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MACHINE LEARNING BASED FAKE DETECTION MODEL USING REGIONAL CONVOLUTION NEURAL NETWORK

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ABSTRACT

Forms of digital media such as blogs, online news media, and social media have taken the place of former news delivery platforms such as newspapers and magazines. The linked recommendations of these platforms help spread the word in no time. This fascination leads to an invasion of negativity such as fake news and misrepresented information. False information negatively affects all areas such as health care, education, government, and the market because people make decisions about anything based on available information. Messages can be text or multimodal. Any combination of text, image, and video can be present in multimodal messages. Attention seekers create fake news by altering text, images, or both. The spread of fake news is in different domains, but fact-checking sites can verify the authenticity of a particular environment; thus, detecting fake news remains challenging. Another reason for the difficulty in detecting fake news is the unstructured representation of news (in the form of articles, images, audio, video, etc.) that a person needs to classify. Despite the large amount of research work that has been done to meet this purpose, proper classification still faces various challenges such as imbalance, multimodality, lack of appropriate structure, and ambiguity of words in datasets. This research proposes four novel deep learning architectures for text and image-based fake news classification. Headlines explain news headlines and draw anyone's attention to some information. The image provides relevant image data about the news. In many fake news, the textual content and visual information will not be related. This work is a hybrid model that uses all three pieces of information, namely title, text, and image. In the first work, a Deep-Learned Bidirectional Gated Recurrent Unit (Bi GRU) - Long Short-Term Memory (RNN) Model (DL-BGLM) is used to detect fake messages using textual content and message title. Detection is done by incorporating two new subframes. The first sub-framework of the Glove Embedded Bidirectional Predicted Attention Scheme (GEBPA) gets significant information from the name. The second subframe Multi-Layered Convolution and Bidirectional LSTM (MCBL) scheme extracts salient features from the text.

Keywords: Fake News Detection, Deep Features, Ensemble based methods, Machine Learning, RNN.

1 . INTRODUCTION

Rapid progress and technological advancement, internet trends, and digitization of media have shortened the problems in reaching any kind of news source irrespective of the location. Nowadays, along with conventional news sources, online social media serves as another important platform for sharing news.

There may be many reasons behind the shift in user mindset towards social media platforms, but the main reason is the frequent distribution of content on social media, which is cheaper. Information that is published through various social media with attractive images influences the public and users more than the usual press releases. As a result, people are more interested in surfing the Internet than conventional sources of news such as television and newspapers.

However, social media plays a vital role in real-time events by creating public awareness. Many studies have shown that social media is more effective during disasters and countless emergencies. As shown in Figure 1.1, while the digitization of news and the development of social media are advancing at a faster pace, false and fake news have adverse effects that harm society.

Research shows that any information or content that includes both text and images will have more credibility than messages that only have text content. Unfortunately, fake news with text and images can mislead consumers. This can lead to harm in the community and confuse users. In 2016, when the US presidential election was held, the false information that was developed and published went crazy among the public, which was then shared by masses of people on social media platforms.

These types of fake news can create bigger ones adverse effects on individuals and the public such as:

• The ability to break the credibility and authenticity of the news ecosystem

• Directs end users to believe distorted or false information

• People's misinterpretation and reaction to current news

Identifying fake news has therefore become an important task. To overcome the negative impact of fake news, its automatic detection is more important. However, this will not be an easy task and will be difficult to implement due to the complexity of analyzing the content of the messages and verifying their authenticity. Designing a reliable and persistent approach to identifying fake news is important.

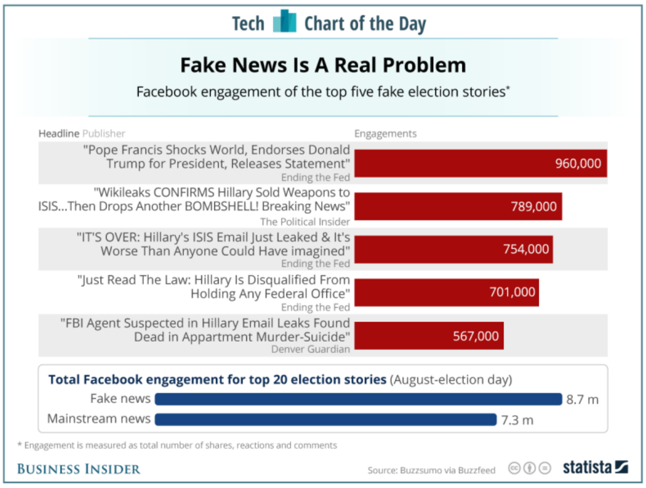

Figure 1.1 Analysis illustrating the outperformance of fake news over the original news

2. RELATED WORK

2.1 INTRODUCTION

[5] Fake news spreads faster than genuine news through the Internet or social media, and visitors or Internet consumers are influenced by its appeal. Elisa et al. (2021) depicted that 59% of news spread on social media in 2020 is largely inaccurate. This fake or false information is mostly harmful to the users and even to the company. There is a lot of research going on to detect fake news and now it has become a big challenge due to the versatility of features in news. Features such as text, titles, and visuals can be used to detect fake news. This chapter discusses methodologies designed by researchers to detect fake news. Therefore, we analyze existing works based on the following categories: Title, Text content, images, and an integrated model that uses title, text, and images in detection.

2.2 FAKE NEWS DETECTION BASED ON TEXT FEATURES

Among many features, the text feature is mainly used to detect fake news. The text feature helps detect unverified information. In the last few years, many research and surveys based on computational techniques have been done to identify fake news using textual content, and a few of them are discussed below.

[6] Recent work that uses deep learning to have the ability to categorize fake news from real has been proposed (Chauhan et

al. 2021). False detection is done by vector representation of text words using Glove (Global Vectors for Word Representation) word embedding. A new LSTM NN is also used along with this insertion of the word Glove. The tokenization method is used for vectorization and feature extraction. The concept of N-grams further improves the accuracy of the proposed model. Several analyses were performed and model results were evaluated with accuracy metrics. This model provides 99.88% accuracy for a text article.

Textual information consists of many features. By extracting elements such as explicit and latent from the text, (Zhang et al. 2020) proposed the idea of a new Neural Network with Gate Graph. Named FAKEDETECTOR, the method learns representations of news articles, news creators, and content simultaneously by building or evolving a deep diffusion network model. Many experiments have been performed in real time with a fake news dataset. FAKEDETECTOR and its results are superior compared to many other available models.

[7] Kong et al. (2020) derived a fake news detection methodology that is based on the title or content of the news. The model is trained using natural language processing (NLP) techniques. First, the text is pre-processed. It includes stop word removal, tokenization, lemmatization, and regular expression. Next, Terms Frequency The inverse document frequency is used to vectorize the preprocessed data into N-gram vectors. This is followed by TensorFlow with built-in deep learning libraries for further tuning and refinement of text data. The performance has shown better results than many other models of a similar pattern.

[8] To classify fake news published online and also on social media (Ozbay et al. 2020) a two-step method. The first step is to convert the unstructured data into structured data and the data is pre-processed. The preprocessed data as vectors were represented by a document matrix. The second step is text analysis, which is implemented by supervised AI algorithms. The results of this methodology are better compared to several other methods.

For detecting fake news, it was found that text elements connected to text elements are more effective, and based on this idea (Olivieri et al. 2019) proposed another method. This technique involves the Google search engine to which metadata is attached. Fine-tuning and development are also done through crowdsourcing. An experimental validation of this method to determine and identify fake news is using the PolitiFact website. The results obtained after experimental validation show a 3% improvement over the current state, which is significant.

[9] Kresnakova et al. (2019) proposed deep learning techniques to identify fake news in text data. Several neural network-trained models were used in this method. The main goal of these trained neural networks is to identify if there is any mismatch between article titles and article content. If a mismatch is detected, the percentage of false text is also determined. The results show better performance than other deep learning methods.

Table 2.1 Fake News Detection Based on Textual features

Sl. No.	Paper Title	Reference	Methodologies
1.	Optimization and improvement of fake news detection using deep learning approaches for societal benefit	(Chauhan *et al.* 2021)	LSTM Neural Networks
2.	Fakedetector: Effective fake news detection with deep diffusive neural network	(Zhang *et al.* 2020)	FAKEDETECTOR
3.	Fake news detection using deep learning	(Kong *et al.* 2020)	NLP techniques and deep learning models
4.	Fake news detection within online social media using supervised artificial intelligence algorithms	(Ozbay *et al.* 2020)	Two-step method for fake news detection
5.	Fake news detection method based on text-features	(Drif *et al.* 2019)	Hybrid CNN-LSTM model
6.	Truth and Lies: Deception and Cognition on the internet	(Olivieri *et al.* 2019)	Task-Generic features coupled with textual features
7.	Deep learning methods for Fake News detection	(Kresnakova *et al.* 2019)	Detection of fake news from the textual data using deep learning techniques
8.	Neural User Response Generator: Fake News Detection with Collective User Intelligence	(Qian *et al.* 2018)	Two-Level Convolutional Neural Network with User Response Generator (TCNN-URG)
9.	Fake News Detection: A Deep Learning Approach	(Thota *et al.* 2018)	Neural Network architecture
10.	" liar, liar pants on fire": A new benchmark dataset for fake news detection	(Wang W.Y. *et al.* 2017)	Hybrid Convolutional Neural Network

2.3 FAKE NEWS DETECTION BASED ON VISUAL FEATURES

Visual features also play a vital role in detecting fake news. Images can easily grab the attention of readers and it helps tremendously in misleading readers to unverified information. Research and surveys conducted over the past few years to identify fake news using visual content are described below.

[10] Palani et al. (2022) proposed a method wherein informative features from an image were extracted using a Capsule Neural Network. The extracted informative features are combined with other data representations. The combination is used to identify whether the news is authentic or genuine. The model achieves an accuracy of 93% on the PolitiFact dataset and 92% on the Gossip Cop dataset.

[11] Dimitrina Zlatkova et al. (2019) designed a framework for faux news detection using visuals. Features that model the claim for fact-checking, the visual features, and the association between the claim and visuals are identified. The results showed significant improvements over the other methods.

[12] Peng Qi et al. (2019) designed a novel framework that fuses the frequency and pixel information from the visuals using multi-domain visual NN. The fusion of frequency and pixel domains is carried out using an attention mechanism. Experimental analysis proves that MVNN outperforms the other methods by approximately 9.2% in accuracy.

[13] Xin Yang et al. (2019) designed a method to identify fake face images or videos that are AI-generated. There is a general observation that Deep Fakes are formed by merging the created image into that of the source image. Extensive experimental analysis was conducted using an SVM classifier on a set of original face images.

[14] (Jaiswal et al. 2017) designed an approach based on deep learning methodology. The image-caption Consistency score was generated using deep multimodal representation learning on the reference dataset. The query media packages were also assessed for their integrity. A novel dataset of media packages termed as MultimodAl Information Manipulation dataset (MAIM), from Flickr was used. The method was able to achieve 0.75, 0.89, and 0.94 F-1 scores on MAIM.

[15] Zhiwei et al. (2017) An attention mechanism termed a Recurrent Neural Network(att-RNN) that combines multimodal features for rumor identification. The textual features and social context are incorporated with image features employing Long-Short Term Memory which produces reliable classification. The attention mechanism is used when the visual features are combined.

Table 2.2 Fake news detection based on visual features

Sl. No.	Paper Title	Reference	Methodology
1.	CB-Fake: A multimodal deep learning framework for automatic fake news detection using capsule neural network and BERT	(Palani *et al.* 2022)	Capsule Neural Network
2.	Fact-checking meets fauxtography: Verifying claims about images.	(Dimitrina Zlatkova *et al.* 2019)	Fact checking using images
3.	Exploiting multi-domain visual information for fake news detection	(Peng Qi *et al.* 2019)	Multi-domain Visual Neural Network (MVNN)
4.	Exposing deep fakes using inconsistent head poses	(Xin Yang *et al.* 2019)	AI-generated fake face images or video
5.	Multimedia semantic integrity assessment using joint embedding of images and text	(Jaiswal *et al.* 2017)	A joint embedding of images and captions with deep multimodal representation learning
6.	Multimodal fusion with recurrent neural networks for rumor detection on microblogs	(Zhiwei *et al.* 2017)	Recurrent Neural Network with an attention mechanism (att-RNN)
7.	Novel visual and statistical image features for microblogs news verification	(Zhiwei *et al.* 2016)	Visual and statistical features for fake news detection
8.	Deep visual-semantic alignments for generating image descriptions	(Karpathy *et al.* 2015)	Alignment model
9.	Image forgery detection using steerable pyramid transform and local binary pattern	(Ghulam Muhammad *et al.* 2014)	Image forgery detection method
10.	Defending against fingerprint-copy attack in sensor-based camera identification	(Goljan *et al.* 2010)	Detection of fake finger prints

[16] Zhiwei et al. (2016) used visual and statistical features. Extensive experiments were conducted on datasets that show the efficiency of the methodology.

[17] Karpathy et al. (2015) proposed an alignment model that fuses Structured objective, Bi-RNN, and CNN. CNN was used over visuals, Bi-RNN was used over texts, and a structured objective combines the two types of features through an embedding technique. Extensive experiments were conducted on datasets that produced better results than the other baseline methods.

2.4 FAKE NEWS DETECTION BASED ON MULTIMODAL FEATURES

Most false information is text, multimedia, links, and audio. Textual information is characterized by its grammar, tone, pragmatics, and sentence, with which discourse evaluation is carried out. Other information such as video, text, image, sound, and so on can be incorporated into the multimedia form of information. False information detection is primarily done entirely based on the relationship between a number of these information styles (Conroy et al. 2015) and (Parikh et al. 2018). In the past few years, many research studies based on deep neural networks have been done to identify fake news using multimodal features, and a few of them are discussed below.

[18] Wang et al. (2022) propose a fine-grained multimodal fusion network that combines visual features and text features for false information detection. A pair of characteristic vectors representing special image features and additionally captures dependencies between text features and visible features. They conducted extensive experiments on Weibo's public dataset. This technique achieves aggressive effects compared to different strategies for combining visible illustration and textual content illustration, which shows that the common illustration detected by FMFN, which combines several visible features and several textual features, is higher than the received joint illustration. combining visible illustration and textual content illustration in false information detection.

[19] Peng et al. (2022) proposed a multimodal fake news detection framework that combines both attention and adversary mechanisms. Variations across modalities are identified using an attentional mechanism, and correlations between different modalities are identified using an adversarial mechanism. Experiments conducted on a Chinese public dataset show that it achieves a 5% higher F1 score compared to other state-of-the-art methods.

[20] Dhawan et al. (2022) proposed GAME-ON, a graph neural network that detects fake news in both unimodal and multimodal features. It uses two datasets Twitter and Weibo. It outperforms experiments on the Twitter dataset by 11% and provides competitive performance on Weibo.

[21] The probability of fact (Ciampaglia et al. 2015) was derived using structured fact stores that assign greater values to records than false ones. This approach was evaluated using ten thousand statements related to history, entertainment, geography, and biological information

[22] Rhetorical Structure Theory (RST) (Rubin et al. 2015) and Vector Space Modeling (VSM) have been used for methods based on deception modeling. A unique relationship was created from the textual content. False information was identified using these techniques. Twitter records were used as hyperlinked records to distinguish authentic content from fake records using questionable sources.

[23] Network evaluation or hyperlinks (Feng et al. 2012) and (Feng et al. 2013) have been used along with textual content to detect false information in some research. In this approach, factual statements from information networks are used to represent data where place deception has been recognized by leveraging collective human expertise from Google Relation Extraction Corpus (GREC), Dpedia ontology, etc.

[24] Centering resonance evaluation (Papacharissi et al. 2012) has been used as a device for network evaluation of textual content through the detection of hypertext links between phrases in networks.

[25] Chu et al. (2010) focused on the categorization of humans and bots on Twitter. Experiments were performed on 500,000 accounts. Differences were analyzed based on tweet behavior and tweet content. The method uses a combination of characters for classification. Sentiment evaluation shows another way to figure out false information through online ranking. The efficiency of the extracted features plays a key function in the accuracy of information detection. Various kinds of aspects were accessible to classify false information.

The above methods use multimodal features to detect fake news. To summarize the hybrid features, it is better than identifying authenticity using textual or visual features.

Table 2.3 Fake news detection based on hybrid features

Sl. No.	Paper Title	Reference	Methodology
1.	FMFN: Fine-Grained Multimodal Fusion Networks for Fake News Detection	(Wang *et. al* 2022)	Fine-grained Multimodal Fusion network (FMFN)
2.	An effective strategy for multi-modal fake news detection	(Peng *et al.* 2022)	Attention and Adversarial mechanism
3.	GAME-ON: Graph Attention Network based Multimodal Fusion for Fake News Detection	(Dhawan *et al.* 2022)	GAME-ON - A Graph-based Neural Network
4.	Fake News Detection Based on Multi-Modal Classifier Ensemble	(Shao *et al.* 2022)	Multi-modal classifier ensemble method
5.	Fake news detection for epidemic emergencies via deep correlations between text and images	(Zeng *et al.* 2021)	FND-SCTI
6.	Hierarchical multi-modal contextual attention network for fake news detection	(Qian *et al.* 2021)	Hierarchical Multi-modal Contextual Attention Network (HMCAN)
7.	ConvNet frameworks for multi-modal fake news detection	(Raj *et al.* 2021)	Multi-modal Coupled ConvNet structure
8.	Improving fake news detection by using an entity-enhanced framework to fuse diverse multimodal clues	(Qi *et al.* 2021)	Textual content-photo correlations
9.	Entity-oriented multi-modal alignment and fusion network for fake news detection	(Li *et al.* 2021)	Entity-orientated Multi-modal Alignment and Fusion network (EMAF)

10.	Predicting image credibility in fake news over social media using multi-modal approach	(Singh *et al.* 2021)	Multi-modal method
11.	Knowledge-aware multi-modal adaptive graph convolutional networks for fake news detection	(Qian *et al.* 2021)	Knowledge-aware Multi-modal Adaptive Graph CN (KMAGCN)

2.5 SUMMARY

In this chapter, the overview of feature extraction and fake detection methodologies based on textual features, visual features, and multimodal features by the previous researchers has been presented. The next chapter summarizes the problem statement and the overall architecture.

3. METHODOLOGY

3.1 INTRODUCTION

Forms of digital media such as blogs, online news media, and social media have taken the place of former news delivery platforms such as newspapers and magazines. This fascination leads to an invasion of negativity such as fake news and misrepresented information. False information negatively affects all areas such as health care, education, government, and the market because people make decisions about anything based on available information. Messages can be text or multimodal. Any combination of text, image, and video can be present in multimodal messages. People create fake news by changing text, images, or both. This can lead to loss of money or lives. Checking the authenticity or identifying fake news in these reports is a hurdle for researchers. The sheer volume of data and the level of its dissemination make this a daunting task. With the help of fact-checking websites (eg: Snopes, PolitiFact), it is possible to analyze fake news based on textual content. The spread of fake news is in different domains, but fact-checking sites can verify the authenticity of a particular environment; therefore, false analysis remains challenging. Another reason for the difficulty in mock analysis is the unstructured representation (in the form of articles, images, audio, video, etc.) of the messages that humans need to classify. Classification algorithms are also used to identify fake news. The classification accuracy depends on the efficiency of the algorithm and the data set used. Despite the large amount of research work that has been done to meet this purpose, proper classification still faces various challenges such as imbalance, multimodality, lack of appropriate structure, and ambiguity of words in datasets. Fake messages should be identified by proper analysis, and better classification accuracy can only be achieved with complete knowledge of the messages. Research on different machine learning algorithms provides different aspects that can be used for classification. Advances in deep learning techniques are yielding promising results regardless of the numerous challenges of the nature of the dataset.

3.2. RESEARCH CONTRIBUTION

3.2.1. Introduction

As shown in Figure 3.1, this work proposes four novel frameworks for detecting fake news using title, text, and image. Headlines are what grab anyone's attention information. The text explains the headline of the message. The image provides a relevant image data about the news. In many fake news, the textual content and visual information will have no relationship. This work uses all three of these pieces of information.

In the first work, the RCNN (RCNN)-Long Short-Term Memory (LSTM) Model (DL-BGLM) is used to detect fake news using textual content. It is a two-step process where first salient features are extracted from the title and then salient features are extracted from the text and the outputs are combined to verify the similarity between the title and text features to identify fake news. In the second work, the Deep-Learned Prominent Similar Terms Model (DL-PSTM) is used to detect fake news by extracting and deep-learning prominent intelligence information. In this work, deep similar terms (PSTs) are derived from the title and text of the considered news article, and the correlations between the title, text, and PST are analyzed to identify the authenticity of the considered news. In the third paper, the Multiscale-Multi-layered Jointly Squeezed (DL-M2 JS) model is used to detect fake news by extracting prominent images from the news. In this work, visual elements are combined with textual elements to identify the authenticity of the mentioned messages. Deep Learned Information Integrated Model (DLI2M) is the fourth work where title, text, and image are used to detect fake news. This hybrid model combines all features – title, text, PST, and image to identify whether the messages are authentic or not.

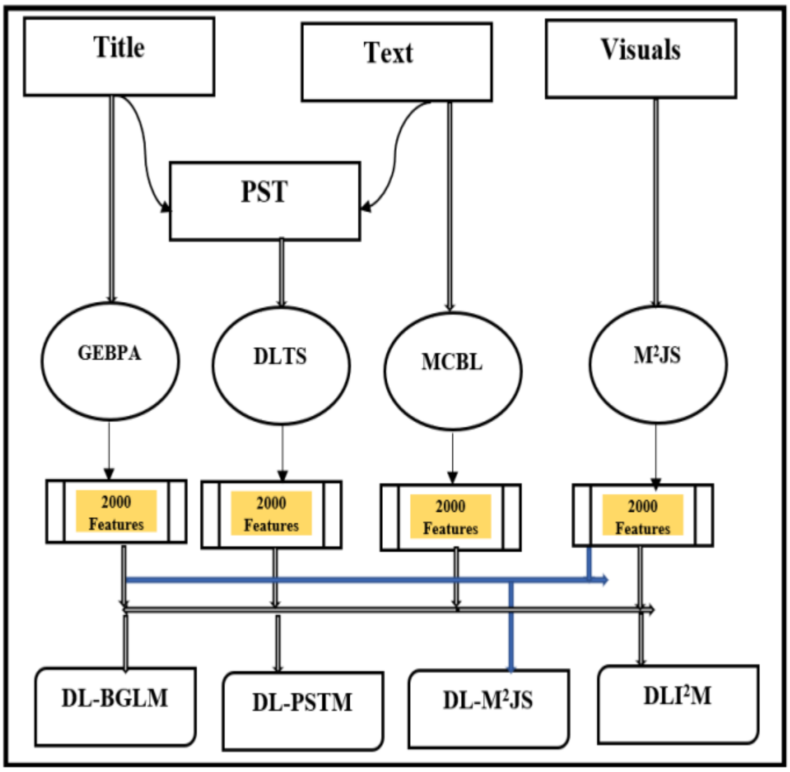

Figure 3.1 Proposed Work Flow

3.2.2 Deep-learned BI-GRU-LSTM Model (DL-BGLM)

The first work, the Deep-Learned bi-GRU-LSTM Model (DL-BGLM), uses text content and message title. Detection is done by incorporating two new subframes. The Bidirectional Predicted Attention Scheme (GEBPA) gets significant information from the name. The second subframe Multi-Layered Convolution and Bidirectional LSTM (MCBL) scheme extracts significant information from the text.

The two sub-frames are integrated, and deep learning layers learn salient features of both sub-frames to find similarity between the title and salient text elements. Based on the similarity score, the name and text elements are analyzed to determine whether the given name and text content are fake.

3.2.3 Deep-Learned Similar Concept Model (DL-PSTM)

The second work, the Deep-Learned Profound Similar Terms Model (DLPSTM), is used to detect fake news using similar prominent terms, textual content, and message titles by incorporating three sub-frameworks. Detailed information is collected from the title and text. It uses three subframes. The first subframe of the Glove Embedded Bidirectional Predicted Attention Scheme (GEBPA) is used to extract meaningful information from the title. The second sub-frame Multi-Layered Convolution and Bidirectional LSTM (MCBL) scheme is used to extract apparent information from the text. The third subframe Dual-Layered Temporal-Semantic (DLTS) Scheme is used to extract features from apparent information from PST. The sub-frames are integrated to find the similarity between the headline, text, and main features of the PST, thereby determining whether the given news content is fake.

3.3 EXPERIMENTAL SETUP AND DATA SET

3.3.1 Data Files

Datasets play a major role in identifying and detecting fake news. Many datasets are available (Zhou et al. 2020), of which PolitiFact (DB1) (Shu et al. 2018), Gossip Cop (DB2) (Wang et al. 2017), and Media Eval (DB3) (zhou et al. 2020) are the predominant datasets for this experiment. The quality of news depends on the quantity of truth in it. This is determined by ground truth labels obtained from industry experts. The following table 3.1 shows the statistics of data sets obtained from experts in the field.

Table 3.1 Statistics of Datasets

	Fake	True	Total
PolitiFact	432	624	1056
GossipCop	5323	16817	22140
MediaEval	11000	6000	17000

3.3.2 PolitiFact

PolitiFact (DB1) is a website that provides information regarding US politics. It provides facts, news, and statements about US politics from May 2002 to July 2018. Statistics say that out of 1056 news articles, 432 are fake articles and the remaining 624 are real. Both textual information and image articles are exhibited in 928 and 783 articles respectively. Figure 3.1 shows an example of a news article on the PolitiFact dataset.

Image			
Title	h r rd congress brady handgun violence prevention act	preventing the flu good health habits can help stop germs	statement by the president
Text	there are summaries for h r conference report filed in house introduced in house bill summaries are authored by crs\n\nshown here \n\nconference report filed in house \n\ntable of contents \n\ntitle i brady handgun control	the single best way to prevent seasonal flu is to get vaccinated each year but good health habits like covering your cough and washing your hands often can help stop the spread of germs and prevent respiratory illnesses like the flu there also are flu antiviral drugs that can be used to treat and prevent flu	rose garden\n\n p m edt\n\nmr barden hello my name is mark barden just four months ago my wife jackie and i lost our son and our children james and natalie they lost their little brother daniel daniel was a first grader at sandy hook elementary school our sweet year old daniel was one of children six adults lost on december th i have to say it feels like it was just yesterday
	(a)	(b)	(c)

Figure 3.2 Example of news articles in PolitiFact (DB1) dataset

3.3.3 Gossip Cop

Gossip Cop (DB2) is a website that is meant for entertainment-related news. The articles published in newspapers and magazines related to entertainment from the year July 2000 to December 2018 are available on this website. A total of 22140 news articles are available of which 16817 are real and the remaining 5323 are fake. Both the articles based on textual information totaling 21641 and visual information totaling 18417 are available on the website.

3.3.4 Media Eval

Medieval (DB3) is a dataset in which information about titles, images, and tweets is available. The dataset contains a total of 17000 tweets about various events of which 6000 are real and the remaining is fake. For the test set, 2000 tweets are used.

Medieval (DB3) dataset contains tweets, titles, and images. It has 17000 tweets about different events, of which 6000 are real and 9000 are fake. 2000 tweets are used as the test set. A sample of it is shown in Figure 3.3.

Image			
Title	Globe_Pics \nSolar eclipse at the ISS #eclipse #eclipse2015	Mashable	GarissaAttack
Text	das toch een pak impressionanter precies... RT	#socialmedia #tech Nepal's historic Dharahara Tower collapses in massive earthquake: The historic... http://t.co/fFLXuT0uX9 di	UPDATE: Gunman kill 2 guards after storming#Kenya University, take hostages.
	(a)	**(b)**	**(c)**

Fig.3.3 Sample text and images from the Media Eval (DB3) dataset

The accuracy based on the confusion matrix is calculated by positive True negative/ True positive+ True negative + False positive + False negative. The precision based on the confusion matrix is calculated by True positive/ True positive + False positive. The accuracy of the DL-BGLM method using the PolitiFact dataset is 82% and by using the Gossip Cop dataset, the accuracy is 83% and by using the Mediaeval dataset, the accuracy is 52%. The accuracy of the DL-PSTM method using the PolitiFact dataset is 84%, by using the Gossip Cop dataset the accuracy is 84%, by using the Gossip Cop dataset the accuracy is 54%.

The accuracy of the M2 JS method for the PolitiFact dataset is 89%, for the Gossip Cop dataset is 85%, and for the Media Eval dataset is 89%. The accuracy of DLI2M using the PolitiFact dataset is 91%, for the Gossip Cop dataset the accuracy is 89% and for the Media Eval dataset, the accuracy is 91%.

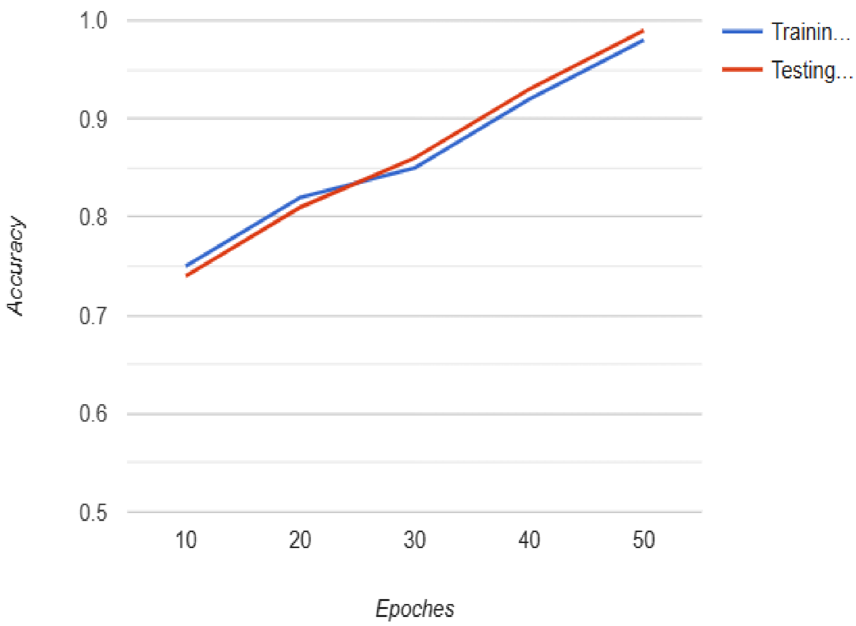

Fig.3.4 Accuracy Plot

4. CONCLUSION AND FUTURE WORK

In this work, various novel combinations of features are presented that are useful for detecting fake news. With the growing popularity of social media, the number of people getting news from social media is more than traditional news media. However, social media has been used to spread fake news that negatively affects individuals and society. Several methods related to fake news detection using textual, visual, and hybrid features is discussed in the literature survey, and each of these methods has advantages and disadvantages in terms of precision, accuracy, recall, and F1 score. The main emphasis of the proposed methodology is the use of unimodal and multimodal features for detecting fake news using deep learning algorithms. The features used are textual, visual, and deep similar expressions (PSTs), which are derived from the message text and title, and are checked for authenticity. The performances of the proposed works are analyzed by performing tests on three different types of datasets. Reference datasets used are PolitiFact, Gossip Cop, and Media Eval.

A four-layer framework was designed to combine prominent features extracted from the title, text, images, and prominent similar terms using deep learning layers. Experiments and discussions show that the proposed work shows considerable improvement in terms of accuracy (accuracy, recall, etc.). In this research work, similar expressions are proposed which are derived from the message text and title, which are used for fake news detection. Compared to various other methods using their respective datasets, they show significant improvement in terms of their evaluation measures.

4.1 FUTURE PERSPECTIVES

Based on the current research work, the following future perspectives are established to achieve further improvement of the fake news detection system.

• In this thesis, the work focuses on various features and their integration for fake news detection. There is room to improve detection efficiency by adding additional features such as video

• In Chapters 4, 5, 6, and 7, the proposed work can be extended by combining the proposed works with some other features such as continuous images and videos

• The proposed work can also be extended by applying works in video databases and incorporating some feature learning methods. The proposed works show a noticeable improvement in terms of their evaluation measures compared to the previously available fake news detection methodologies in their respective databases.

5. REFERENCES

[1] S. B. Parikh and P. K. Atrey, "Media-Rich Fake News Detection: A Survey",*IEEE Conference on Multimedia Information Processing and Retrieval (MIPR)*, Miami, FL, USA, 2018, pp. 436-441, DOI: 10.1109/MIPR.2018.00093.

[2] S. Helmstetter and H. Paulheim, "Weakly Supervised Learning for Fake News Detection on Twitter," *IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, Barcelona, Spain, 2018, pp. 274-277, DOI: 10.1109/ASONAM.2018.8508520.

[3] M. K. Elhadad, K. Fun Li and F. Gebali, "Fake News Detection on Social Media: A Systematic Survey," *IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM)*, Victoria, BC, Canada, 2019, pp. 1-8, DOI: 10.1109/PACRIM47961.2019.8985062

[4] M. L. Della Vedova, E. Tacchini, S. Moret, G. Ballarin, M. DiPierro and L. de Alfaro, "Automatic Online Fake News Detection Combining Content and Social Signals," *22nd Conference of Open Innovations Association (FRUCT)*, Jyvaskyla, Finland, 2018, pp. 272-279, DOI: 10.23919/FRUCT.2018.8468301.

[5] Soares, H. (2024). "The Spread of Fake News by Social Bots: Perspectives on Social Bot Regulation". *Springer Journal Legal Aspects of Autonomous Systems ICASL.* Data Science, Machine Intelligence, and Law, vol.4, 2019, DOI:10.1007/978-3-031-47946-511.

[6] Yimin Chen , Niall J.Conroy and Victoria L.Rubin "Misleading Online Content" November 2015. Pages 15-19, DOI:10.1145/2823465.2823467

[7] Chris Reed, D. Walton, and F. Macagno. “Argument diagramming in logic, law and artificial intelligence”. *The Knowledge Engineering Review*, 22(01):87–109, 2007.

[8] Douglas Walton, Christopher Reed, and Fabrizio Macagno. “Argumentation Schemes. Cambridge University Press”, 2008.

[9] Alice Toniolo, Federico Cerutti, Nir Oren, Tj Norman, and Katia Sycara. “Making Informed Decisions with Provenance and Argumentation Schemes”. *In 11th International Workshop on Argumentation in Multi-Agent Systems*, pages 1–20. Aamas2014.Lip6.Fr, 2014.

[10] Alice Toniolo, Timothy Dropps, Robin Wentao, and John a Allen. “Argumentation-based collaborative intelligence analysis in spaces”. *In COMMA*, pages 6–7, 2014.

[11] Conroy, Niall J., Victoria L. Rubin, and Yimin Chen. "Automatic deception detection: Methods for finding fake news." *Proceedings of the Association for Information Science and Technology* 52.1 (2015): 1-4.

[12] Kolari, Pranam, et al. "Detecting spam blogs: A machine learning approach." *AAAI*. Vol. 6. 2006.

[13] Wang, William Yang. "" Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection." *arXiv preprint arXiv:1705.00648* (2017).

[14] Kolari, Pranam, Tim Finin, and Anupam Joshi. "SVMs for the Blogosphere: Blog Identification and Splog Detection." *AAAI spring symposium: Computational approaches to analyzing weblogs*. 2006.

[15] Jin, Zhiwei, et al. "News credibility evaluation on microblog with a hierarchical propagation model." *Data Mining (ICDM), 2014 IEEE International Conference on*. IEEE, 2014

[16] Rubin, Victoria, et al. "Fake news or truth? using satirical cues to detect potentially misleading news." *Proceedings of the Second Workshop on Computational Approaches to Deception Detection*. 2016.

[17] Volkova, Svitlana, et al. "Separating facts from fiction: Linguistic models to classify suspicious and trusted news posts on twitter." *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. Vol. 2. 2017.

[18] Ver´onica P´erez-Rosas, Bennett Kleinberg, Alexandra Lefevre and Rada Mihalcea. “Automatic Detection of Fake News”. *Michigan University* 2017.

[19] Brian Edmonds, Xiaojing Ji, Shiyi Li, Xingyu Liu. “Fake News Detection Final Report”. *Chicago University*, 2017.

[20] Davis, Wynne. "Fake Or Real? How To Self-Check The News And Get The Facts." *NPR*, 05 Dec. 2016. Web. 22 Apr. 2017.

[21] Samir Bajaj. “The Pope Has a New Baby!” Fake News Detection Using Deep Learning”. *Stanford University*, 2017.

[22] A. Martínez-Garcia, S. Morris, M. Tscholl, F. Tracy, and P. Carmichael, “Case-based learning, pedagogical innovation, and semantic web technologies,” *IEEE Trans. Learn. Technol.*, vol. 5, no. 2, pp. 104–116, 2012.

[23] P. R. Humanante-Ramos, F. J. Garcia-Penalvo, and M. A. Conde-Gonzalez, “PLEs in Mobile Contexts: New Ways to Personalize Learning,” *Rev. Iberoam. Tecnol. del Aprendiz.*, vol. 11, no. 4, pp. 220–226, 2016.

[24] T. Granskogen and J. A. Gulla, “Fake news detection: Network data from social media used to predict fakes,” *CEUR Workshop Proc.*, vol. 2041, no. 1, pp. 59–66, 2017.

[25] R. V. L, C. Yimin, and C. N. J, “Deception detection for news: Three types of fakes,” *Proc. Assoc. Inf. Sci. Technol.*, vol. 52, no. 1, pp. 1–4, 2016.

[26] V. Rubin, N. Conroy, Y. Chen, and S. Cornwell, “Fake News or Truth? Using Satirical Cues to Detect Potentially Misleading News,” pp. 7–17, 2016.