all derived from "walk." However, stemming is not without drawbacks. We might encounter the problem of over-stemming. Over-stemming is a false positive that occurs when many meanings of a term are derived from the same source. The operation of removing stop words is then carried out since they cannot be removed without having any meaningful impact on the text's meaning. an impact on the text for the intended goal. The Natural Language Toolkit (NLTK) package comes in handy in this situation as the deletion of stop words from the lexicon caters to noise reduction as well as decrease of dimension of the characteristic in Python. You can obtain a set of stop words and English words to compare them with the input tokens. The return tokens are solely English and not stop words in order to identify bogus news. Tokenization, the process of dividing the raw text into little units, is the last step. These tokens are essential for creating context understanding and for the creation of the Natural Language Processing model. Tokenization simplifies the task of determining the text's meaning throughout. It is possible to accomplish tokenization using a variety of techniques.

The Regexp Tokenizer in the NLTK package was used in this study, and it uses either using pattern matching to match characters or separators Sample datasets before and after preprocessing are shown in Figure (3.3)

id	title	text	url	top_img	authors	source	ublish_dat	movies	images	nonical_li	meta_data
Real_1-W	Trump Just Insulted Millions Who Lost Everything In Bus	16.8k	http://occ	http://occ	Brett Bose	http://occ	{'$date': 147493440		http://occ	http://occ	{"generator": "Powered by Visual Compo
Real_10-W	Famous dog killed in spot she waited a year for her own	Famous	http://righ	http://rightwingnew		http://righ	{'$date': 147494833		http://righ	http://righ	{"googlebot": "noimageindex", "og": {"sit
Real_100-'	House oversight panel votes Clinton IT chief in contemp	Story	http://cnn	http://i2.c	Tom Lobia	http://cnn.it			http://i2.c	http://ww	{"description": "Members of the House C
Real_101-'	America Just Tragically Lost A Country Music Icon, Please	We are	http://new	http://new	Nancy We	http://new	{'$date': 1	https://w	http://0.g	http://new	{"shareaholic": {"site_name": "NewsBake
Real_102-'	Monuments to the Battle for the New South	Nine	http://pol	http://sta	Jack Shafe	http://pol	{'$date': 147394182		http://sta	http://ww	{"description": "Virginia, increasingly dive
Real_103-'	RACE TIED on debate day; Colo. and Pa. have turned tig	RACE	http://pol	http://sta	Daniel Lip	http://pol	{'$date': 1474873832		http://sta	http://ww	{"og": {"site_name": "POLITICO", "title": "
Real_104-'	Giuliani slams Lester Holt for fact-checking like Candy Cr	Giuliani	http://pol	http://v.p	Jack Shafe	http://pol	{'$date': 1474971551		http://v.p	http://ww	{"description": "Giuliani took issue with H

A

nnamed:	title	text	source	news_type	contain_movies	contain_images
0	trump million lost everyth bush recess busi	rs one level trump wrong	/occupydemocrat	1	0	1
1	famou dog spot year owner return video	ror write advic everyon	//rightwingnews	1	0	1
2	hous oversight panel chief contempt	appear nake polit agend	http://cnn.it	1	0	1
3	tragic lost countri music icon pleas pray jean famili	still love quit much terrib	tp://newsbake.cc	1	1	1
4	battl new south	s ultim success campaign	http://politi.co	1	0	1
5	e debat day pa turn tight host watch playbook intervie	playbook need know p	http://politi.co	1	0	1
6	holt fact like candi	k real estat fals assert ne	http://politi.co	1	0	1
7	feel bad penc	ike penc defend got con	http://politi.co	1	0	1
8	anti trump super pac debat video	tr part commun campai	http://abcn.ws	1	1	1

B

Figure 3.3: Sample of dataset: a- before pre-processing, b- After pre-processing

3.3 Auto-enhancement of data

The second step attempts to generate a new instance from the first data, train the classifier effectively to prevent fitting problem during training, improving the recognition (or classification) accuracy. An alternative to the GAN is the ACGAN (Generative Adversarial Network). High quality examples that are derived from original instances and have greater training stabilization are provided by the ACGAN. Figure (3.4) shows the ACGAN's architecture.

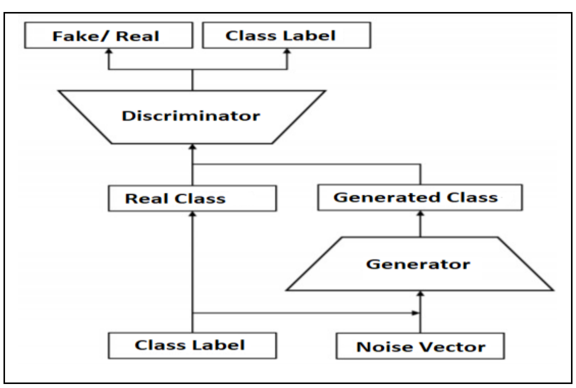

Figure 3.4: Architecture of ACGAN

A training instance or a synthesis instance is fed into the discriminator D by the generation, and it produces a probability distribution P(S | X) = D(X) across potential instance sources. Whereas the generator minimizes the second term, the discriminator optimizes the log-likelihood that it allocates to the proper source. The fundamental GAN framework could be improved with the help of the input data. For the aim of creating class conditional instances, one of the solutions provides class labels to both the discriminator and the generator. The use of class conditional synthesized can significantly improve the quality of generated samples. In addition to the noise z, each produced sample in the ACGAN contains a corresponding class label, c pc. To create text, G uses both. Xfake = G (c, z). P(S | X), P(C | X) = D, the discriminator offers a probability distribution over the sources and a probability distribution over the class labels (X). The log-likelihood of the correct source, abbreviated LS, and the log-likelihood of the correct class, abbreviated LC, make up the optimal solution [46].

LS is equal to E [log P(S = real | Xreal)] plus E [log P(S = f ake | Xfake)]. LC = E[log P(C = c | Xreal)] in equation (3.1)

Log P(C = c | Xfake) + E Eq (3.2)

In contrast to G, who is trained to maximize LC LS, D is trained to maximize LS + LC. The representation for z that AC-GANs learn is unrelated to the class label. This system is fundamentally different structurally from all past models. This structural alteration, which is attributable to the traditional GAN formulation, results in significantly better training stabilization outcomes. And the technological contribution of this endeavor has produced the ACGAN model as its end product.

However, the hybrid model that will be suggested in the following step will employ both the produced dataset instances and the original dataset instances as input. (i.e., the third stage).

3.4 MERGE CNN WITH RNN

In the third phase, false information is identified (i.e., classified) using the suggested detection algorithm, known as CNNRNN-based detecting. Despite the fact that CNN-based detection models perform well when using feature extracted from spatial data (such as digital text), they are not appropriate for processing sequential data (i.e., textual data). models for detection using RNNs on the other hand, have strong skills for modeling sequence information. A mixed model termed CNNRNN-based detection model See Figure (3.5) was developed as a result of their characteristics.

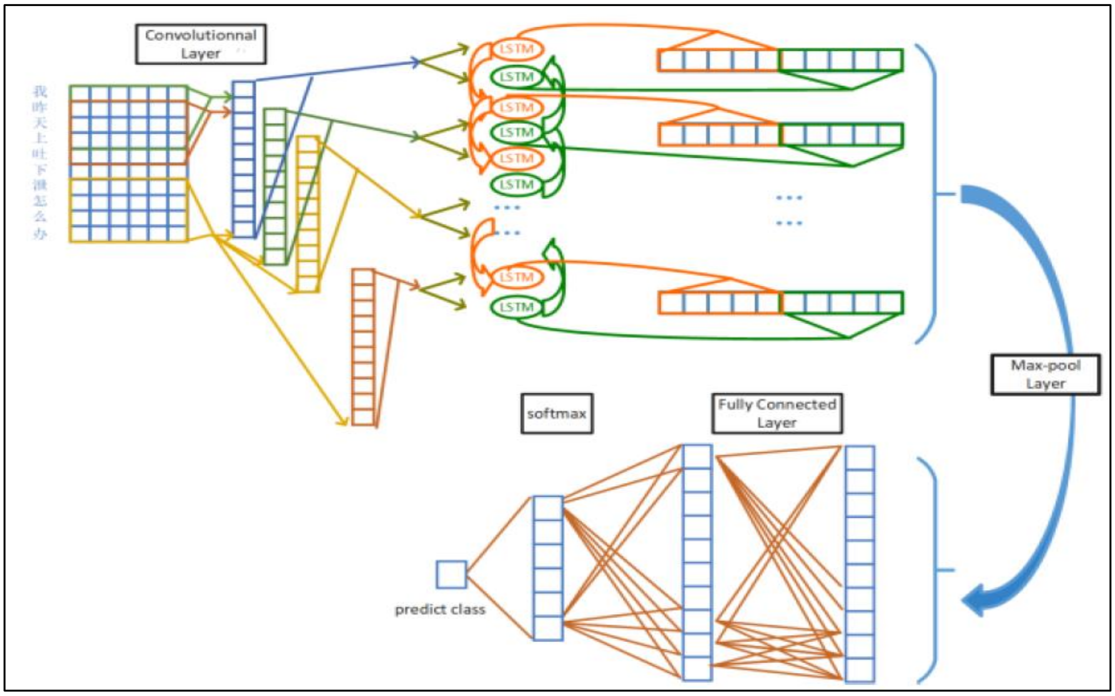

Figure 3.5: CNNRNN- based Detection Model

When using characteristics from spatial information like photos, CNN-based models perform exceptionally well. While CNN struggles to handle sequential data, RNN-based models are particularly effective at handling sequential data like texts. Therefore, a combination model called CNNRNN is suggested by fusing merage convolutional neural network with recurrent neural network technic together. A CNNRNN model is created by adding CNN to the front of the RNN in detail. Y=F(X,) of CRNN can be modeled as follows:

Y=Softmax (FC(LSTM(Pool(Conv(X,CONV), Pool), LSTM), FC)) Eq (3.3)

Another mix involves placing RNN in front of CNN to create the CNNRNN model. CNNRNN's Y=F(X,) can be shown as:

$$Y = \mathrm{Softmax}(FC(\mathrm{Pool}(\mathrm{Conv}(LSTM(X,LSTM),CONV),\mathrm{Pool}),FC)) \quad \text{Eq (3.4)}$$

The input data , which represents brief, sequential sentences, is included. As a result, a new, enhanced version of mixed convolutional neural network with recurrent neural network technic has been proposed, When CNN is not positioned in front of the RNN and the pooling layer is moved behind the LSRMM-RNN layers.The LSRM layer, which is incorporated into this system, analyses the text information protected by the convolution layer and derives the temporal features from the input data. The max-pooling layer comes next, which highlights and compresses the mix of textual and temporal data. The idea behind this enhanced CRNN model is to approach problems sequentially and briefly. The CNNRNN model highlights both the text features and the temporal characteristics by placing the LSRM layer's pooling layer, which has distinguishing properties.

$$Y = \mathrm{Softmax}(FC(\mathrm{Pool}(LSTM(\mathrm{Conv}(X, CONV), LSTM), \mathrm{Pool}), FC)) \quad \text{Eq (3.5)}$$

4. EXPERIMENTAL RESULT AND DISSECTION

4.1 INTRODUCTION

The findings of the suggested approach are discussed in this section. Section 4.2 describes the benchmark datasets, including Buzzfeed news dataset, Fake Newsnet, and FNC-1. Section 4.3 illustrates the effectiveness metrics that will be used to assess the proposed model to detect fake news, including accuracy, precision, and recall. The classification method in Section 4.4 is tested using various evaluation methods. Described in Section 4.5 the programming language and setup of the experimental environment used to implement and test the detection model. In section 4.6, the experimental findings obtained by train and testing the proposed detection model are presented and interpreted. Finally, Section 4.7 conclude this chapter and provides a comparison between state-of-the-art technique and the link prediction model.

4.2 BENCHMARK DATASETS

In total, three datasets were used in this thesis. Buzzfeed news dataset[1], FakeNewsNet[2] and FNC-1[3]. Buzzfeed news dataset comprises the output of nine key publishers in seven days close to the United States elections. Indeed, each publisher gained Facebook's blue checkmark, ensuring authenticity and the status of elevation within the network. For one week, every post and linked digital news article of the nine publishers were fact-traced by expert journalists at BuzzFeed. In sum, about 1,627 digital articles were traced and validated, 826 normal, 256 left-wing, and 545 right-wing individuals are present. as well.

However, the Buzzfeed news dataset contains six main features, as depicted in Table 4.1, including Id, title, text, source, images, and movies.

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[1] https://github.com/BuzzFeedNews.

[2] https://github.com/KaiDMML/FakeNewsNet.

[3] https://paperswithcode.com/dataset/fnc-1.

In this thesis, some features such as “url, top_img, authors, publish date, canonical link and metadata” are not considered since these features often provide redundant and misleading information (i.e., not significant features).

Table 4.1: Buzzfeed features

Feature	**Description**
Id	For every news report, a true or false flag.
Title	Title of the article that draws visitors in and accurately summarizes the news story's subject.
Text	Article's main body
source	the media article's creator or publication
images	The story's visual clues to structure it.
movies	a video or movie clip embedded in a piece of writing.

On the other hand, the Fake News Net dataset comprises digital Space-time, contextual factors, and online media content as well. A principled methodology was/k used to gather relevant data from different sources [47].. Fake News Net dataset covers every piece of bogus news with the following characteristics as depicted in Table 4.2.

Table 4.2: Fake News Net features

Feature	Description
Source	The author/writer of the news article
Headline	The shortened digital text, which catches the readers’ attention.
Bodytext	It resembles the details of news articles.
Imagevideo	It gives visual cues to frame the story.

Last, the FNC-1 dataset comprises three main features including headline, body, and stance, as illustrated in Table 4.3. The dataset is provided as two CSVs, the first is “train_bodies.csv” which includes the body article with the correspond.ing identifier (ID). The second is “train_stances.csv”, which includes the labeled news stances for the corresponding pairs of headlines and the ID of article body.

Table 4.3: FNC-1 features

Feature	Description
Headline	The shortened digital version of the news item.
B,ody	The lengthy news article's text
y/Stankce	The unrelated, discuss, agree or disagree decision regarding the news article

4.3 EVALUATION METRICS

Accuracy, precision, and recall are used to evaluate how well the suggested model performs in identifying false information. These metrics are typically applied in previous related research to validate experimental results.

Calculations for accuracy, precision, and recall are made using the confusion matrix shown in Table 4.4. The true-positive (TP) column of the confusion matrix typically represents the total amount of real news items that have been accurately identified as such. The number of phony news stories that have been successfully identified as false information is shown as True-Negative (TN). False-Positive (FP), which represents the total number of news items that were mistakenly labeled as phony. The final indicator is False-Negative (FN), which shows the overall amount of false reports that were mistakenly labeled as authentic news. The evaluation metrics (accuracy, precision, and recall) are calculated using the respective equations (Eqs 4.1–4.3).

Table 4.4: Confusion Matrix

	Real News	**Fake News**
Real News	TP	FP
Fake News	FN	TN

$$Average\ Accuracy = \frac{\sum(\frac{TP+TN}{TP+TN+FP+FN})}{Total_{Runs}}$$ Eq. (4.1)

$$Precision = \frac{\sum(\frac{TP}{TP+FP})}{Total_{Runs}}$$ Eq. (4.2)

$$Recall = \frac{\sum(\frac{TP}{TP+FN})}{Total_{Runs}}$$ Eq. (4.3)

In this context, the letters TP, TN, FP, and FN stand for true positive, true negative, false positive, and respectively, false negative.

4.4 TESTING APPROACHES

In this thesis, two testing approaches were used to evaluate the detecting model's efficacy, specifically (i) cross validation-based testing approach, and (ii) supplied set-based testing approach.

In the cross validation-based testing approach, the detection model is trained and validated on a part(s) of the dataset, then it will be tested using the remaining part(s) of the dataset. As illustrated in Figure (4.1), every dataset (Buzzfeed news, FakeNewsNet and FNC-1) is broken up into two main parts (i.e., 80% for training and validation purposes, and 20% for testing purpose).

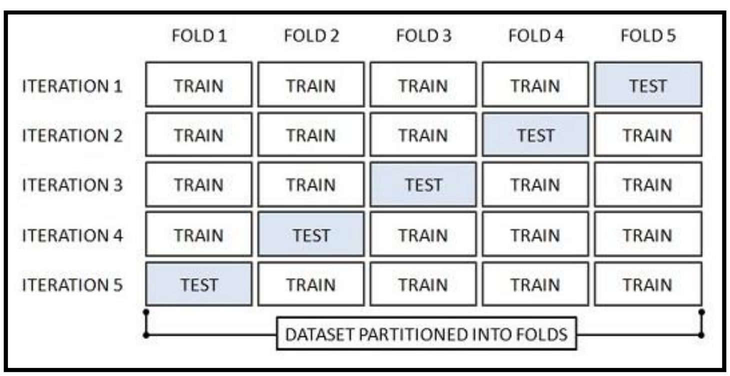

Figure 4.1: 5-fold Cross-validation

Whilst, in the supplied set-based testing approach, as depicted in Figure 4.2, the detection model is trained and validated on a separate dataset part and tested on a completely different dataset that intentionally prepared for testing intent.

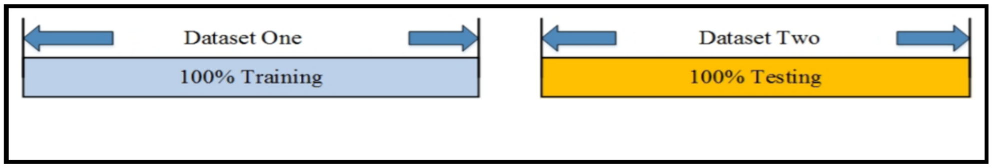

Figure 4.2: supplied set-based testing approach

4.5 IMPLEMENTATION ENVIRONMENT

The programming language and setup of the experimental environment used to implement and test the detection model are described in detail is the following subsections.

4.5.1 Programing Language

The detection model was implemented using Python programming language, because of its easiness and robustness, as Python comprises several libraries that provide developers/implementers to implement deep learning easily as a black and white box [48] However, Table 4.5 illustrates the main Python libraries utilized to implement the proposed detection model.

Table 4.5: Python Libraries

Library	Version	Description
nltk	3.6.5	Natural Language Toolkit is used to remove stop words, extract word tokenization, and find a stem of the words at preprocessing stage.
re	2.2.1	It is a regular expression used in the preprocessing stage to identify the numbers and punctuation marks.
pandas	1.3.4	it reads the data from the CSV file and converts it to a data frame to deal with data efficiently.
numpy	1.20.3	It is used for applied linear algebra on matrices and generated random numbers.
tensorflow	2.9.1	To build deep learning model and finding evaluation metrics.
sklearn	1.1.1	It used to extract features based on TF-IDF technique. Note: sklearn.feature_extraction.text import TfidfVectorizer

4.5.2 Experimental Environment

4.5.2.1 Hardware specifications

Table 4.6 presents the hardware specifications used to implement the proposed detection model and to evaluate its performance.

Table 4.6: Hardware Specifications

Hardware	Specification
Central Processing Unit	Core i7-8565 U
Random Access Memory	16 GB
Hard Disk Drive	512 GB SSD
Graphics Processing Unit	NVIDIA GeForce RTX 3070

4.5.2.2 Software specifications

Table 4.7 presents the hardware specifications used to implement the proposed detection model and to evaluate its performance.

Table 4.7: Software Specifications

Hardware	Specification
OS	Windows 10
Implementation Environment	Anaconda, Spider
Implementation Language	Python

4.6 RESULTS AND DISCUSSION

This section describes and discusses the results of the experiment by train and test the proposed detection model. As mentioned earlier, the proposed detection model was trained and tested evaluated using three benchmark datasets, namely: (i) Buzzfeed news dataset, (ii) FakeNewsNet, and (iii) FNC-1. Each dataset experiment has repeatedly performed with science's test (Devore, 2015several runs to achieve the basic requirements of computer). The following subsections present the overall conclusions drawn from the suggested detection model. Additionally, the usefulness of the suggested detection model is provided along with its accuracy, precision, and recall.

Figure (4.3) represents the evaluation strategy used in evaluating the proposed detection model.

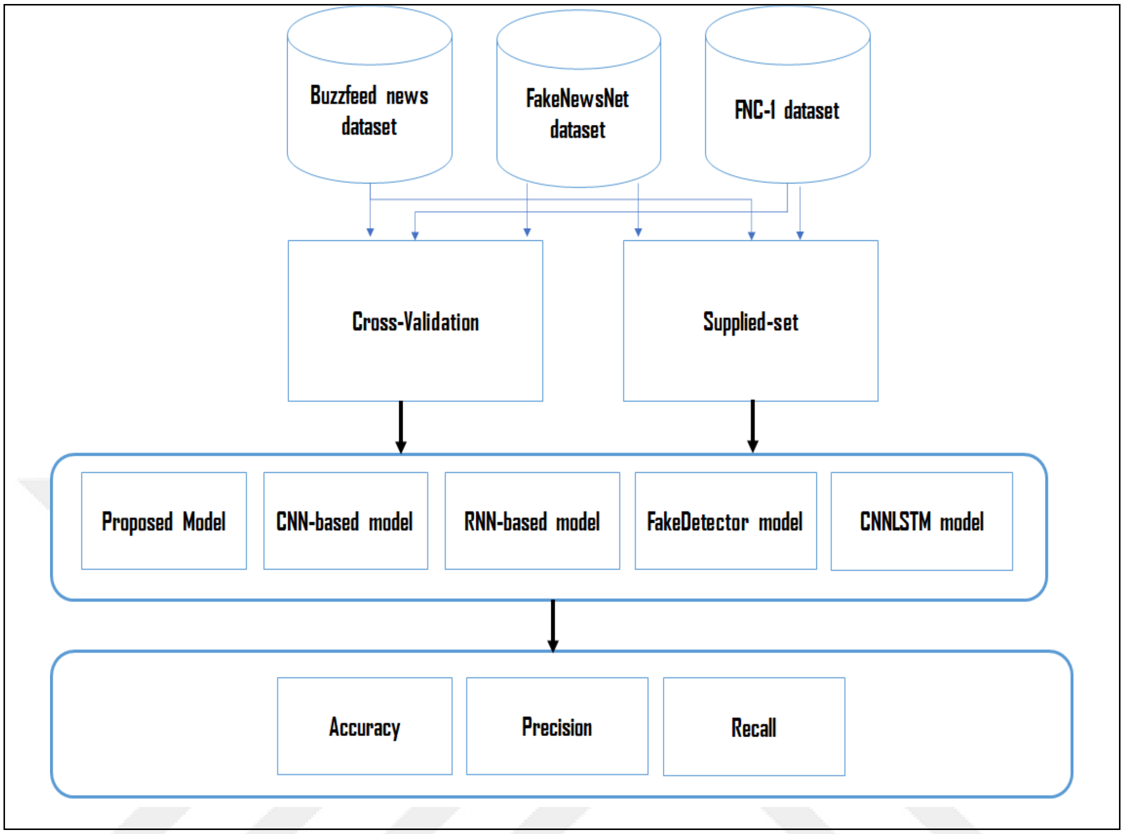

Figure 4.3: The evaluation strategy

4.6.1 Evaluation of the Proposed Detection Model using Buzzfeed Dataset (First Scenario)

The analysis of the suggested prediction model is presented in this section using Buzzfeed dataset by presenting the experimental results of using both cross validation-based and supplied set-based testing approaches.

The proposed detection model was executed along with 1000, 2000, 2500, 3000, and 4000 epochs, respectively using the Buzzfeed dataset, to calculate the average results and therefore achieve the test requirements of computer science as aforementioned. In terms of average detection accuracy, the proposed detection model achieves 96.1%, 96.8%, 97.24%, 97.58%, and 97.83% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 97.11% detection accuracy when used with Buzzfeed dataset. Table 4.8 illustrates the average detection accuracy of fake news in Buzzfeed dataset using the proposed detection model.

Table 4.8: Average Detection Accuracy using Buzzfeed Dataset

No. of Epochs	Accuracy
1000	0.961
2000	0.968
2500	0.9724
3000	0.9758
4000	0.9783
Average	**0.9711**

In terms of precision, the proposed detection model achieves 92%, 94.1%, 94.8%, 95.67%, and 96.5% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 94.614% precision when used with Buzzfeed dataset. Table 4.9 illustrates the average precision of detecting fake news in Buzzfeed dataset using the proposed detection model. This means that the proposed detection model detects more relevant cases (fake news) than irrelevant ones.

Table 4.9: Average Precision using Buzzfeed Dataset

No. of Epochs	Precision
1000	0.92
2000	0.941
2500	0.948
3000	0.9567
4000	0.965
Average	**0.94614**

Last, in terms of recall, the proposed detection model achieves 93%, 93.9%, 94.6%, 95.1%, and 95.9% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 94.5% precision when used with Buzzfeed dataset. Table 4.10 illustrates the average recall of detecting fake news in Buzzfeed dataset using the proposed detection model. This means that the proposed detection model detects most of the relevant cases.

Table 4.10: Average Recall using Buzzfeed Dataset

No. of Epochs	Recall
1000	0.93
2000	0.939
2500	0.946
3000	0.951
4000	0.959
Average	**0.945**

4.6.2 Evaluation of the Proposed Detection Model using Fake News Net Dataset (Second Scenario)

The proposed method model is evaluated in this section utilizing FakeNewsNet Dataset by presenting the experimental results of using both cross validation-based and supplied set-based testing approaches.

The proposed detection model was executed along with 1000, 2000, 2500, 3000, and 4000 epochs, respectively using the FakeNewsNet dataset, to calculate the average results and therefore achieve the test requirements of computer science as aforementioned. In terms of average detection accuracy, the proposed detection model achieves 93.1%, 95.8%, 95.9%, 96.13, and 96.9% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 95.566% detection accuracy when used with FakeNewsNet dataset. Table 4.11 illustrates the average detection accuracy of fake news in Fake News Net dataset using the proposed detection model

Table 4.11: Average Detection Accuracy using Fake News Net Dataset

No. of Epochs	Accuracy
1000	0.931
2000	0.958
2500	0.959
3000	0.9613
4000	0.969
Average	**0.95566**

In terms of precision, the proposed detection model achieves 90.8%, 93.4%, 94.6%, 95.32, and 95.39% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 93.902% precision when used with FakeNewsNet dataset. Table 4.12 illustrates the average precision of detecting fake news in FakeNewsNet dataset using the proposed detection model. This means that the proposed detection model detects more relevant cases (fake news) than irrelevant ones.

Table 4.12: Average Precision using FakeNewsNet Dataset

No. of Epochs	Precision
1000	0.908
2000	0.934
2500	0.946
3000	0.9532
4000	0.9539
Average	**0.93902**

Last, in terms of recall, the proposed detection model achieves 93%, 93.9%, 94.6%, 95.1%, and 95.9% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 94.5% precision when used with FakeNewsNet dataset. Table 4.13 illustrates the average recall of detecting fake news in FakeNewsNet dataset using the proposed detection model. This means that the proposed detection model detects most of the relevant cases.

Table 4.13: Average Recall using Fake News Net Dataset

No. of Epochs	Recall
1000	0.93
2000	0.939
2500	0.946
3000	0.951
4000	0.959
Average	**0.945**

4.6.3 Evaluation of the Proposed Detection Model using FNC-1 Dataset (Third Scenario)

The evaluation of the suggested prediction model is presented in this section using FNC-1 Dataset by presenting the experimental results of using both cross validation-based and supplied set-based testing approaches.

The proposed detection model was executed along with 1000, 2000, 2500, 3000, and 4000 epochs, respectively using the FNC-1 dataset, to calculate the average results and therefore achieve the test requirements of computer science as aforementioned. In terms of average detection accuracy, the proposed detection model achieves 95.5%, 95.8%, 96.2%, 97.4%, and 97.43% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 96.466% detection accuracy when used with FNC-1 dataset.

Table 4.14 illustrates the average detection accuracy of fake news in FNC-1 dataset using the proposed detection model.

Table 4.14: Average Detection Accuracy using FNC-1 Dataset

No. of Epochs	Accuracy
1000	0.955
2000	0.958
2500	0.962
3000	0.974
4000	0.9743
Average	**0.96466**

In terms of precision, the proposed detection model achieves 92.3%, 93.2%, 95.1%, 96%, and 96.4% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 94.6% precision when used with FNC-1 dataset. Table 4.15 illustrates the average precision of detecting fake news in FNC-1 dataset using the proposed detection model. This means that the proposed detection model detects more relevant cases (fake news) than irrelevant ones.

Table 4.15: Average Precision using FNC-1 Dataset

No. of Epochs	Precision
1000	0.923
2000	0.932
2500	0.951
3000	0.96
4000	0.964
Average	**0.946**

Last, in terms of recall, the proposed detection model achieves 94%, 94.5%, 95.2%, 95.4%, and 95.56% in 1000, 2000, 2500, 3000, and 4000 epochs, respectively. On average, the proposed detection model achieves 94.932% precision when used with FNC-1 dataset.

Table 4.16 illustrates the average recall of detecting fake news in FNC-1 dataset using the proposed detection model. This means that the proposed detection model detects most of the relevant cases.

Table 4.16: Average Recall using FNC-1 Dataset

No. of Epochs	Recall
1000	0.94
2000	0.945
2500	0.952
3000	0.954
4000	0.9556
Average	**0.94932**

4.7 COMPARISON WITH STATE-OF-THE-ART MODELS

To demonstrate its effectiveness, The proposed methodology has been contrasted with various cutting-edge models, including CNN-based models [49], RNN-based [50], FakeDetector [51], and CNNLSTM [52]. In comparison to existing state-of-the-art models, the outcomes showed that the suggested model is more successful at identifying false information and achieves great results (in terms of accuracy, precision, and recall), as shown below in Figure (4.4)

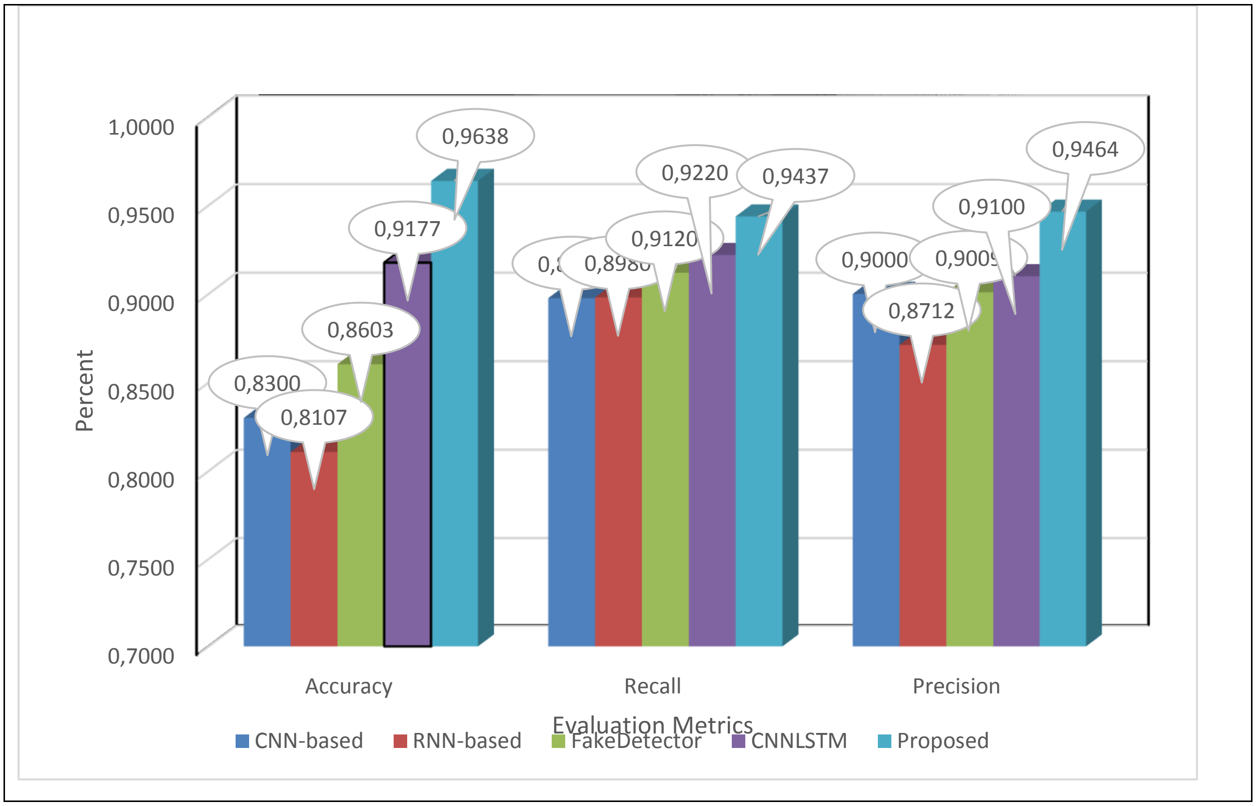

Figure 4.4: Comparison with State-of-the-Art Models

As shown in Figure 4.12, the results ensure the superiority of the proposed detection model over the other state-of-art detection models in terms of the average accuracy, precision, and recall, as the proposed detection model obtained the highest average fake news detection accuracy (i.e., 96.38%) and the highest precision (94.64%), and the highest recall (94.37%).

Ultimately, concluded from the above results, the proposed detection model is indeed a practical automatic fake news detection model to overcome the research gaps mentioned in Chapter One (refer to research problem section). In sum, the use of appropriate preprocessing and automatic data augmentation has increased the overall performance and avoided overfitting and underfitting problems during model training, then in detecting fake news, respectively. Though the use of deep learning models carries out more efficiently than machine learning models, particularly when learning from, a massive volume of data, the overall performance of deep learning models declines remarkably in the case of learning from overfitting or underfitting. And, whereas there is a lot of prior research on deep learning, most of them still suffer from these weaknesses that may result in data loss, underfitting or/and overfitting. The proposed detection model demonstrates that it copes with these issues by using automatic data augmentation.

In sum, particularly the proposed detection model might be applied to detect fake news automatically, without being vulnerable to wrong detection (false detection). When this detection model is implemented on real digital news, this digital news is efficiently classified into real and fake ones; thus, the reader/publisher can distinguish the fake news from real ones; and consequently, it will have the ability to recognize the writer/author of fake news. The proposed detection model achieves the requirements of providing high performance and efficient and automatic self-decision. This detection model also demonstrates outstanding performance compared with CNN-based, RNN-based, FakeDetector, and CNNLSTM in terms of accuracy, precision, and recall.

5. CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

In this work, a mixed deep learning model-based method for automatically recognizing fake information is proposed. Modern models that only take into account the individual sentences or specific phrases of the news are not as comprehensive as the developed framework, which focuses primarily based on the news's headline and content. The suggested developed system uses an automated addition of data technique called Auxiliary Classifier Generative Adversarial Networks to create new items of false information on purpose. Convolutional neural networks should then be combined with recurrent neural networks to effectively recognize fake stories. To make certain that the data are ready to be entered through deep learning algorithms, Title collection, breaking, removing stop words and blockchain are the first steps in data before processing. Following, therefore, Auxiliary Classifier Generative Adversarial Systems are employed to enhance the richness of these databases and guarantee that information loss and overfitting are prevented the classification training phase. Last but not least, the mixed predictor between the CNN with RNN is trained using the dataset produced by the Auxiliary Classifier Generative Adversarial nets validation data and is utilized to assess the recognition rate the present design. In comparison to other state-of-the-art recognize techniques, this model consistently achieves results that are promising, scoring 93.87%, 10.39%, and 93.12% efficiency, recalled, and precision, respectively. It is important to note includes preprocessing and automatically enhancing data help to maintain the high efficiency of the suggested classifiers while lowering the amount of noise in the data and overfitting.

5.2 FUTURE WORK

Future works may explore new algorithms, hybridize existing techniques, and incorporate sophisticated optimization algorithms to improve the current work. The performance of the models can be improved by combining ensemble methods and other feature extraction techniques. Feature selection techniques can be used to improve classification performance by reducing the dimensionality of the data. Other textual elements could also be taken into account to improve the effectiveness of the detecting process.

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