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Fake news detection with deep neural networks

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DEDICATION

Almighty God, thank you for always being with me.

In the name of love and respect, I dedicate this work to my dear Mother and my dear father Allah Yarahmo for all their sacrifices, their love, their tenderness, their support, and their prayers throughout my educational journey.

I would like to say thank you:

To my brothers (Tarek and Ahmed and Yacine)& sisters(Amira and aala)They always have been my source of happiness, support and motivation.

To all my friends with whom I spent my best moments.(Chahrazed and Nour...)

OuddaneBelkisse

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Hamaidia Zainab

Abstract

The proliferation of fake news has become a significant concern in today's digital age, where information spreads rapidly through various online platforms. This search presents a comprehensive study on the detection of fake news using deep neural networks (DNNs). We explore the application of advanced deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based models, to identify and classify fake news. Our approach leverages large datasets to train the models, ensuring robustness and accuracy. By incorporating natural language processing (NLP) techniques, such as word embeddings and attention mechanisms, we enhance the models' ability to understand and analyze the context and semantics of news articles. Experimental results demonstrate that our deep learning models outperform traditional machine learning methods, achieving high accuracy in distinguishing between genuine and fake news. The findings underscore the potential of deep neural networks as effective tools in combating misinformation and highlight the importance of ongoing research in this domain.
Key words : fake news Detection , Deep Neural Networks(DNNs) , Convolutional Neural Networks (CNNs) ,Machine Learning (ML) ,Misinformation,Long Short Term Memory(LSTM)

Résumé

La prolifération des fausses nouvelles est devenue une préoccupation majeure à l'ère numérique d'aujourd'hui, où les informations se propagent rapidement via diverses plateformes en ligne. Cet recherche présente une étude approfondie sur la détection de fausses nouvelles à l'aide de réseaux de neurones profonds (DNN). Nous explorons l'application de techniques avancées d'apprentissage en profondeur, notamment les réseaux de neurones convolutifs (CNN), les réseaux de neurones récurrents (RNN) et les modèles basés sur des transformateurs, pour identifier et classer les fausses nouvelles. Notre approche exploite de grands ensembles de données pour entraîner les modèles, garantissant ainsi robustesse et précision. En incorporant des techniques de traitement du langage naturel (NLP), telles que l'intégration de mots et les mécanismes d'attention, nous améliorons la capacité des modèles à comprendre et à analyser le contexte et la sémantique des articles d'actualité. Les résultats expérimentaux démontrent que nos modèles d'apprentissage profond surpassent les méthodes traditionnelles d'apprentissage automatique, atteignant une grande précision dans la distinction entre les vraies et les fausses nouvelles. Les résultats soulignent le potentiel des réseaux neuronaux profonds en tant qu'outils efficaces pour lutter contre la désinformation et soulignent l'importance des recherches en cours dans ce domaine.

Mots clés : détection de fausses nouvelles, réseaux de neurones profonds (DNN), réseaux de neurones convolutifs (CNN), apprentissage automatique (ML), désinformation, mémoire à long terme (LSTM)

ملخص

أصبح انتشار الأخبار المزيفة مصدر قلق كبير في العصر الرقمي اليوم، حيث تنتشر المعلومات بسرعة عبر منصات مختلفة عبر الإنترنت. يقدم هذا البحث دراسة شاملة حول اكتشاف الأخبار المزيفة باستخدام الشبكات العصبية العميقة.(**DNNs**)نحن نستكشف تطبيق تقنيات التعلم العميق المتقدمة، بما في ذلك الشبكات العصبية التلافيفية(**CNNs**)، والشبكات العصبية المتكررة(**RNNs**)، والنماذج القائمة على المحولات، لتحديد وتصنيف الأخبار المزيفة. يستفيد نهجنا من مجموعات البيانات الكبيرة لتدريب النماذج، مما يضمن المتانة والدقة. ومن خلال دمج تقنيات معالجة اللغة الطبيعية(**NLP**)، مثل تضمين الكلمات وآليات الانتباه، فإننا نعزز قدرة النماذج على فهم وتحليل سياق ودلالات المقالات الإخبارية. وتظهر النتائج التجريبية أن نماذج التعلم العميق لدينا تتفوق على أساليب التعلم الآلي التقليدية، وتحقق دقة عالية في التمييز بين الأخبار الحقيقية والمزيفة. تؤكد النتائج على إمكانات الشبكات العصبية العميقة كأدوات فعالة في مكافحة المعلومات الخاطئة وتسلط الضوء على أهمية مواصلة البحث في هذا المجال.

الكلمات المفتاحية: اكتشاف الأخبار المزيفة، الشبكات العصبية العميقة (CNNs)، الشبكات العصبية التلافيفية (CNNs)، التعلم الآلي (ML)، المعلومات المضللة، الذاكرة طويلة المدى (LSTM)

Table of contents

Abstract

Table of contents

Table of Figures

Table of tables

General Introduction..1

Chapter I: RELATED WORKS 2

False information and fake news 3

1.1. Introduction 3

1.2. False information 3

1.2.1 What is false information?...3

1.2.2 False information Categories 3

Misinformation 4

Disinformation 4

The components of false information 4

1.2.3 Type of false information..5

1.2.4 False Information Actors..6

1.3. Fake news: 7

1.3.1 What is fake news? 7

1.3.2 Types of fake news...7

1.3.3 Identifying False News 9

1.4 RELATED WORK...12

1.5 Conclusion... **Error! Bookmark not defined.**

Chapter II: Methodology..13

Machine Learning and Deep Learning 14

2.1. Introduction: 14

2.2. What is Artificial Intelligence? 14

2.3. How Does AI Work? 14
2.4. What is Machine Learning? 15
2.5.1. Supervised machine learning: 16
2.5.2. Unsupervised machine learning: 18
2.5.3. Semi-supervised learning: 19
2.6. Algorithms of Machine Learning: 20
2.7. Deep Learning 22
2.7.1 What is Deep Learning? 22
2.7.2. Difference Between Deep learning And Machine learning: 24
2.8. Neural networks 25
2.9. Deep Neural Network: 26
2.10. Convolution neural network (CNN) 27
2.11. Long Short Term Memory (LSTM): 29
2.12. Conclusion 30
Chapter 03: Discussion and findings results 32
3.1. Introduction: 33
3.2. Objective and Motivations 33
3.2.. Solution: 33
3.3. Problematic description: 34
3.3.1. Method and Implementation Tools: 34
3.3.2. Implementation Tools: 36
3.3.3. Proposed model: 39
3.4. Results and Discussion: 49
3.4.1. Results 49
3.5. Conclusion 50
General Conclusion 51
Bibliography 53

Liste of Figures

Figure I.1: Definitions of Related Terms and Their Relationship 4

Figure I.2: Automatic News Fact-checking Process 11

Figure II.1: Types of machine learning 16

Figure II.2: Model of supervised learning 17

Figure II.3: Classification and Regression 18

Figure II.4: Unsupervised machine learning 19

Figure II.5: Deep learning types 23

Figure II.6:Relationship between AI, ML, DL, and NLP 23

Figure II.7: Schematic of Different between Deep learning And Machine learning 25

Figure II.8: Architecture of Artificial Neural Network 26

Figure II.9: Deep neural network with three hidden layers 27

Figure II.10: Architecture of Convolutional Neural Network 28

Figure II.11: The LSTM Cell in Artificial Neural Networks (ANNs) 29

Figure III.1: Virtual Environments in Anaconda Jupyter notebook 37

Figure III.2: MATRICS OF LSTM MODEL 42

Figure III.3: Model Evaluation metrics of BILSTM 45

Figure III.4: Model Evalution Metrics of CNN-BILSTM 49

Figure III.5: Graph columns representing each model 50

Liste of tables

Table III.1: Examples from dataset..35

Table III.2: Results 50

General Introduction

There has been a revolution since the introduction of social media and the Internet. When it comes to publishing news, the idea of news has drastically evolved. With the advent of live news, the media made it possible for anybody to access and distribute news to millions of people worldwide for essentially free in a matter of seconds.

Fake news detection is a critical challenge in today's digital age, where misinformation can spread rapidly and have serious consequences. An introduction to fake news detection could start by highlighting the importance of distinguishing between accurate information and false or misleading content. It could also mention the role of technology, such as machine learning and natural language processing, in developing tools and algorithms to identify and combat fake news. Additionally, it could touch upon the need for critical thinking and media literacy to help individuals discern the credibility of information they encounter online. Such misinformation (also known as "Fake News") has a broad spectrum of types and forms. For example, rumors, fake advertisements, satires, and false political reports are different types of fake news [1]. The spread of fake news becomes more viral than the true news urged many researchers to concentrate on innovating efficient automated solutions for detecting fake news .Google has announced a new service named "Google News Initiative" aimed at tracking and eliminating fake news. This project will assist users in distinguishing fake news and reports .

Regrettably, the quality of news has significantly decreased as a result of the news's quick dissemination. Additionally, it has resulted in a notable surge in the dissemination of misleading information and fake news. People may now easily and quickly acquire information thanks to it, but this occurs far too frequently. It is challenging to determine its credibility. False information spreading widely: They present serious issues and have a variety of social effects.This thesis seeks to develop a model for identifying false information disseminated on social media.

This thesis seeks to develop a model for identifying false information that is disseminated on social media.The goal of this thesis is to create a model for spotting misleading content that circulates on social media. We make use of the fake news dataset, which is made up of news stories gathered from various social media sites, such as Twitter, Facebook, Instagram, and others. Our approach consists of compiling two deep learning models: long short-term memory (LSTM) and convolutional neural network (CNN).

Chapter I

False information and fake news

1.1. Introduction

Spreading accurate or inaccurate information Misinformation, whether through media, word-of-mouth, or other sources, has long existed. But technology keeps getting better every day. False information is spreading at a rate and scale never seen before due to changes in how individuals interact with information. As a result, information disorder, including disinformation, is now dangerously affecting information ecosystems.

Since fake news is the main focus of our work, we will first discuss false information, including its history, categories, and components. Next, we will discuss fake news and its spreaders. Finally, we will close the chapter with a discussion on fighting fake news, its dangers, and some detection techniques.

For facilitating the understanding and explaining of false information on web and social media, Kumar et alsummarize and classify false information based on its intention .

1.2. False information

1.2.1 What is false information?

False information means any written or verbal statement or representation of fact that is not true and that was made intentionally, knowingly or without having taken reasonable steps to realization whether or not the information was true. [2]

False information is divided into two categories: misinformation and disinformation, depending on the motivation behind its dissemination. Both have detrimental effects, but the latter might do more harm because its primary developer wants to do evil.. Disinformation is the creation and dissemination of false information with the intent to mislead, deceive and confuse readers .

Disinformation is prevalence with the intention of making money, spreading false information, and harming an individual, group, or nation.

1.2.2 False information Categories

False Information can be divided into 2 important categories:

- Misinformation,
- Disinformation

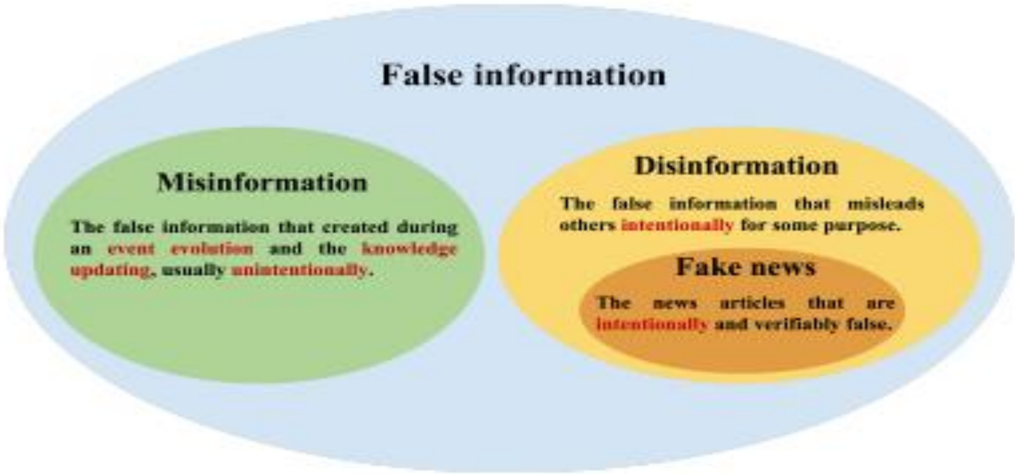

Figure I.1:The Definitions of Related Terms and Their Relationship.

Misinformation

Is information that is false, but the person who is disseminating it believes that it is true. [3]

Misinformation has dire effects, and has recently become increasingly widespread on the Internet, fueled by new technologies. The result is that digital misinformation, in polarized contexts, threatens to overtake quality Traditional journalism and truth. However, we may be looking for a strategy aimed at mitigating misinformation while protecting and promoting freedom of expression.

Disinformation

It is false information that is spread intentionally in order to mislead society and public opinion and cause problems: “is also information deliberately and often covertly spread (as by the planting of rumors) in order to influence public opinion or obscure the truth”

The components of false information

The term false information consists of four elements

1) **Creator/Spreader** False information is created and spread by people who are either spreaders or creators of disinformation on the internet; these individuals may or may not be human??

2) **News content** We refer to the main body of the news as news content. In other words, it has both tangible content and (such as title, body text, and multimedia) and intangible content (such as purpose, sentiment, and themes).

3) **Targeted victims** Any user of social media or other contemporary platforms and websites could be one of the victims. Targets in society could include a variety of groups, including parents, senior folks, students, and voters.

4) **Social context** The social environment reveals the online news distribution model. User and network analysis are included in social context analysis. (the way people interact with news on the internet) and broadcast pattern analysis.

1.2.3 Type of false information

False information has different forms found on the Internet, including:

- **Fabricated (F)** Completely fictional stories disconnected entirely from real facts. This type is not new and it exists since the birth of journalism. Some popular examples include fabricated stories about politicians and aliens
- **Hoaxes (H)** News stories that contain facts that are either false or inaccurate and are presented as legitimate facts. This category is also known in the research community either as half-truth or factoid stories.
- **Clickbait (CL)** refers to the practice of using deceptive headlines and content descriptions to draw attention and persuade users to click on a link that leads to a specific webpage. It is one of the less dangerous types of fake information because it is immediately identifiable after clicking the link and reading the content. It is frequently produced for financial gain.
- **Rumors (R)** Refers to stories whose truthfulness is ambiguous or never confirmed. This kind of false information is widely propagated on OSNs , hence several studies have analyzed this type of false information.
- **Satire News (S)**. Stories that contain a lot of irony and humor. This kind of news is getting considerable attention on disseminated via social networks, this fact is obfuscated, overlooked, or ignored by users who often take them at face value with no additional verification.
- **Fake News (F**) False stories that are embellished to trick readers into believing they are authentic are known as fake news .This issue has persisted since the invention of the press, making it difficult to determine whether the news being reported is accurate and trustworthy or not. [4].

- **Biased or one-sided (B)**. Refers to stories that are extremely one-sided or biased. In the political context, this type is known as Hyper partisan news and are stories that are extremely biased towards a person/party/situation/event. Some examples include the wide spread diffusion of false information to the alt-right community from small fringe Web communities .

1.2.4 False Information Actors

Fake information actors are those responsible for spreading false information and those who help spread it. There are many types that work to spread misinformation via the Internet which is listed below.

- **"True Believers" and Conspiracy Theorists**. Refer to individuals that share false information because they actually believe that they are sharing the truth and that other people need to know about it. They, for example,might take a side of an ideological debate without being aware of the malicious agenda driving the ideology [5] .
- **Journalists** . Individuals that are the primary entities responsible for disseminating information both to the online and to the offline world. However, in many cases, journalists are found in the center of controversy as they post false information for various reasons. For example, they might change some stories so that they are more appealing, in order to increase the popularity of their platform, site, or newspaper.
- **Bots** .In the context of false information, bots are programs that are part of a bot network (Botnet) and are responsible for controlling the online activity of several fake accounts with the aim of disseminating false information. Botnets are usually tied to a large number of fake accounts that are used to propagate false information in the wild. A Botnet is usually employed for profit by 3rd party organizations to diffuse false information for various motives. Note that various types of bots exist, which have varying capabilities and others post "original" content. However, this distinction is outside of the scope of this work, which provides a general overview of the information ecosystem on the Web.
- **Governments** . Historically, governments were involved in the dissemination of false information for various reasons.More recently, with the proliferation of the Internet, governments utilize the social media to manipulate public opinion on specific topics. Furthermore, there are reports that foreign governments share false information on other countries in order to manipulate public opinion on specific topics that regard the particular country [6].

- **Hidden Paid Posters** [7] **and State-sponsoredTrolls** . They are a special group of users that are paid in order to disseminate false information on a particular content or targeting a specific demographic. Usually, they are employed for pushing an agenda; e.g., to influence people to adopt certain social or business trends. Similar to bots, these actors disseminate false information for profit. However, this type is substantially harder to distinguish than bots because they exhibit characteristics similar to regular users.
- **Activist or Political Organizations** False information is disseminated by several organizations to support one another, denigrate competitors, or tell the public a particular story. Political parties that disseminate misleading information are one example, particularly in the run-up to important elections [8].

1.3. Fake news:

1.3.1 what is fake news?

Fake news has been around for a very long time and has spread widely. However, it has several definitions, including:

Definition 1 False information that may be independently confirmed is included in fake news, which is produced with the malicious goal to deceive customers. In recent studies, this definition has been widely used. [9]

Definitions 2 fake news have grow to be a significant phenomenon on social media. It is a representation of inaccurate and fraudulent information sent through the mainstream media as a news item or message, with the intention of tricking readers into thinking they are reading the actual thing.

Fake news is typified by mimicking the appearance of news media, acting authentic, and attempting to look authentic by adopting a legitimacy and credibility that aligns with the news paradigm. In addition to using accounts and bots to propagate over the network, fake news is produced for a variety of reasons.

1.3.2Types of fake news

Fake news is largely used to manipulate the public for so many different reasons. Here are the most common types of fake news [10]:

- **News Fabrication**

This **research** indicates that it is not its true basis, but it is published articles that are extremely important and then credible. Unlike parodies, there is no implicit understanding between the authors and the reader that the article is false. The truth is that the intent is often quite the exact opposite, and it is usually on a published website or blog Or on social media platforms and we talked about great suffering between training on news and fake news.

- **Satire News**

Satire news uses the style of a television news broadcast and often focuses on current affairs and uses humor to provide critique of political, economic or social affairs. Sometimes, audience with no knowledge might mistakenly consider news satire as actual news .therefore satirical websites often disclose their satirical nature in the description provided by their website .

- **Parody news**

Parody, like satire, uses humor to draw its audience who is aware that the information presented are fictitious, but the main difference is that the news stories used to inject humor are entirely fictional .

Rather than using humor to make a direct remark on current events, parodies use humor to illustrate the ridiculousness of certain topics.

- **Viral publications**

Every second,There are an endless amount of new publications that appear on social media.

Users consequently don't take the time to confirm each one's legitimacy. The most popular posts are shared more frequently, even if they are fraudulent, because the main social media platforms are focused on shares, likes, and followers.

- **False Headlines**

False headlines designed to grab attention .Frequently, after reading the article, one discovers that the title is purposefully deceptive and does not match to the text's content. Another term for these titles is "clickbait titles."

- **Photo Manipulation**

The term "fake news" has also been used to describe the fabrication of a story by altering real photos or videos. Refer to the "Visual News" category in situations when the preceding classifications for text-based articles are generally discussed.

With the introduction of digital pictures, the ability to manipulate images with powerful software, and an understanding of techniques, image manipulation has become more widespread. There could be simple or complex effects. Simple alterations include boosting color saturation and eliminating little details. More drastic alterations could involve taking someone out of or adding them to an image.

1.3.3 Identifying False News

The best defense against false information is to only believe news that can be independently confirmed. As we have seen throughout this chapter, identifying false information is a difficult undertaking. In the fast-paced world of today false news permeates social media and is there everywhere, every day. Therefore, we must exercise caution and consider our options carefully before sharing any information. The following actions can aid in against fake news:

Examining the Source

Analyzing the sources cited in the piece, taking into account the main source of the story as well as any sources that provide confirmation.Do they have credibility in themselves? Do they even be there?

Examining several sources

It is a mistake to rely solely on an article. Making accurate conclusions can be aided by reading from a variety of sources and viewpoints.

Examining the Writer

investigating the identity, credibility, field of expertise, and reputation of the author of the posting; investigating the author's possible agenda.

Checking the Date

Ensuring the publication date is recent and not just an older story rehashed.

Checking the comments

Verifying the comments left in response is essential, even if the post, video, or article is authentic. Links and comments left in response are frequently automatically generated by bots or by individuals paid to spread inaccurate, misleading, or deceptive content.

1.3.4 Fake news detection

The primary source of fake news is social media , where people regularly consume news because of the low cost and quick and simple access to information [11]. Fake news's extensive distribution on social media and its detrimental effects on Researchers were interested in this topic because of the enormous interest society generated in fake news detection, which turned out to be a difficult task. The technique of determining whether a news piece is phony or legitimate is known as fake news detection. Various methods have been proposed in the literature to identify false information on internet platforms. Based on their primary input sources, we divide the current false news detection techniques into two categories: social context approaches and news content methods:

Content based methods: By examining the data and elements included in the news material, such as the title, image, video, and source, you can try to identify bogus news. The following methods can be applied in order to identify fake news based on content:

1. **knowledge-based**

When detecting fake news from a knowledge-based perspective, one often uses a process known as fact-checking. Fact checking, initially developed in journalism, aims to assess news authenticity by comparing the knowledge extracted from to-be-verified news content (e.g., its claims or statements) with known facts. In this section, we will discuss the traditional fact-checking (also known as manual fact-checking) and how it can be incorporated into automatic means to detect fake news (i.e., automatic fact-checking).

- **Manual Fact-checking** Broadly speaking, manual fact-checking can be divided into (I) expert-based and (II) crowd-sourced fact-checking. Expert-based Manual Fact-checking. Expert-based fact-checking relies on domain-experts as fact-checkers to verify the given news contents.
  - ✓ **Expert-based fact-checking** is often conducted by a small group of highly credible fact-checkers, is easy to manage, and leads to highly accurate results, but is costly and poorly scales with the increase in the volume of the to-be-checked news contents

✓ **Crowd-sourced fact-checking** relies on a large population of regular individuals acting as fact-checkers (i.e., the collective intelligence). Such large population of fact-checkers can be gathered within some common crowd-sourcing marketplaces such as Amazon Mechanical Turk, based on which CREDBANK , a publicly available large-scale fake news dataset, has been constructed. Compared to expert-based fact-checking, crowd-sourced fact-checking is relatively difficult to manage, less credible and accurate due to the political bias of fact-checkers and their conflicting annotations, and has better (though insufficient) scalability.

- **Automatic Fact-Checking** Since human techniques are not scalable with the volume of created data, automatic methods have been developed to perform fact checking in a reasonable amount of time. These methods primarily depend on artificial intelligence. This method consists of two steps that follow one another. first extracting the facts, then verifying them. Actually, information is taken out of reputable sources (one source or many sources .then ,in the fact checking the data to be checked is compared with the knowledge extracted and then classified as factual or non-factual [12].

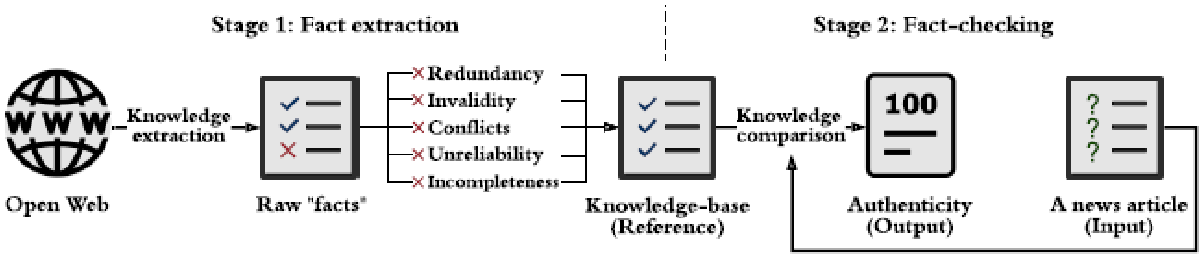

Figure I.2: Automatic News Fact-checking Process.

- **Visual-oriented techniques** Visual elements that are depicted in photos and videos related to the news piece are employed in visual-based tactics, these elements are frequently used as cues to frame the story, evidence to support it, or attention-getters. The act of misappropriating and the fabrication of visual content, such as photos, contribute to the spread of fake news because consumers often mistake photos for reliable sources of information. In a research by , compared to methods that solely used textual elements, the accuracy of detecting false news rose by more than 7% when image content was taken into account. Two sources of image features were used: statistics and visual content. On the other hand, a classification system was created in [13] to differentiate between tweets that contained real photos and those that did not. There are two types of features for tweets and users. Never the less, the majority of fake news detection methods now in use in the literature disregard visual cues in favor of linguistic characteristics that are taken from the news text.

2. **ML Content–based Methods**
   - -support vector machine (SVM)
   - -k nearestNeighbour (KNN)
3. **Deep Learning Content–based Methods**
   - -Convolutional Neural Networks(CNN)
   - -Recurrent neural network(RNN)

1.4 RELATED WORK

In our research this, different methods for detecting fake news on social media are analysed, including the use of deep neural networks. Several machine learning-based models and techniques for analyzing and identifying fake news are discussed. This research provides a comprehensive review of the work carried out in the field of fake news detection using deep learning. The research discusses different models such as CNN, RNN, LSTM, and Transformers, and compares their performance in news classification**. [14].**

This research deals with developing a model based on deep learning to detect fake news. A combination of natural language processing techniques and deep neural networks is used to achieve accurate results **.**

1.5 conclusion

In this chapter we defined false information and fake news, along with their types, creation methods, and detection techniques .We've included a couple more examples as well. In the next chapter, we'll talk about machine learning and artificial neural networks,and deep learning .They are extensively employed in numerous domains, including computer science ,We'll discuss machine learning and deep learning. two incredibly effective methods for automatically identifying false news, in the upcoming chapter.

This research deals with developing a model based on deep learning to detect fake news. A combination of natural language processing techniques and deep neural networks is used to achieve accurate results **.**

Chapter II

Machine Learning and Deep Learning

2.1. Introduction:

The spread of fake news has become a significant issue in today's digital age, impacting public opinion, elections, and even public health. Machine learning (ML) and deep learning (DL) techniques have been employed to address this problem by detecting and combating the dissemination of misinformation. Overall, ML and DL techniques offer promising approaches to combatting the spread of fake news by leveraging large-scale data analysis and automated detection mechanisms. However, ongoing research is needed to improve the accuracy, robustness, and fairness of these models, as well as to address the broader societal challenges posed by misinformation in the digital age.

In the first we will introduce the concepts of Artificial Intelligence and haw does Al work Then, we will talk about machinelearning, its different types, algorithms, and applications. Next, we will present what is Deep Learning and then different between ML and DL and then talk DNN and CNN and LSTM.

2.2. What is Artificial Intelligence?

Artificial intelligence (AI), in its broadest sense, is intelligence exhibited by machines, particularly computer systems. It is a field of research in computer science that develops and studies methods and software which enable machines to perceive their environment and uses learning and intelligence to take actions that maximize their chances of achieving defined goals[15] Such machines may be called AIs, AI encompasses a broad range of technologies, including machine learning, natural language processing, computer vision, robotics, and more. The goal of AI is to create systems that can perform tasks autonomously, adapt to changing environments, and solve complex problems with efficiency and accuracy.

2.3. How Does AI Work?

In general, Large volumes of labelled training data are ingested by AI systems, which then examine the data for correlations and patterns before using the patterns to forecast future states. In this manner, a chatbot that receives text chat examples can be trained to generate realistic conversations with people. or an image recognition tool can learn to identify anddescribe objects in images by reviewing millions of examples [16].

AI programming focuses on three cognitive skills:

Learning processes. This area of AI programming is concerned with gathering information and formulating the rules necessary to transform it into useful knowledge. The rules, whichare called algorithms, provide computing devices with step-by-step instructions forhow to complete a specific task [17].

Reasoning processes. Selecting the appropriate algorithm to achieve the desired result is the main emphasis of this area of AI programming.

Self-correction processes. The goal of this AI programming feature is to continuously improve algorithms so they can deliver the most accurate results.

2.4. What is Machine Learning?

Machine learning is a subset of artificial intelligence that involves the development of algorithms and statistical models that enable computers to learn and improve their performance on a specific task without being explicitly programmed. Instead of relying on explicit instructions, machine learning algorithms analyze large datasets to identify patterns, trends, and insights, which are then used to make predictions or decisions.[18]

The term "machine learning" was coined by Arthur Samuel in 1959, who defined it as the "field of study that gives computers the ability to learn without being explicitly programmed." Since then, machine learning has evolved significantly, with contributions from various fields such as statistics, mathematics, computer science, and cognitive psychology.

2.5. Types of Machine Learning

ML algorithms can be broadly classified into four categories: Supervised, Unsupervised, semi- supervised and Reinforcement learning.

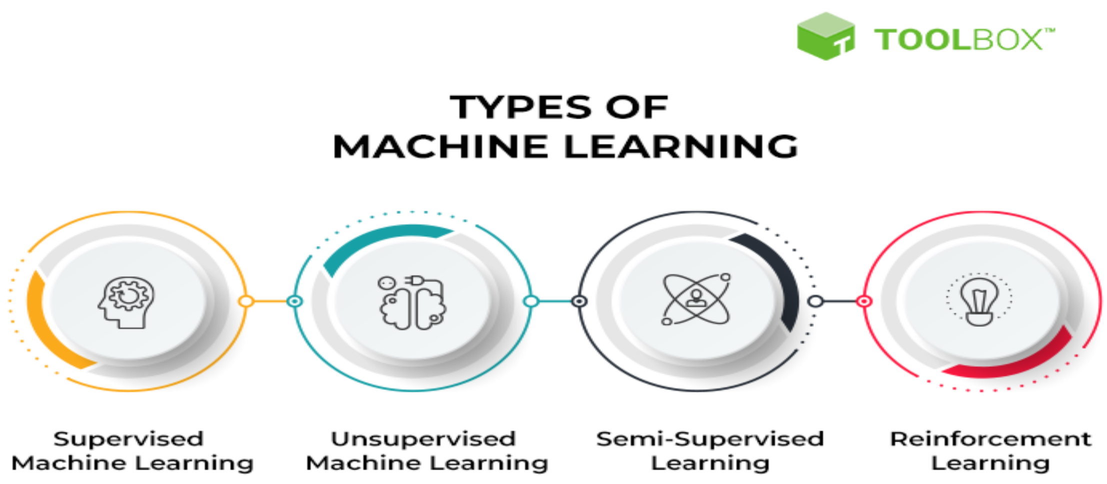

Figure II.1: Types of machine learning.

2.5.1. Supervised machine learning:

Supervised learning algorithms build a mathematical model of a set of data that contains both the inputs and the desired outputs.[19] The data is known as training data, and consists of a set of training examples. Each training example has one or more inputs and the desired output, also known as a supervisory signal. In the mathematical model, each training example is represented by an array or vector, sometimes called a feature vector, and the training data is represented by a matrix. Through iterative optimization of an objective function, supervised learning algorithms learn a function that can be used to predict the output associated with new inputs.[20] An optimal function allows the algorithm to correctly determine the output for inputs that were not a part of the training data. An algorithm that improves the accuracy of its outputs or predictions over time is said to have learned to perform that task[21] .Types of supervised-learning algorithms include classification and regression

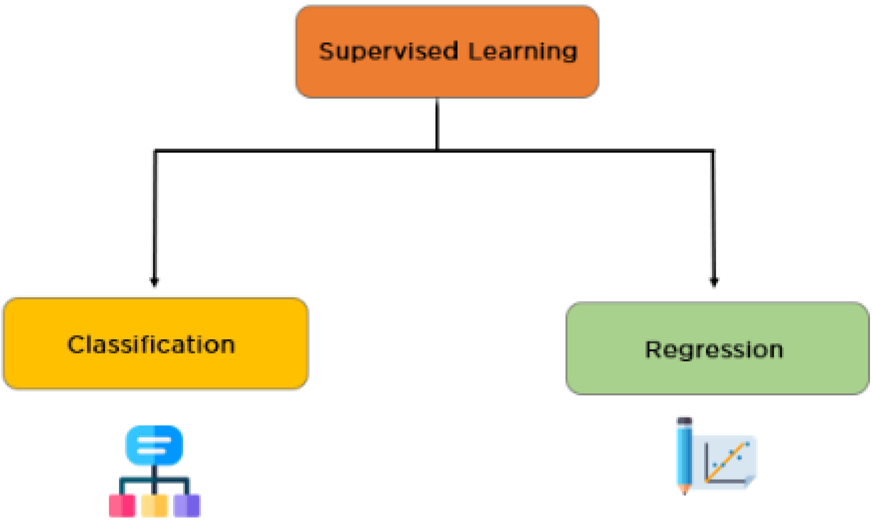

Figure II.2: Model of supervised learning.

1_Classification:

deals with predicting categorical target variables, which represent discrete classes or labels. For instance, classifying emails as spam or not spam, or predicting whether a patient has a high risk of heart disease. Classification algorithms learn to map the input features to one of the predefined classes.

2_Regression :

on the other hand, deals with predicting continuous target variables, which represent numerical values. For example, predicting the price of a house based on its size, location, and amenities or foreca sting the sales of a product. Regression algorithms learn to map the input features to a continuous numerical value.

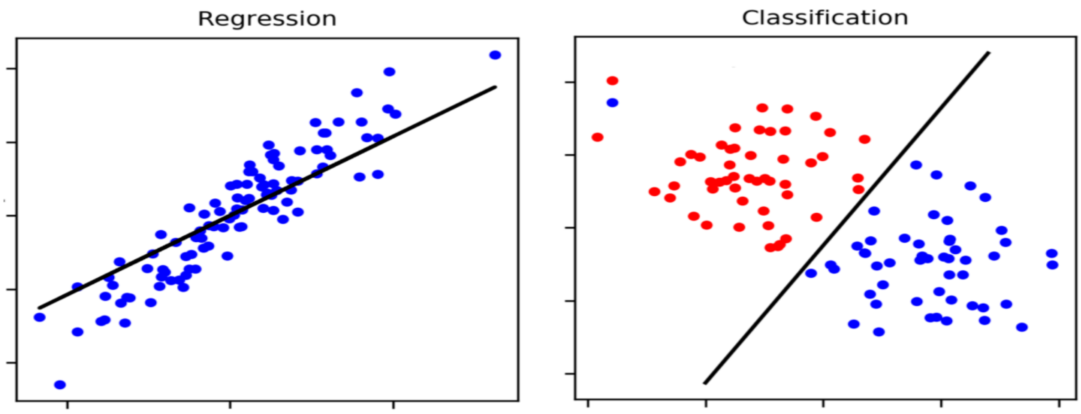

Figure II.3: Classification and Regression.

2.5.2. Unsupervised machine learning:

Unsupervised Learning Unsupervised learning is a type of machine learning technique in which an algorithm discovers patterns and relationships using unlabeled data. Unlike supervised learning, unsupervised learning doesn't involve providing the algorithm with labeled target outputs. The primary goal of Unsupervised learning is often to discover hidden patterns, similarities, or clusters within the data, which can then be used for various purposes, such as data exploration, visualization, dimensionality reduction, and more…In unsupervised Learning, Without the intended output, the algorithm will receive the input.This approach's primary goal is to use a clustering model to identify structure in the inputs.Unsupervised learning is looking at multiple instances of a random vector x and trying to figure out the probability distribution p(x) or some intriguing characteristics of that distribution, either implicitly or explicitly. [22]

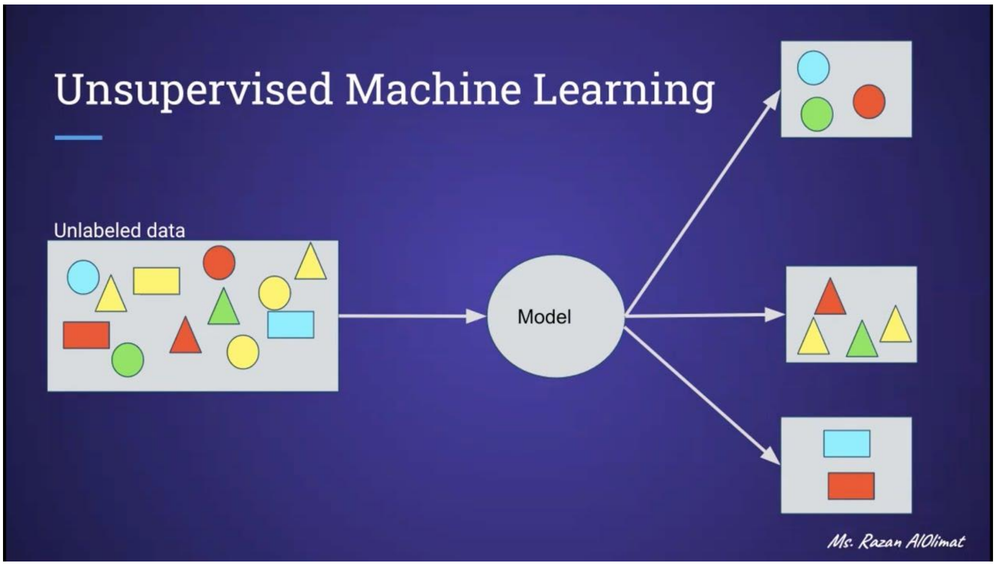

Figure II.4: Unsupervised machine learning.

2.5.3.Semi-supervised learning:

Semi-supervised learning comprises characteristics of both supervised and unsupervised machine learning. It uses the combination of labeled and unlabeled datasets to train its algorithms. Using both types of datasets, semi-supervised learning overcomes the drawbacks of the options mentioned above. Consider an example of a college student. A student learning a concept under a teacher's supervision in college is termed supervised learning. In unsupervised learning, a student self-learns the same concept at home without a teacher's guidance. Meanwhile, a student revising the concept after learning under the direction of a teacher in college is a semi-supervised form of learning.

The process of reinforcement learning is feedback-driven. Here, the AI component acts, learns from mistakes, and enhances performance by automatically assessing its environment through the hit-and-trial method. The component is rewarded for every successful action and punished for each unsuccessful one. Therefore, by doing well, the reinforcement learning component seeks to maximize rewards.

2.5.4. Reinforcement learning:

Reinforcement learning is an area of machine learning concerned with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward. Due to its generality, the field is studied in many other disciplines, such as game theory, control theory, operations research, information theory, simulation-based optimization, multi-agent systems, swarm intelligence, statistics and genetic algorithms. In reinforcement learning, the environment is typically represented as a Markov decision process (MDP). Many reinforcements learning algorithms use dynamic programming techniques. Reinforcement learning algorithms do not assume knowledge of an exact mathematical model of the MDP and are used when exact models are infeasible. Reinforcement learning algorithms are used in autonomous vehicles or in learning to play a game against a human opponent.

Reinforcement learning is further divided into two types of methods or algorithms:

- **Positive reinforcement learning**: This refers to adding a reinforcing stimulus after a specific behavior of the agent, which makes it more likely that the behavior may occur again in the future, e.g., adding a reward after a behavior.
- **Negative reinforcement learning**: Negative reinforcement learning refers to strengthening a specific behavior that avoids a negative outcome.

2.6.Algorithms of Machine Learning:

Machine learning algorithms are computational procedures or methods used by machines to learn patterns and relationships from data. These algorithms enable machines to make predictions, decisions, or generate insights without being explicitly programmed to perform specific tasks. Here's an overview of some common machine learning algorithms:

Below is the list of most commonly used Machine Learning algorithms. [23]

1. Linear regression: Linear regression is a simple algorithm used to map the linear relationship between input features and a continuous target variable. It works by fitting a line to the data and then using the line to predict new values.

2. Logistic Regression

Logistic regression is an extension of linear regression that is used for classification tasks to estimate the likelihood that an instance belongs to a specific class.

3. SVM (Support Vector Machine)

SVMs are supervised learning algorithms that can perform classification and regression tasks. It finds a hyperplane that best separates classes in feature space.

4. KNN (K-nearest Neighbour)

KNN is a non-parametric technique that can be used for classification as well as regression. It

works by identifying the k most similar data points to a new data point and then predicting the label of the new data point using the labels of those data points.

5. Decision Tree

Decision trees are a type of supervised learning technique that can be used for classification as well as regression. It operates by segmenting the data into smaller and smaller groups until each group can be classified or predicted with high degree of accuracy.

6. Random Forest

Random forests are a type of ensemble learning method that employs a set of decision trees to make predictions by aggregating predictions from individual trees. It improves the precision and resilience of single decision trees. It can be used for both classification and regression tasks.

7. Naive Bayes

Naive Bayes is a probabilistic classifier based on Bayes' theorem that is used for classification tasks. It works by assuming that the features of a data point are independent of each other.

8. PCA (Principal Component Analysis)

PCA is a dimensionality reduction technique used to transform data into a lower-dimensional space while retaining as much variance as possible. It works by finding the directions in the data that contain the most variation, and then projecting the data onto those directions.

9. Apriori algorithms

Apriori algorithm is a traditional data mining technique for association rules mining in transactional databases or datasets. It is designed to uncover links and patterns between things that regularly co-occur in transactions. Apriori detects frequent itemsets, which are groups of items that appear together in transactions with a given minimum support level.

10. K-Means Clustering

K-Means clustering is an unsupervised learning approach that can be used to group together data points. It works by finding k clusters in the data so that the data points in each cluster are as similar to each other as feasible while remaining as distinct as possible from the data points in other clusters

2.7. Deep Learning

2.7.1 What is Deep learning ?

Deep learning is a simulation technique wherein data is processed by digital devices—like computers—in a manner that emulates the functioning of the human brain. Multiple layers of abstraction are present in deep learning computer models, which have been improved by a variety of technologies, including speech recognition and visualizations. A subfield of machine learning known as "deep learning" uses numerous layers of neurons made up of intricate structures or nonlinear transformations to try and model high-level abstract data.

As the amount of data and computing power increases. [24]. Artificial neural networks(ANN) are used to simulate the human mind and its intelligence, and these networks consist of multiple neural layers. Deep learning relies on hidden and subtle neural layers,which makes it different from traditional neural networks.

Different types of Several tasks are performed by deep neural networks. Face recognition, image processing, and image recognition are the areas of expertise for convolutional neural networks (CNNs). A specialty of recurrent neural networks (RNNs) is the comprehension and processing of sequential data..

The tasks and functionalities of deep neural networks vary throughout their many forms. Neural networks have been extensively employed in numerous fields, including language processing, autonomous system control, and picture classification and interpretation. These networks function by layer-by-layer mapping inputs to outputs..

In each layer, the input to that layer undergoes an affine transformation followed by a simple nonlinear transformation before being passed to the next layer .[25]

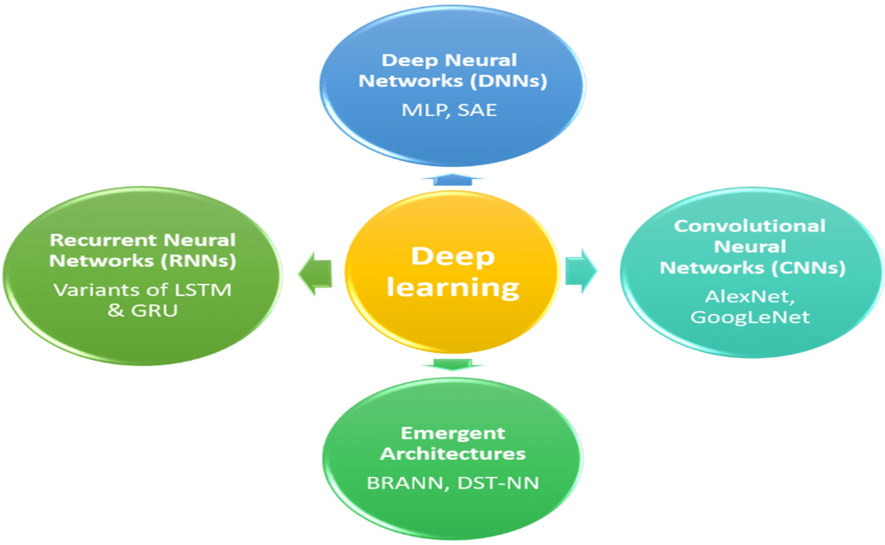

Figure II.5: Deep learning types.

The relationship between artificial intelligence, natural language processing, machine learning, and deep learning is illustrated in Figure:

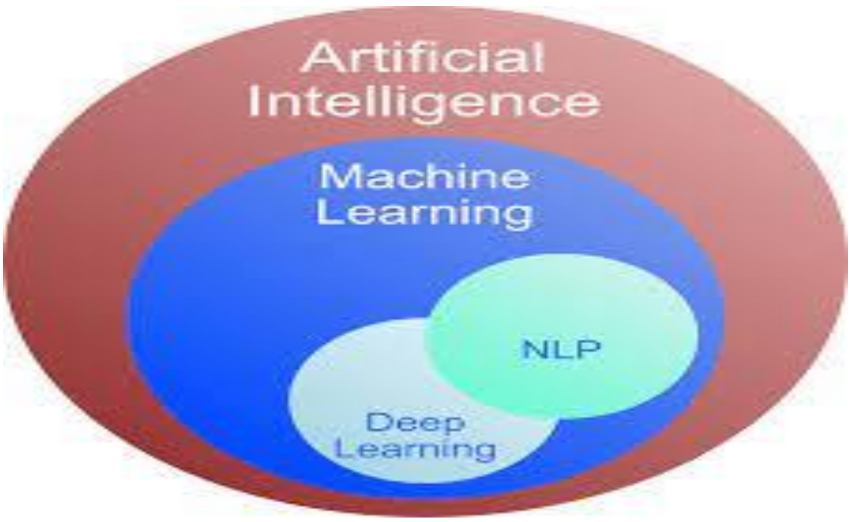

Figure II.6:Relationship between AI, ML, DL, and NLP.

2.7.2. Difference Between Deep learning And Machine learning:

Deep learning and machine learning are both subfields of artificial intelligence, but they differ in their approach, architecture, and application. Here are the keydifferencesbetween the two:

1. **Representation Learning**:
   - **Machine Learning**: In traditional machine learning, feature engineering is a crucial step where domain experts manually extract relevant features from the data. These features are then used to train machine learning models.
   - **Deep Learning**: Deep learning models can automatically learn hierarchical representations of data from raw inputs, eliminating the need for manual feature engineering. Deep neural networks learn feature representations at multiple levels of abstraction, allowing them to capture complex patterns in the data.
2. **Architecture**:
   - **Machine Learning**: Traditional machine learning models are often shallow and rely on handcrafted features. They use algorithms such as decision trees, support vector machines, and linear regression.
   - **Deep Learning**: Deep learning models are composed of multiple layers of interconnected neurons, known as artificial neural networks. These models can have hundreds or even thousands of layers, allowing them to learn complex representations of data. Examples of deep learning architectures include convolutional neural networks (CNNs) for image recognition and recurrent neural networks (RNNs) for sequential data.
3. **Feature Engineering**:
   - **Machine Learning**: Feature engineering is a manual and time-consuming process that requires domain knowledge and expertise. Engineers and data scientists select and engineer features that are relevant to the problem at hand.
   - **Deep Learning**: Deep learning models can learn feature representations directly from raw data. This eliminates the need for manual feature engineering and allows deep learning models to automatically extract relevant features from the data.

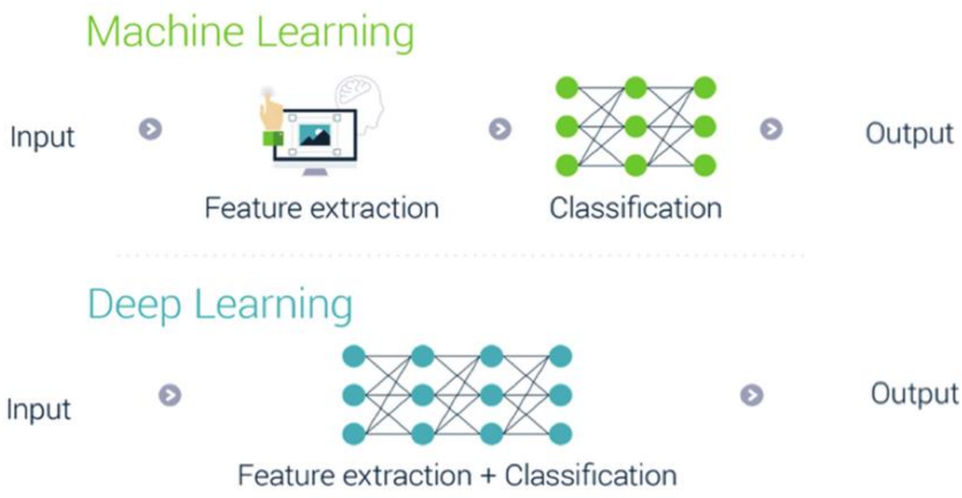

Figure II.7: Schematic of Different between Deep learning And Machine learning.

2.8. Neural networks

Neural networks, alternatively referred to as artificial neural networks (ANNs).The structure and operation of biological neural networks in the human brain served as the paradigm for artificial neural networks (ANNs), which are computer models.Artificial neurons, also referred to as "units," are interconnected nodes arranged into layers that make up ANNs.Each neuron in the network receives input signals, performs a transformation, and then passes the outcome to the layer below. This is how information moves through the network. Weights are assigned to the connections between neurons, and these weights change as the network learns to maximize its efficiency.The availability of large-scale datasets and improvements in processing capacity led to the evolution of ANNs over time. Consequently, new architectures have emerged, including recurrent neural networks (RNNs) and convolution neural networks (CNNs).

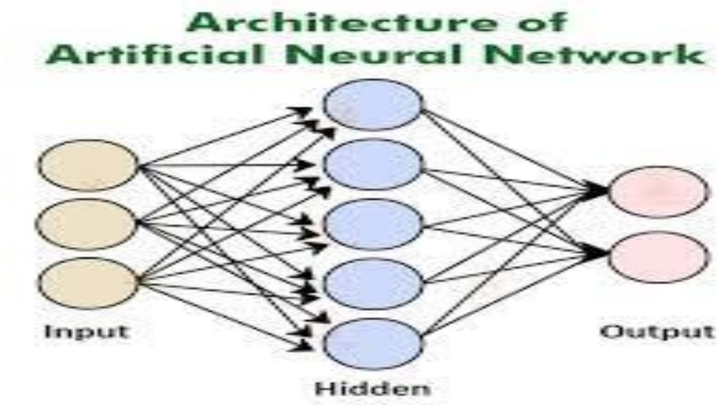

Figure II.8: Architecture of Artificial Neural Network.

2.9. Deep Neural Network:

Deep learning is a Neural Network consisting of a hierarchy of layers, whereby each layer transforms the input data into more abstract representations. These series of layers between input and output, identify the input features and create a series of new features based on the data, [27] just as our brain. In deep learning the more layers a network has,the higher the level of features it will learn. The output layer combines all these features and makes a prediction. This is different from a classical Artificial Neural Network.

Because artificial neural networks lack many hidden layers and can only learn the weights of a network with a single hidden layer, they are unable to learn complicated features. Large amounts of datasets are needed for deep learning to teach itself, which can be costly.Because deep learning generates more features the more neurons (cells in hidden layers) it has, it requires more data to train on.

Any Deep neural network will consist of three types of layers:

• The Input Layer

• The Hidden Layer

• The Output Layer

1.The input layer

It receives all the inputs and the last layer is the output layer which provides the desired output.

2. Hidden Layers

All the layers in between these layers are called hidden layers. There can be n number ofhidden layers. The hidden layers and perceptrons in each layer will depend on the use-caseyou are trying to solve [28].

3. Output Layers

It provides the desired output

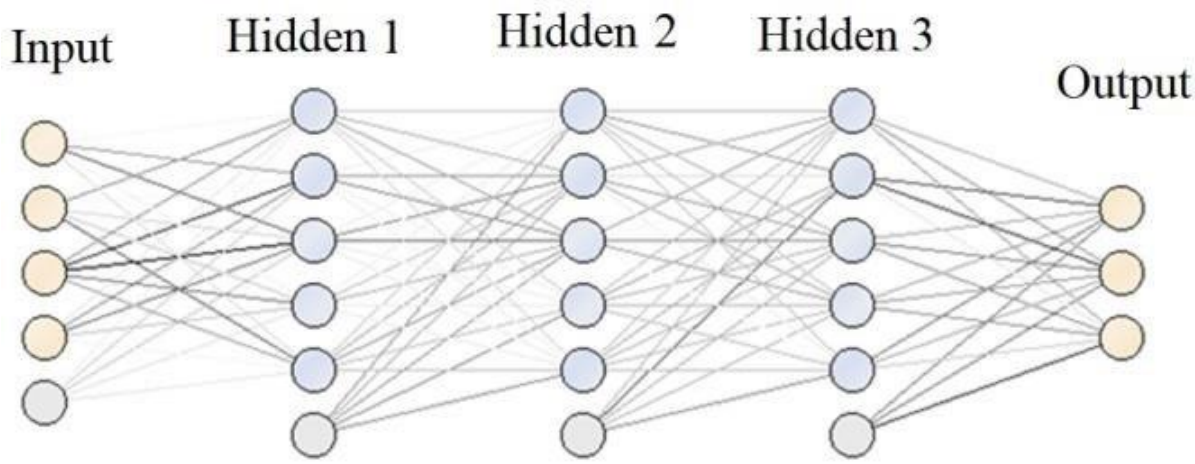

Figure II.9: Deep neural network with three hidden layers.

2.10.Convolution neural network (CNN)

CNNs are a kind of deep artificial neural network that are frequently employed in image processing and recognition. Its purpose is to automatically and effectively extract feature spatial hierarchies from input photos. CNNs are made up of several layers, such as completely linked, pooling, and convertible layers., which work together to extract and classifyvisual features in an image.[29]

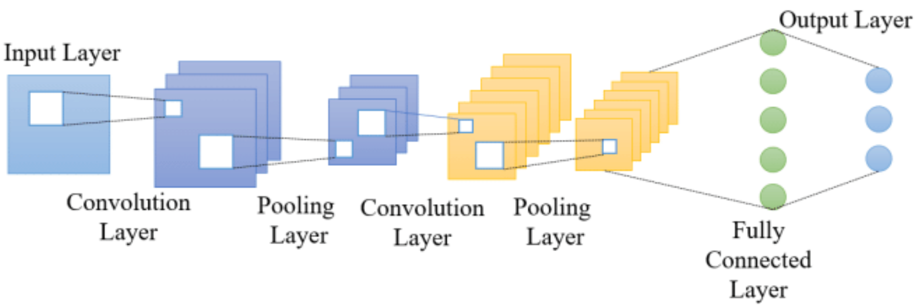

Figure II.10: Architecture of Convolutional Neural Network.

CNN is composed of many stacked layers, convolution and pooling layers being the first, then fully connected and soft-max layers. The sections provide a detailed description of each of these layers.

Convolutional layer:

These layers process the incoming image by applying a collection of learnable filters, or kernels. Every filter computes the dot products between the filter weights and the pixel values in the receptive field as it convolves over the input image. Every filter produces a feature map as its output, emphasizing the existence of particular visual patterns or features.

pooling layer:

Usually placed one or more convolutional layers before the pooling layer, which is often referred to as down sampling. Its primary goal is to preserve the most crucial information while reducing the input feature maps' spatial dimensions (width and height). The most popular kind of pooling is called max pooling, in which the filter goes across the input feature map (usually 2x2 or 3x3) and chooses the pixel with the maximum value. The output feature map is created using this chosen value.

Fully connected layer:

Usually found near the network's edge are these levels.Fully connected layers' primary goals are to understand intricate linkages and generate predictions using the features that the network's earlier layers collected. A collection of neurons that generate the final prediction are connected to the one-dimensional vector formed by the output of the preceding layers..

2.11. Long Short Term Memory (LSTM):

Long Short-Term Memory networks or simply LSTMs are a special kind of RNN, capable oflearning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997),and were refined and popularized by many people in following work. They work tremendously well on a large variety of problems, and are now widely used.LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn!All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as asingle tanh layer..

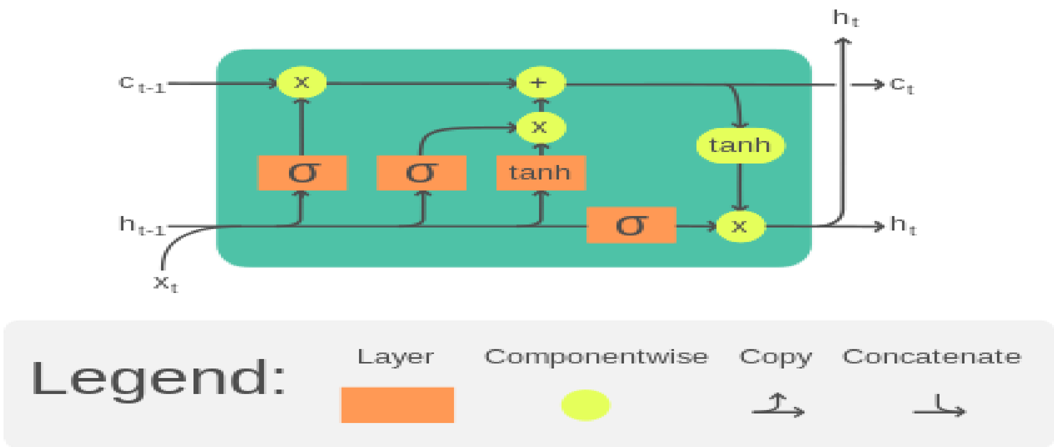

Figure II.11: The LSTM Cell in Artificial Neural Networks (ANNs).

Bidirectional long short Memory

Bidirectional Long Short-Term Memory (BLSTM) represents a significant advancement in recurrent neural network (RNN) architectures, particularly suited for tasks requiring a comprehensive understanding of sequential data. Unlike traditional LSTMs that process input sequences in only one direction, BLSTM incorporates bidirectional processing, leveraging both past and future contexts simultaneously. This is achieved through the integration of two LSTM layers: one processes the input sequence from beginning to end, while the other processes it in reverse. By capturing dependencies from both directions, BLSTM networks excel in tasks where context plays a crucial role, such as speech recognition, machine translation, sentiment analysis, and named entity recognition. The outputs from the forward and backward LSTM layers are typically concatenated or combined to form a unified representation of the input sequence, enabling the network to capture rich contextual information. BLSTM's ability to comprehend and retain long-range dependencies makes it a powerful tool for various sequential data analysis tasks, driving advancements in natural language processing, time series prediction, and beyond.

CNN-BILSTM

A CNN-BiLSTM (Convolutional Neural Network - Bidirectional Long Short-Term Memory) model is an advanced architecture used in various Natural Language Processing (NLP) tasks. This model leverages the strengths of both CNNs and BiLSTMs. The CNN component captures local features and patterns in the text, such as n-grams, through convolutional layers. These features are then fed into the BiLSTM layers, which process the sequence in both forward and backward directions, effectively capturing long-term dependencies and context. This combination makes the CNN-BiLSTM model particularly effective for tasks like text classification, sentiment analysis, and fake news detection, where understanding both local and global text features is crucial.

Natural Language Processing (NLP) :

Natural Language Processing (NLP) is a subfield of Artificial Intelligence that equips machines with the ability to understand and process human language. In the fight against fake news, NLP plays a crucial role by enabling the analysis and understanding of textual content.It also serves as a foundational layer for various techniques used in machine learning models for detection. Text Preprocessing, Feature Extraction, Named Entity Recognition (NER), and Semantic Analysis are some key NLP techniques used in fake news detection. In the next subsection, we will explain some of these techniques that help to achieve this detection purpose.By leveraging NLP techniques for feature extraction and analysis, ML models can betrained to identify patterns and characteristics often associated with fake news. However, it iscrucial to remember that NLP is just one piece of the puzzle. Combining NLP with human expertise, fact-checking, and critical thinking remains essential for a comprehensive approach to tackling the challenge of fake news.

2.12. Conclusion

The terms artificial intelligence, machine learning, deep learning, natural language processing, and ensemble learning have all been defined in this chapter. Additionally, we presented a collection of deep learning methods, including long short-term memory (LSTM) and convolution neural networks (CNN). Some of these algorithms will be put into practice for our system's application, and the idea of ensemble learning will aid in putting these algorithms together. Within the section,, we will explain more about them in the addition to the model and implementation tools used in our work.

Chapter 3

3.1. Introduction:

It became necessary to combat the spread of fake news by identifying fake news and those who spread it, as was detailed in chapter one. Fake news has become a daily issue that we encounter every time we check our social media accounts, posing serious risks to prominent figures, large corporations, and even regular people.The artificial intelligence methods and machine learning algorithms discussed in Chapter 2 have made it possible to identify bogus news and the people who propagate it, and they can even do so extremely accurately. We will discuss the creation and use of our model for the identification of fake news spreaders at the end of this chapter, drawing on a few previous research..We will use classification supervised machine learning and deep learning algorithms and several programming tools to organize the database of two types, fake articles spreaders and real articles spreaders then train our model.

3.2.1Objective and Motivations

Fake news is often created with specific objectives and motivations that drive its dissemination. One primary objective is the manipulation of public opinion for political gain. Political actors and interest groups spread false information to influence voters, sway election outcomes, discredit opponents, and promote specific agendas. Additionally, economic profits serve as a strong motivation, as sensational or controversial fake news stories attract high traffic, generating substantial ad revenue and boosting sales or subscriptions. Another objective is the disruption and destabilization of societies. By spreading misinformation, malicious actors aim to create confusion, social chaos, and erode trust in institutions like the media, government, and scientific bodies. Ideological reinforcement is also a key motivation; propagandists use fake news to promote specific narratives, reinforce existing biases, and mobilize support for their causes. In the realm of cyber and information warfare, fake news is used strategically to undermine the political and social stability of rival nations, often as part of broader cyber espionage or sabotage efforts. Psychological factors, such as confirmation bias and emotional appeal, further drive the spread of fake news, as individuals are more likely to believe and share information that aligns with their preexisting beliefs and triggers strong emotional responses [30]

3.2.2.Solution:

To solve the fake news spreaders problem, Deep learning (DL) offers powerful tools for combating fake news through the development of sophisticated detection systems. By leveraging neural networks, particularly convolutional neural networks (CNN_Bs) and recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM)and lstm_B networks, DL models can analyze vast amounts of data and identify patterns indicative of fake news. These models can be trained on large datasets containing both real and fake news articles, learning to distinguish between the two based on linguistic cues, writing styles, and metadata. Additionally, advanced techniques like transformer models (e.g., BERT) can be employed to understand the context and semantics of the content more accurately. Ensemble methods that combine multiple models can further enhance detection accuracy. Beyond text analysis, DL models can also analyze images and videos, detecting manipulated media content that often accompanies fake news. Continuous retraining of these models with new data helps maintain their effectiveness against evolving fake news tactics. Integrating DL-based detection systems into social media platforms and search engines can significantly reduce the spread of misinformation by automatically flagging or demoting suspicious content, thereby protecting users from misleading information.

3.3. Problematic description:

3.3.1. Method And Implementation Tools:

We describe in this section the data-base we used in our work and the implementation tools that we used to have the results we had.

3.3.1.1. Data-set Description:

The dataset contains two types of articles fake and real News. This dataset was collected from realworld sources; the truthful articles were obtained by crawling articles from Reuters.com (News website). As for the fake news articles, they were collected from different sources. The fake news articles were collected from unreliable websites that were flagged by Politifact (a fact-checking organization in the USA) and Wikipedia. The dataset contains different types of articles on different topics, however, the majority of articles focus on political and World news topics.The dataset consists of two CSV files. The first file named “True.csv” contains more than 12,600 articles from reuter.com. The second file named “Fake.csv” contains more than 12,600 articles from different fake news outlet resources. Each article contains the following information: article title, text, type and the date the article was published on. To match the fake news data collected for kaggle.com, we focused mostly on collecting articles from 2016 to 2017. The data collected were cleaned and processed, however, the punctuations and mistakes that existed in the fake news were kept in the text.

The **Table III.1** is a breakdown of the some categories:

Table III.1: Examples from dataset

	TITEL	TEXT	LABEL
11	",politicsNews, "December 28, 2017 "	Alabama official to certify Senator-elect Jones today despite challenge: CNN,"WASHINGTON (Reuters) - Alabama Secretary of State John Merrill said he will certify Democratic Senator-elect Doug Jones as winner on Thursday despite opponent Roy Mooreâ€™s challenge, in a phone call on CNN	True
30	",politicsNews," December 22, 2017	Mexico to review need for tax changes after U.S. reform-document,"MEXICO CITY (Reuters) - Mexicoâ€™s finance ministry will evaluate whether to make fiscal changes in response to the U.S. tax reform, according to a document seen by Reuters on Friday	True
8916	News ,january 7,2016	The most cc it is the most just not the monies they personally get .Featured image via Wikipedia	Fake
9591	“Politics “oct 26,2017	Hilarious !ther will be semoene to listen.becouse you know what?it is on us information liberation	Fake

3.3.2. Implementation Tools:

To make this work,

3.3.2.1 Python:

Python is a high-level, interpreted programming language known for its simplicity, readability, and versatility. It was created by Guido van Rossum and first released in 1991. Python emphasizes code readability and maintainability, making it an ideal choice for both beginners and experienced programmers alike. Here are some key characteristics and features of Python: Simple and Easy to Learn: Python has a straightforward syntax and clean code structure, making it easy to understand and learn, even for individuals with little or no programming experience. Interpreted and Interactive: Python is an interpreted language, meaning that code is executed line by line, allowing for interactive development and rapid prototyping. Python interpreters are available for various platforms, including Windows, macOS, and Linux. High-level and Portable: Python is a high-level[31]

Overall, Python's simplicity, readability, and versatility have contributed to its widespread popularity and adoption in various fields, including web development, data science, machine learning, scientific computing, and more.

3.3.2.2 Google colab:

Colab is a cloud-based Jupyter notebook environment that is available for free. The fact that it doesn't require setup and that team members can update the produced notebooks simultaneously is crucial. Many well-known machine learning libraries are supported Colab.

3.3.2.3 Anaconda Distribution:

Anaconda [75] With more than 20 million users worldwide, the individual edition of Python is the most widely used distribution platform. You can rely on us to uphold the Anaconda open-source environment for a long time, as it is the preferred platform for Python data science. To install the Python-related requirements for a particular project, Virtual Environment is used to build a container or isolated environment. With its many packages, Python may be used with a wide range of versions. The Anaconda distribution is often used by data scientists since it has a lot of helpful pre-installed packages that are simple to install and maintain. The Anaconda distribution comes with Anaconda Navigator, a desktop graphical user interface (GUI) that makes it simple to manage conda packages, environments, and applications. Linux, macOS, and Windows can all use it. The following programs are available in Navigator by default: RStudio, Glueviz, VSCode, JupyterLab, Jupyter Notebook, Spyder, PyCharm, and Orange 3 App. And Jupyter Notebook was used to develop our project. [32] is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations,and narrative text. Uses include data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and more.

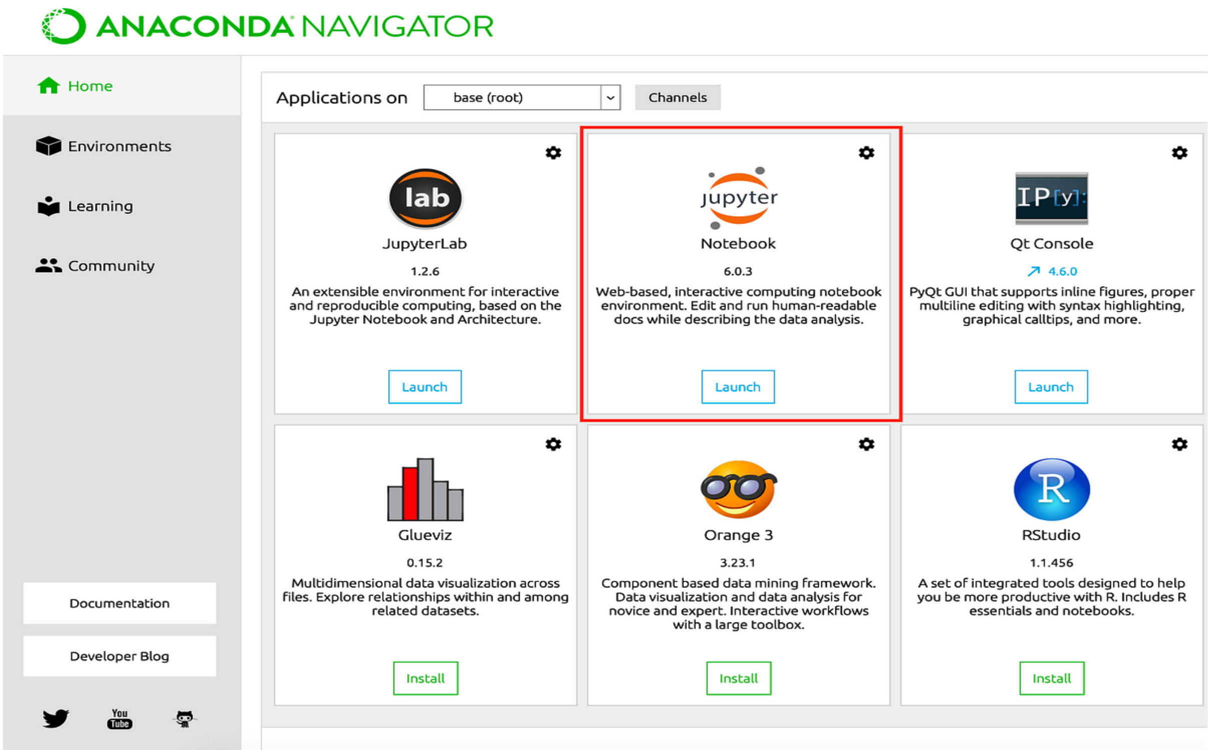

Figure III.1: Virtual Environments in Anaconda Jupyter notebook.

Evalution:

We evaluate the results using the following metrics:

Confusion Metrics

The confusion matrix provides more insight into not only the performance of a predictive model, but also which classes are being predicted correctly, which incorrectly, and what type of errors are being made .The simplest confusion matrix is for a two-class classification problem, with negative (class 0) and positive (class 1) classes. In this type of confusion matrix, each cell in the has a specific and well-understood name, summarized as follows:

- ✓ **True Positive (TP):** when predicted fake news pieces are actually annotated as fake news;
- ✓ **True Negative (TN):** when predicted true news pieces are actually annotated as true news;
- ✓ **False Negative (FN):** when predicted true news pieces are actually annotated as fake news
- ✓ **False Positive (FP):** when predicted fake news pieces are actually annotated as true news.

1. ***Precision***

A statistic called precision counts how many positive, accurate forecasts were made.As a result, precision determines the accuracy for the minority class.It is computed as follows: the ratio of accurately anticipated positive examples to the total number of predicted positive examples.The precision measures the percentage of correctly categorized instances among the positive ones. It can be calculated as in Equation

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

2. **Accuracy**

Accuracy, used in classification problems, is a metric used to tell the percentage of accurate predictions. We calculate it by dividing the number of correct predictions by the total number of predictions that the model has made. Equation 3.1 shows how accuracy is calculated.

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

3. **F1 score**

F-Measure provides a single score that balances both the concerns of precision and recall in one number [77]. It can be calculated as in Equation 3.4

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

3.3.5. Proposed model:

Aiming for a better prediction, we combine all of the three deep learning-based models(LSTM,BI LSTM, CNN-BILSTM) . The likelihood of the news class—fake or real—is predicted by each estimator, and the average of the forecasts is used to aggregate the results. The news is classified as authentic if the calculated average is greater than 0.5; else, it is classified as fake news.

LSTM MODEL :

The provided code snippet demonstrates how to build and train a Long Short-Term Memory (LSTM) model using TensorFlow and Keras. It initializes a sequential model and adds an embedding layer to convert words into dense vectors. Two dropout layers are included to prevent overfitting, surrounding an LSTM layer with 100 units. The model ends with a dense layer using a sigmoid activation function, suitable for binary classification tasks. It is compiled with binary cross-entropy loss and the Adam optimizer, and its summary is printed to show the model's architecture.

LSTM

```
#Building And Training LSTM Model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Embedding, Input, LSTM, Conv1D, MaxPool1D, Bidirectional, Dropout, BatchNormalization

## Creating model Using LSTM
embedding_vector_features=40
model=Sequential()
model.add(Embedding(total_words,embedding_vector_features,input_length=20))
model.add(Dropout(0.3))
model.add(LSTM(100))
model.add(Dropout(0.3))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
print(model.summary())
```

Architrcture of LSTM:

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 20, 40)            766960

 dropout (Dropout)           (None, 20, 40)            0

 lstm (LSTM)                 (None, 100)               56400

 dropout_1 (Dropout)         (None, 100)               0

 dense (Dense)               (None, 1)                 101

=================================================================
Total params: 823461 (3.14 MB)
Trainable params: 823461 (3.14 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

This figure shows the summary of a neural network model. indicating the architecture and parameters of each layer The output shapes and parameters indicate the dimensions of the data as it flows through each layer and the number of parameters involved in each layer. The embedding layer transforms the input into a dense vector, the dropout layers prevent overfitting, the LSTM captures temporal dependencies, and the final dense layer outputs a single value for binary classification ,Here' s a detailed explanation:

- Embedding Layer:

  - Type: `embedding (Embedding)`
  - Output Shape: `(None, 20, 40)`
  - Param #: `766960`

- Explanation: The Embedding layer converts input indices into dense vectors of fixed size (here, 40). The input shape (None, 20) indicates a batch of sequences, each of length 20. The total number of parameters is the product of the vocabulary size and the embedding dimension.

- Dropout Layer:
    - Type: `dropout (Dropout)`
    - Output Shape: `(None, 20, 40)`
    - Param #: `0`
    - Explanation: The Dropout layer is used for regularization to prevent overfitting by randomly setting a fraction of input units to 0 during training. It has no parameters.

- LSTM Layer:
    - Type: `lstm (LSTM)`
    - Output Shape: `(None, 100)`
    - Param #: `56400`
    - Explanation: The LSTM (Long Short-Term Memory) layer is a type of recurrent neural network (RNN) layer that processes sequences of data. Here, it outputs sequences of length 100. The number of parameters is based on the size of the LSTM cell.

- Dropout Layer:
    - Type: `dropout_1 (Dropout)`
    - Output Shape: `(None, 100)`
    - Param #: `0`
    - Explanation: Another Dropout layer applied after the LSTM layer for regularization.

- Dense Layer:
    - Type: `dense (Dense)`
    - Output Shape: `(None, 1)`
    - Param #: `101`
    - Explanation: The Dense (fully connected) layer with a single output neuron, typically used for regression or binary classification tasks. The number of parameters includes the weights and bias for the single output neuron.

- Total Parameters:
    - Total params: `823461` (3.14 MB)
    - Trainable params: `823461` (3.14 MB)
    - Non-trainable params: `0`
    - Explanation: The total number of parameters in the model is 823,461, all of which are trainable. Non-trainable parameters would include parameters that are not updated during training, but here there are none..

.

```
Validation Metrics:
Accuracy: 0.9604677060133631
Precision: 0.9615842763549732
Recall: 0.9541962174940898
F1 Score: 0.9578760011865914
```

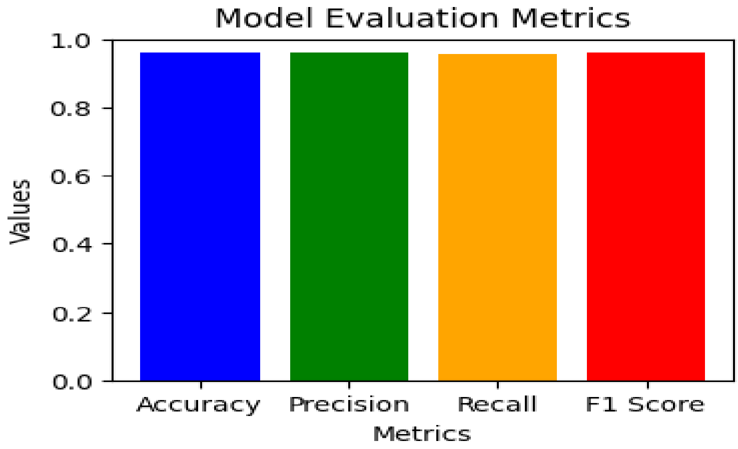

Figure III.2:MATRICS OF LSTM MODEL.

Bidirectional LSTM model:

This code snippet constructs and compiles a bidirectional Long Short-Term Memory (LSTM) neural network model using Keras, tailored for binary classification tasks. It starts with an embedding layer to convert input words into dense vectors, followed by a dropout layer to prevent overfitting. A bidirectional LSTM layer with 100 units captures patterns from both past and future contexts in the input sequences, enhancing the model's understanding. Another dropout layer is added for further regularization. The final dense layer with a sigmoid activation outputs probabilities for binary classification. The model is compiled with the binary_crossentropy loss function and the 'adam' optimizer, and it is evaluated using accuracy as the metric. The summary of the model architecture is printed to provide an overview of its structure. This setup is ideal for tasks like sentiment analysis or spam detection where the sequence context is crucial.

Bidirectional LSTM

```
[ ] #Building And Training Bidirectional LSTM Model
    ## Creating model Using LSTM
    embedding_vector_features=40
    model=Sequential()
    model.add(Embedding(total_words,embedding_vector_features,input_length=20))
    model.add(Dropout(0.3))
    model.add(Bidirectional(LSTM(100)))
    model.add(Dropout(0.3))
    model.add(Dense(1,activation='sigmoid'))
    model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
    print(model.summary())
```

ArchitactureBidirectional LSTM

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, 20, 40)            1068320

 dropout_2 (Dropout)         (None, 20, 40)            0

 bidirectional (Bidirection  (None, 200)               112800
 al)

 dropout_3 (Dropout)         (None, 200)               0

 dense_2 (Dense)             (None, 1)                 201

=================================================================
Total params: 1181321 (4.51 MB)
Trainable params: 1181321 (4.51 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
```

This figure shows the summary of another neural network model, , similar to the previous model, but it uses a bidirectional LSTM layer. This allows the model to process the input sequences in both forward and backward directions, capturing more context information. The embedding layer maps input tokens to dense vectors, the bidirectional LSTM processes these sequences, and the dense layer produces the final output.Here's a detailed explanation of each component

- Embedding Layer:

- **Type**: `embedding_2 (Embedding)`
- **Output Shape**: `(None, 20, 40)`
- **Param #**: `1068320`
- **Explanation**: Similar to the previous model, this Embedding layer converts input indices into dense vectors of fixed size (here, 40). The input shape `(None, 20)` indicates a batch of sequences, each of length 20. The total number of parameters is the product of the vocabulary size and the embedding dimension.

- **Dropout Layer**:

  - **Type**: `dropout_2 (Dropout)`
  - **Output Shape**: `(None, 20, 40)`
  - **Param #**: `0`
  - **Explanation**: This Dropout layer is used for regularization to prevent overfitting by randomly setting a fraction of input units to 0 during training. It has no parameters.

- **Bidirectional LSTM Layer**:

  - **Type**: `bidirectional (Bidirectional)`
  - **Output Shape**: `(None, 200)`
  - **Param #**: `112800`
  - **Explanation**: This layer wraps an LSTM layer to make it bidirectional, meaning it processes the input sequence in both forward and backward directions. The output shape `(None, 200)` indicates that the outputs from both directions are concatenated. The number of parameters is based on the size of the LSTM cell and the bidirectional configuration.

- **Dropout Layer**:

  - **Type**: `dropout_3 (Dropout)`
  - **Output Shape**: `(None, 200)`
  - **Param #**: `0`
  - **Explanation**: Another Dropout layer applied after the Bidirectional LSTM layer for regularization.

- **Dense Layer**:

  - **Type**: `dense_2 (Dense)`
  - **Output Shape**: `(None, 1)`
  - **Param #**: `201`
  - **Explanation**: The Dense (fully connected) layer with a single output neuron, typically used for regression or binary classification tasks. The number of parameters includes the weights and bias for the single output neuron.

- **Total Parameters**:

- **Total params**: `1181321` (4.51 MB)
- Trainable params: `1181321` (4.51 MB)
- **Non-trainable params**: `0`

- **Explanation**: The total number of parameters in the model is 1,181,321, all of which are trainable. There are no non-trainable parameters in this model.

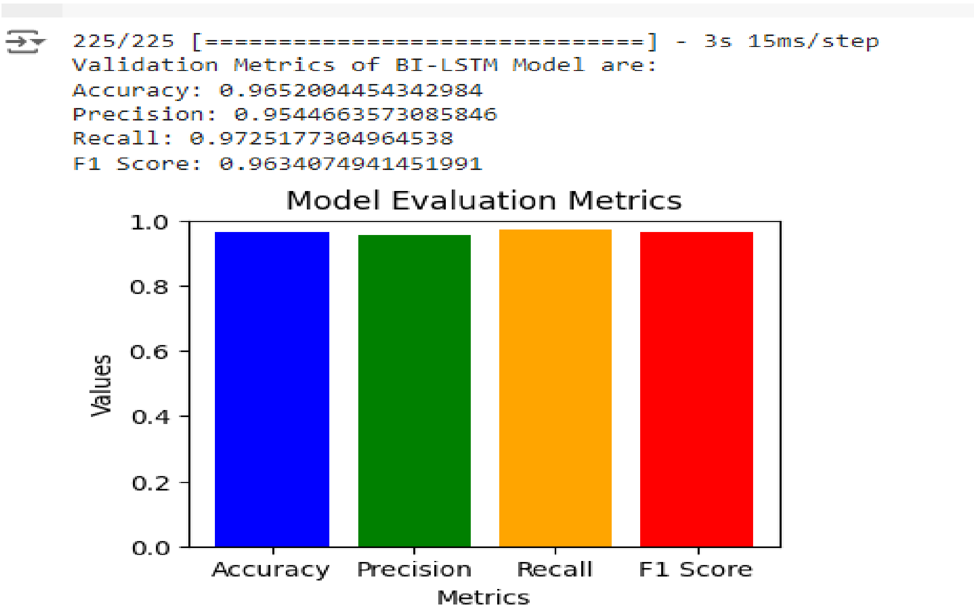

Figure III.3:Model Evaluation metrics of BILSTM

CNN-BiLSTM:

The code snippet illustrates the construction of a hybrid Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) model using TensorFlow and Keras. It starts with a sequential model, adding an embedding layer for word representation. After a dropout layer, it includes two Conv1D layers with ReLU activation and MaxPooling layers for feature extraction. A Bidirectional LSTM layer with 100 units follows for capturing temporal dependencies in both directions. Another dropout layer is added before the final dense layer with a sigmoid activation for binary classification. The model is compiled with binary cross-entropy loss and the Adam optimizer, and its architecture summary is printed.

CNN-BiLSTM

```
[ ] #Building And Training CNN Model
    ## Creating model Using CNN
    embedding_vector_features=40
    model=Sequential()
    model.add(Embedding(total_words,embedding_vector_features,input_length=20))

    model.add(Dropout(0.3))

    model.add(Conv1D(32, 5, activation='relu'))
    model.add(MaxPool1D())

    model.add(Conv1D(32, 5, activation='relu'))
    model.add(MaxPool1D())

    model.add(Bidirectional(LSTM(100)))
    model.add(Dropout(0.3))

    model.add(Dense(1,activation='sigmoid'))
    model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
    print(model.summary())
```

ARCHITACTURE OF CNN BILSTM

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_3 (Embedding)     (None, 20, 40)            1068320

 dropout_4 (Dropout)         (None, 20, 40)            0

 conv1d (Conv1D)             (None, 16, 32)            6432

 max_pooling1d (MaxPooling1  (None, 8, 32)             0
 D)

 conv1d_1 (Conv1D)           (None, 4, 32)             5152

 max_pooling1d_1 (MaxPoolin  (None, 2, 32)             0
 g1D)

 bidirectional_1 (Bidirecti  (None, 200)               106400
 onal)

 dropout_5 (Dropout)         (None, 200)               0

 dense_3 (Dense)             (None, 1)                 201

=================================================================
Total params: 1186505 (4.53 MB)
Trainable params: 1186505 (4.53 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
```

This model architecture is designed for sequence processing tasks, combining the feature extraction capabilities of CNNs with the contextual processing power of bidirectional LSTMs. The embedding layer maps input tokens to dense vectors, the convolutional layers and max pooling layers extract local features and reduce the dimensionality, the bidirectional

LSTM processes these features in both forward and backward directions, and the dense layer produces the final output. Here's a detailed breakdown of each layer and its function:

- **Embedding Layer**:
  - **Type**: `embedding_3 (Embedding)`
  - **Output Shape**: `(None, 20, 40)`
  - **Param #**: `1068320`
  - **Explanation**: This layer converts input indices into dense vectors of fixed size (40). The input shape `(None, 20)` indicates a batch of sequences, each of length 20. The number of parameters is the product of the vocabulary size and the embedding dimension.
- **Dropout Layer**:
  - **Type**: `dropout_4 (Dropout)`
  - **Output Shape**: `(None, 20, 40)`
  - **Param #**: `0`
  - **Explanation**: This layer is used for regularization to prevent overfitting by randomly setting a fraction of input units to 0 during training. It has no parameters.
- **Convolutional Layer**:
  - **Type**: `conv1d (Conv1D)`
  - **Output Shape**: `(None, 16, 32)`
  - **Param #**: `6432`
  - **Explanation**: This layer applies 1D convolution over the input sequence. It uses 32 filters and has a kernel size that reduces the sequence length from 20 to 16. The number of parameters includes the weights of the filters and biases.
- **Max Pooling Layer**:
  - **Type**: `max_pooling1d (MaxPooling1D)`
  - **Output Shape**: `(None, 8, 32)`
  - **Param #**: `0`
  - **Explanation**: This layer performs max pooling on the 1D input, reducing the sequence length from 16 to 8 by taking the maximum value over a pool size (typically 2). It has no parameters.
- **Convolutional Layer**:
  - **Type**: `conv1d_1 (Conv1D)`
  - **Output Shape**: `(None, 4, 32)`
  - **Param #**: `5152`
  - **Explanation**: This layer applies another 1D convolution, reducing the sequence length from 8 to 4. It also uses 32 filters.
- **Max Pooling Layer**:

- **Type**: `max_pooling1d_1 (MaxPooling1D)`
- **Output Shape**: `(None, 2, 32)`
- **Param #**: `0`
- **Explanation**: This layer performs another max pooling, further reducing the sequence length from 4 to 2. It has no parameters.

- **Bidirectional LSTM Layer**:

  - **Type**: `bidirectional_1 (Bidirectional)`
  - **Output Shape**: `(None, 200)`
  - **Param #**: `106400`
  - **Explanation**: This layer wraps an LSTM layer to make it bidirectional, meaning it processes the input sequence in both forward and backward directions. The output shape `(None, 200)` indicates that the outputs from both directions are concatenated.

- **Dropout Layer**:

  - **Type**: `dropout_5 (Dropout)`
  - **Output Shape**: `(None, 200)`
  - **Param #**: `0`
  - **Explanation**: This layer is used for regularization after the Bidirectional LSTM layer.

- **Dense Layer**:

  - **Type**: `dense_3 (Dense)`
  - **Output Shape**: `(None, 1)`
  - **Param #**: `201`
  - **Explanation**: The Dense layer with a single output neuron, typically used for regression or binary classification tasks. The number of parameters includes the weights and bias for the single output neuron.

- **Total Parameters**:

  - **Total params**: `1186505` (4.53 MB)
  - **Trainable params**: `1186505` (4.53 MB)
  - **Non-trainable params**: `0`
  - **Explanation**: The total number of parameters in the model is 1,186,505, all of which are trainable. There are no non-trainable parameters in this model

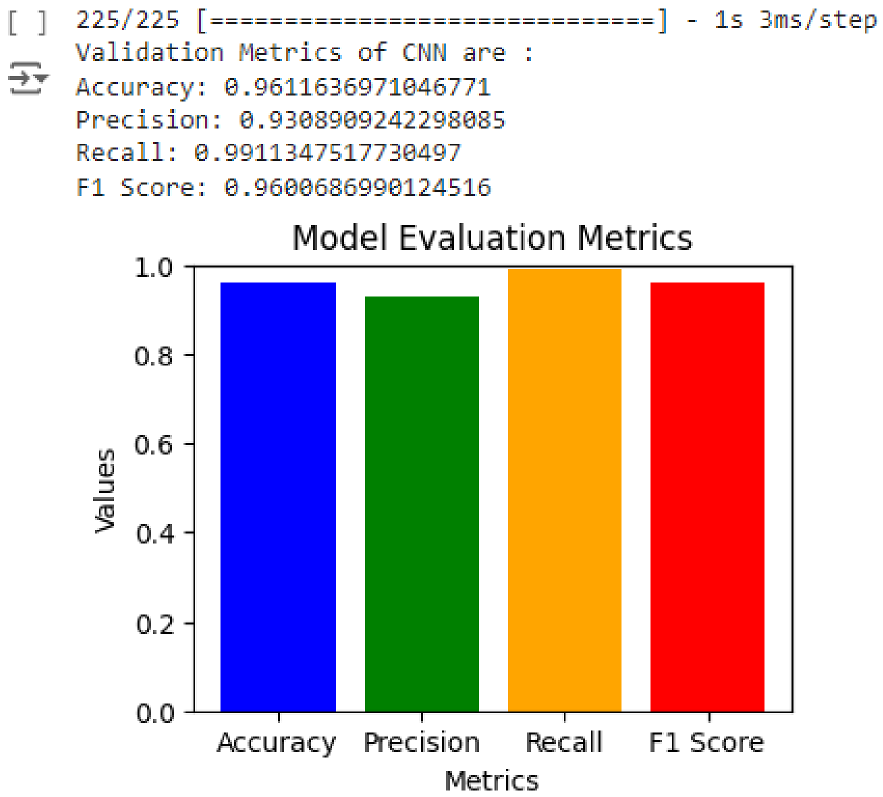

Figure III.4:Model Evalution Metrics of CNN-BILSTM

3.4. Results and Discussion:

3.4.1. Results

In this research, we employed three base learning (LSTM, BILSTM, CNN-BILSTM) and an ensemble that combines them. The models are tested on the testing set provided in the Fake news detection dataset. We evaluated their performance Using four measurements which are accuracy, precision, recall, and the F1-score. The results are reported in graphic curve According to the results, the ensemble scored the greatest accuracy of 93.22%. Meanwhile, LSTM achieved 93.04%, BILSTM achieved 93.52%, and CNN-BILSTM achieved 91.11% accuracy rate. The results clearly demonstrate that models LSTM, BILSTM and CNN-BILSTM and are very good at classifying fake news subject, but the ensemble that combined these three models outperformed all of them with an accuracy of 93.22%. Note that all the results obtained are quite close, within 3% of each other.

Table III.2: Results

	Accuracy	Precision	Recall	F1 score
LSTM	96.04	96.61	95.41	95.78
BILSTM	96.52	95.44	97.25	96.34
CNN-BILSTM	96.11	93.11	99.11	96.00
Proposed Ensemble	96.22	95.05	97.25	96.04

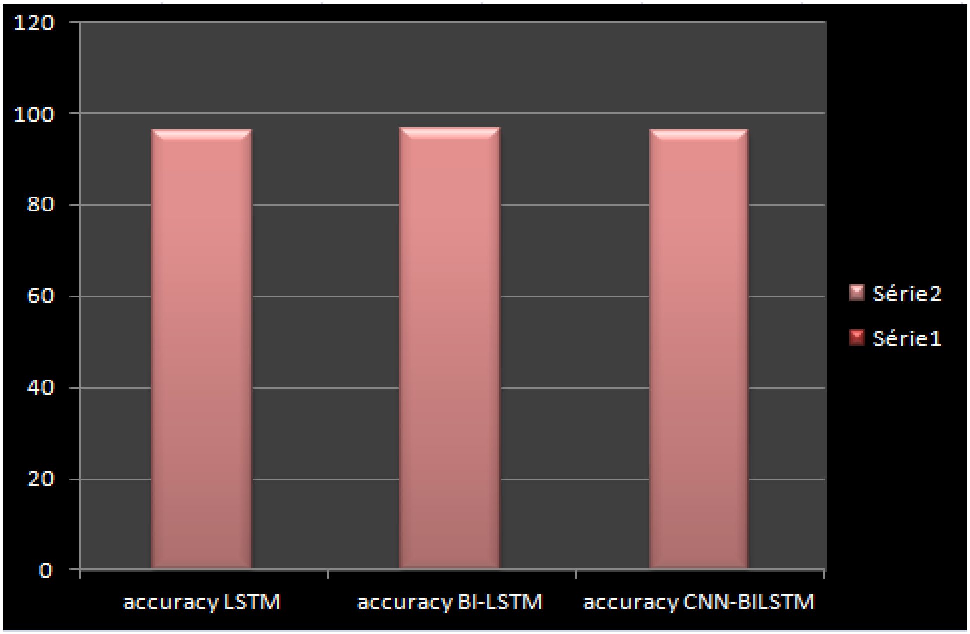

Figure III.5: Graph columns representing each model.

3.5. Conclusion

This chapter outlined the work's practical aspects, clarified the primary issue and the true motivations for the project, and then went into further depth about our model's architecture, which consists of three algorithms. LSTM and BILSTM and CNN-BILSTM the combination of the LSTM and BILSTM and CNN-BILSTM together .we also exposed the results we got out of the combination and last we discussed some related works results and compared them to the results we obtained.

General Conclusion

The detection of fake news is a critical endeavor in today's digital age, where misinformation can spread rapidly and have profound societal consequences .Due to the rapid dissemination of fake news on social media, it is becoming very difficult Despite the difficulties presented by false information, the identification of fake news has significantly benefited society in a number of ways. The following are some significant contributions made by initiatives to identify bogus newsImproved Media Literacy: Efforts to identify fake news have increased public awareness of the value of media literacy and critical thinking abilities. Detection programs enable people to make better judgments about the information they consume by informing them about the prevalence of false information and giving them the tools to spot fake news.Technological developments: Machine learning, natural language processing, and data analytics have all advanced as a result of the creation of algorithms for detecting false news. The field of artificial intelligence has benefited from these technologies' increased sophistication and effectiveness in identifying patterns, language clues, and abnormalities in textual data. The initial chapter was split into two halves . In the first section, false information was defined and its different forms, perpetrators, and reasons were discussed. The second section contained a thorough definition of fake news, along with information on its types, ways to spot them, and potential health risks.

An overview of machine learning, deep learning, and artificial intelligence is given in the second chapter. Additionally, we established a few widely used deep learning algorithms, such as Long Short Term Memory (LSTM), Convolution Neural Network (CNN), The goal and driving forces behind this work were originally outlined in the third chapter.We then presented our work's concept after citing a few relevant works.We then went into great detail about how it was implemented and which dataset was used.Finally, we talked about the outcomes and contrasted them with other studies that used the same dataset. This work's ensemble model worked exceptionally well, with a high accuracy of 96.22%. In conclusion, we suggest more study be done on fake news intervention, which tries to lessen the effects of fake news by using reactive intervention strategies after it gets viral or proactive strategies that limit the spread scope. Proactive measures to combat fake news attempt to: (i) eliminate malicious accounts that disseminate false information in order to keep it away from potential customers; (ii) vaccinate users with accurate information in order to alter their perceptions in the event that they have already been impacted by false information. Recent studies have attempted to employ network-based and content-based immunization strategies for disinformation intervention [33][34]. One method reduces the real-time propagation of false information by modeling both fake and authentic news using a multivariate Hawkes process [35]. The previously mentioned methods for identifying spreaders can also be used to target certain people on social media, such as persuaders, to cease distributing false information, or other users, such as clarifiers, to increase the distribution of related factual news. Our goal is to utilize a bigger dataset with a more extensive vocabulary set in the future. In order to improve the false news detection system, we also plan to look into the effectiveness of novel ensemble learning techniques that make use of several deep learning models.We are also planning to takein consideration other features that would improve the quality of detection like user-basedfeature.

Bibliography

[1] Zhang, X.; and Ghorbani, A. A. (2019). An overview of online fake news: Characterization, detection, and discussion. Information Processing & Management, 57, 102025.

[2] Dale, R. (2017). NLP in a post-truth world. Natural Language Engineering, 23, 319-324.

[3] Horne, B. D.; and Adali, S. (2017). This just in: Fake news packs a lot in title, uses simpler, repeti-tive content in text body, more similar to satire than real news. In Eleventh International AAAIConference on Web and Social Media.

[4] Google News Initiative (2018). https://newsinitiative.withgoogle.com/, Retrieved March 25, 2020.

[5] Misinformation, Disinformation and Mal-Information . https://www.mediadefence.org/ereader/publications/introductory-moduleson-digital-rights-and-freedom-of-expression-online/module-8-false-newsmisinformation-and-propaganda/misinformation-disinformation-and-malinformation/. Accessed: 2022-05-21.
[6]Definitionofdisinformation.https://www.merriamwebster.com/dictionary/disinformation. Accessed: 2022-05-21.

[7] V. L. Rubin, N. J. Conroy, and Y. Chen. Towards news verification: Deception detection methods for news discourse. 2015

[8] S. Heller. Bat Boy, Hillary Clinton's Alien Baby, and a Tabloid's Glorious Legacy. https://www.theatlantic.com/entertainment/archive/2014/10/the-ingenious-sensationalism-of-the-weekly-world-new/381525/, 2014.

[9] S. Kumar, R. West, and J. Leskovec. Disinformation on the web: Impact, characteristics, and detection of wikipedia hoaxes. In WWW, 2016.

[10] Definition of half-truth. https://www.merriawebster.com/dictionary/half-truth.

[11]Jonathan Franceschi and Lorenzo Pareschi. "Spreading of fake news, competence and learning: kinetic modelling and numerical approximation". In: PhilosophicalTransactions of the Royal Society A 380.2224 (2022), p. 20210159.

[12] M. Potthast, J. Kiesel, K. Reinartz, J. Bevendorff, and B. Stein.A Stylometric Inquiry into Hyperpartisan and Fake News. In arXiv 24 preprint arXiv:1702.05638, 2017

[13]Barlamane.com. Useful idiots.url: https://rationalwiki.org/wiki/Useful_ idiot. (accessed: 08.03.2022).

[14] S. T. Lee. Lying to tell the truth: Journalists and the social context of deception.In Mass Communication & Society, 2004.

[15] Y. Boshmaf, I. Muslukhov, K. Beznosov, and M. Ripeanu. The socialbot network: when bots socialize for fame and money. In ACSAC, 2011.

[16] Martin Potthast, Johannes Kiesel, Kevin Reinartz, JanekBevendor_, and Benno Stein. A stylometric inquiry into hyperpartisan and fake news. arXiv preprint arXiv:1702.05638, 2017.

[17] David O Klein and Joshua R Wueller. Fake news: A legal perspective. 2017.

[18] Hunt Allcott and Matthew Gentzkow. "Social media and fake news in the 2016 election" . In: Journal of economic perspectives 31.2 (2017), pp. 211–36.

[19]Xinyi Zhou and Reza Zafarani. "A survey of fake news: Fundamental theories, detection methods, and opportunities". In: ACM Computing Surveys (CSUR) 53.5 (2020), pp. 1–40. doi: 10. 1145/ 3395046.ur l: https: // doi. org/ 10.1145 /3395046.

[20] Jennifer Golbeck et al. "Fake news vs satire: A dataset and analysis". In: Proceedings of the 10th ACM Conference on Web Science. 2018, pp. 17–21.

[21] 2019.SavvasZannettou, Michael Sirivianos, Jeremy Blackburn, and Nicolas Kourtellis. The web of false information: Rumors, fake news, hoaxes, clickbait, and various other shenanigans. Journal of Data and Information Quality (JDIQ), 11(3):1–37, 2019.

[22] *Edson C TandocJr, Zheng Wei Lim, and Richard Ling. "Defining "fake news" A typology of scholarly definitions". In: Digital journalism 6.2 (2018), pp. 137–153.*

[23]OrestisLampridis, DimitraKaranatsiou, and Athena Vakali. "MANIFESTO: a huMAN-centricexplaInable approach for FakE news spreaders deTectiOn". In: Computing (2022), pp. 1–23.doi: 10.1007/s00607-021-01013-w. url: https: //doi.org/10.1007/s00607-021-01013-w.

[24] Kai Shu et al. "Fake news detection on social media: A data mining perspective". In: ACM SIGKDD explorations newsletter 19.1 (2017), pp. 22–36.

[25]Artificial Intelligence versus Machine Learning, Deep Learning, and Neural Networks,"

Computer & Data Articles, September 2, 2021.

[26] s. kumar, "age anf gender detection, "galgotias university, 2020

[27] C. Liu, T. Arnon, C. Lazarus, C. Strong, C. Barrett, M. J. Kochenderfer et al.,

“Algorithms for verifying deep neural networks,” Foundations and Trends® in Op-

[28] MehrdadFarajtabar, Jiachen Yang, Xiaojing Ye, HuanXu, RakshitTrivedi, Elias Khalil, Shuang Li, Le Song, and HongyuanZha. Fake news mitigation via point process based intervention. *arXiv preprint*
arXiv:1703.07823, 2017.

[29] Devlin, J., Chang, M.-W., Lee, K., &Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 4171-4186. Available at: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.

[30] Allcott, H., &Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election.*Journal of Economic Perspectives*, 31(2), 211-236. Available at: Social Media and Fake News in the 2016 Election

[31] Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., ...&Zittrain, J. L. (2018). The science of fake news.*Science*, 359(6380), 1094-1096. Available at: The Science of Fake News

[32] Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online.*Science*, 359(6380), 1146-1151. Available at: The Spread of True and False News Online

[33] Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake News Detection on Social Media: A Data Mining Perspective. *SIGKDD Explorations*, 19(1), 22-36. Available at: Fake News Detection on Social Media

[34] Zhang, X., &Ghorbani, A. A. (2020). An overview of online fake news: Characterization, detection, and discussion. *Information Processing & Management*, 57(2), 102025. Available at: An Overview of Online Fake News

[35] Alkhodair, S. A., Ding, S. H. H., Fung, B. C. M., & Liu, J. (2020). Detecting breaking news rumors of emerging topics in social media.*Information Processing & Management*,