DeepFND: an ensemble-based deep learning approach for the optimization and improvement of fake news detection in digital platform

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Early identification of false news is now essential to save lives from the dangers posed by its spread. People keep sharing false information even after they have been debunked. Those responsible for spreading misleading information in the first place should face the consequences, not the victims of their actions. Understanding how misinformation travels and how to stop it is an absolute need for society and government. Consequently, the necessity to identify false news from genuine stories has emerged with the rise of these social media platforms. One of the tough issues of conventional methodologies is identifying false news. In recent years, neural network models' performance has surpassed that of classic machine learning approaches because of their superior feature extraction. This research presents Deep learning-based Fake News Detection (DeepFND). This technique has Visual Geometry Group 19 (VGG-19) and Bidirectional Long Short Term Memory (Bi-LSTM) ensemble models for identifying misinformation spread through social media. This system uses an ensemble Deep Learning (DL) strategy to extract characteristics from the article's text and photos. The joint feature extractor and the attention modules are used with an ensemble approach, including pre-training and fine-tuning phases. In this paper, we have utilized a unique customized loss function. In this research, we look at methods for detecting bogus news on the internet without human intervention. We have used the Weibo, liar, PHEME, fake and real news, and Buzz feed datasets to analyze fake and real news. Multiple methods for identifying fake news are compared and contrasted. Precision procedures have been used to calculate the proposed model's output. The model's 99.88% accuracy is better than expected.

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ABSTRACT

Early identification of false news is now essential to save lives from the dangers posed by its spread. People keep sharing false information even after they have been debunked. Those responsible for spreading misleading information in the first place should face the consequences, not the victims of their actions. Understanding how misinformation travels and how to stop it is an absolute need for society and government. Consequently, the necessity to identify false news from genuine stories has emerged with the rise of these social media platforms. One of the tough issues of conventional methodologies is identifying false news. In recent years, neural network models' performance has surpassed that of classic machine learning approaches because of their superior feature extraction. This research presents Deep learning-based Fake News Detection (DeepFND). This technique has Visual Geometry Group 19 (VGG-19) and Bidirectional Long Short Term Memory (Bi-LSTM) ensemble models for identifying misinformation spread through social media. This system uses an ensemble Deep Learning (DL) strategy to extract characteristics from the article's text and photos. The joint feature extractor and the attention modules are used with an ensemble approach, including pre-training and fine-tuning phases. In this paper, we have utilized a unique customized loss function. In this research, we look at methods for detecting bogus news on the internet without human intervention. We have used the Weibo, liar, PHEME, fake and real news, and Buzz feed datasets to analyze fake and real news. Multiple methods for identifying fake news are compared and contrasted. Precision procedures have been used to calculate the proposed model's output. The model's 99.88% accuracy is better than expected.

INTRODUCTION

There has been a noticeable rise in people getting their news via social media. Nowadays, more people get their news from social media than any other source. Providing multimedia content for the news through social networks is advantageous since it is inexpensive, facilitates easy access, and speeds up transmission. Because of these benefits, many individuals get their news from these sources. As a result of the fast growth of social networks, many platforms that make up social media have progressed into venues that are excellent for disseminating news. People are increasingly turning to social media platforms to search for and consume news because of the ease it provides. The ease makes it easier for false information to rapidly disseminate and multiply Helmstetter and Paulheim (2021); Zakharchenko et al. (2021), which has a devastating effect both on individuals and on society. People can share and forward tweets on microblogs like Twitter and Weibo, two of the most widespread online platforms. Tweets that include text and photos are more likely to draw attention than tweets containing text.

These characteristics, unfortunately, are frequently abused by producers of bogus posts to expedite the diffusion of news. The quick distribution of false information has the likelihood of detrimental effects on society and even has the probability of changing the results of a significant public event. The early identification of false news on social media has lately become a highly active sector and has grabbed the attention of many people. Microblogs often publish fabricated news stories. If these tweets are not confirmed, they can put a large amount of a microblog's reputation in peril, which is why verification is so important. As a result, it is of the highest significance to distinguish between original and fraudulent news when reading microblogs. Fake news recognition aims to determine, for every given post, whether or not the item in question contains fake news. This activity is frequently represented as a two-way categorization. Although other sources, such as users' comments on the article and reposts, can be beneficial, the information found from these sources in the early phases is frequently noisy and lacking in completeness. Therefore, this research's primary focus is identifying false news based on its substance.

Several other techniques have already been suggested to spot false news. The application of machine learning is the primary strategy utilized in these techniques. In the significant body of this research, having a labeled data set of real and false news allows a classification model to be trained on new attributes. This model is then used to predict whether or not a quantity of news is accurate. There are two likely organizations for the characteristics that are utilized in these methods: 1) features that are dependent on the content and 2) features that are dependent on the context. The elements consequent from the text or the actual substance of the news are referred to as content-based features Noureen and Asif (2017); Reddy et al. (2020); Ajao et al. (2019); Dong et al. (2020). On the other hand, context-based features depend on the news context (e.g., the publisher, the position of other persons in the network, and the dissemination structure) to determine whether or not the news is false. These policies have been able to generate decent outcomes Zhou and Zafarani (2019); Shu et al. (2019), but they frequently need information that is tough to obtain when one is presented with a piece of false news. They are only active when the community has been negatively impacted by fake news. For instance, stance identification in news comments, which is one essential approach in the detection of false news, is only applicable when the network users adopt a position against the news and post their thought about it Pamungkas et al. (2019). These approaches use the evidence possessed by the other users in the network Ahmed et al. (2018); Vivek et al. (2018). Hence, they must wait until at least some of the network associates have confirmed the veracity of a piece of reported information.

Earlier ensemble fake news algorithms Hakak et al. (2021); Aslam et al. (2021); Mahabub (2020); Huang and Chen (2020); Roy et al. (2018); Das et al. (2022) frequently trained numerous deep or shallow models individually and then aggregated the outputs of learners using ensemble procedures such as voting. This was done to produce false news. As a result, these models entail a significant number of trainable parameters, as well as an expensive training method. Additionally, they have issues with the scalability element and are susceptible to the problem of overfitting. To overcome these obstacles, we have developed a unique method for detecting false news that makes use of something resembling deep learning and attention processes. Our learners are constructed on top of a joint deep-feature extractor, and their attention modules are where they depart from one another. By efficiently reducing the amount of training time needed, memory requirements, and the complexity of the proposed model, parameter sharing is beneficial. To detect false news, we propose using ensemble deep learning models that are based on a joint feature extractor. In comparison to other ensemble models, our model requires less time to train and has fewer parameters to configure. Therefore, it is less likely to have the issue of overfitting. We create a unique loss function that, by utilizing an attention mechanism, compels each learner to concentrate on a certain facet of the incoming news. This motivates each model to operate at a high level of efficiency.

The remaining parts of the article are structured as described below. In the next section, we will discourse several practices for detecting false news, with an emphasis on multimodal content-based approaches. In Section 3, the suggested ensemble model and the implementation details of the model are presented. In Section 4, we will detail the experimental setup, and in Section 5, we will examine the findings of the identification of false news using the presented approach. In the conclusion, Section 6 offers some final comments, as well as some suggestions for further study.

RELATED WORKS

This section provides a concise summary of the work that has been done before in the fields of detecting false news and multi-task learning. It is usual practice to employ, in addition to the text information itself, the transmission structure of the news on social networks to identify false news. This applies to news that merely comprises texts. Liu et al. Liu et al. (2019); Vivek et al. (2022) reported a kernel graph attention network. They provided more fine-grained fact verification based on kernel-based attention. Zhong et al.Zong et al. (2021) utilized semantic role labeling to parse each phrase containing evidence and constructed relationships between arguments to create a graph structure for information detection. Ma & Gao Ma and Gao (2020) and Bian et al. Bian et al. (2020) modeled the propagation of postings on the Weibo platform by using tree topologies, which were different from the graph structure that was generated in the approaches described above.

There are a few scholars that have a variety of perspectives about the path that fake news research should take. They believe it is of the utmost significance to investigate the interpretability of false news detection. For instance, a combined attention graph was built by Shu et al. Shu et al. (2019) to collect the top K interpretable sentences and user comments. Wu et al. Fan et al. (2022) suggested a dual-view paradigm that was based on both individual cognition and group cognition to verify interpretive claims.

All potentials were centered on the identification of bogus news, which might be achieved using a variety of machine-learning techniques. Tacchini et al. Tacchini et al. (2017) created a model that could detect hoaxes or not-hoaxes in the news distributed across social network platforms like Facebook. The model was built on two different machine-learning algorithms. On the other hand, the detection of the material evaluates it according to what people have liked or shared. Conroy et al.Conroy (2015) discussed two distinct methods that might be utilized in the search for false news. Both approaches were utilized concurrently to detect fake news more expediently and reliably.

Many different postings, shared materials, and news content are available in audio, video, and text formats. Some authors mainly focused on linguistic cue techniques utilizing machine learning and network study methodologies as their primary areas of application. Multiple methods were used to identify distinct categories of false news, such as serious reporting. In Rubin et al. (2015), the identification of false news on social platforms was based on the severe reporting of their merits and disadvantages, text analytics, and multiple predictive modeling. This was accomplished by examining several postings written by different users.

Ahmed et al. Ahmed et al. (2017) built a model for detecting false news by applying the n-gram and machine learning methodology to the development process. They utilized several characteristics retrieved through two distinct methodologies and then examined them inside six distinct machine-learning contexts. The term frequency inverted document frequency, as feature extraction, and the support vector machine, as a machine learning analyzer, deliver improved accuracy compared to other methods. Fake Detector, an automated bogus news credibility inference model, was created by Zhang et al.Zhou and Zafarani (2019) to identify fake news on social network platforms. Using a deep diffusive neural network, they examined various characteristics, such as user profile information and the link between users and the writer of the false news, to appreciate the characteristics typical of news items. Han et al.Han et al. (2020) presented graph neural networks (GNNs) that use a continually learning-based strategy for detecting fake news on social media platforms. They performed an analysis using GNN that could cope with non-Euclidean data. They often avoided specific text material and relied on data that was hidden from view for the implementation. Ozbay & Alatas Ozbay and Alatas (2020) presented a technique for detecting false news. This approach involved the analysis of supervised artificial intelligence algorithms in social media accounts. The authors employed twenty-three different intelligent categorization strategies to make use of the public data that was accessible.

When applied to a four-class label on news article headlines, a mixture of different deep learning approaches such as Long Short-Term Memory network (LSTM), Convolutional Neural Network (CNN), and Bidirectional LSTM (Bi-LSTM) was used by Abedalla et al. Abedalla et al. (2019). An LSTM-based model was suggested by Fan et al. Fan et al. (2022) to identify erroneous complaints made inside an environmental complaint system. Bhattacharya et al. Bhattacharya et al. (2021) created a Bi-LSTM-based

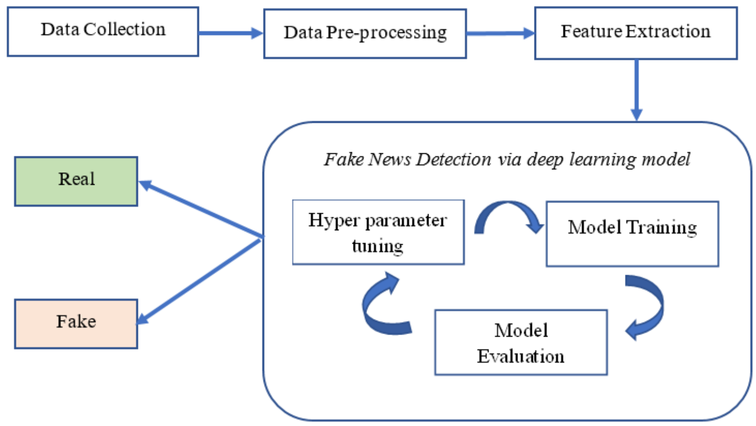

Figure 1. The overall structure of fake news detection

false news detection model. The model was an enhanced version of the LSTM algorithm. By utilizing blockchain networks, this model provides a definitive approach to categorizing fake news and identifying news sources.

Therefore, the Bi-LSTM model could be helpful for a few natural language processing applications, including phrase categorization and translation. One well-known CNN design, Visual Geometry Group (VGG) proved for the first time that a deep network with very few convolutional filters could provide reliable results. There is an attention mechanism built into the main network that gives more weight to the most essential aspects. We utilize the customized loss function to improve the performance of the introduced model.

PROPOSED METHODOLOGY

The news is divided between ”real news” and ”fake news” according to our methodology, which uses deep neural networks. The overarching structure of the suggested system for the identification of bogus news is depicted in Fig. 1. The processing pipeline for the approach consists of four steps. In the beginning, we gathered information on the news. In addition, the facts on the bogus news were gathered from various fact-checking websites. Following that, we cleansed the dataset of any noise or inaccuracies and deleted any occurrences that were a duplicate of others. The second stage is known as ”embedding”. The data from the news articles are embedded in this stage using GloVe’s pre-trained word embedding. In the third step, deep neural networks were trained to detect and identify bogus news. These networks included Bi-LSTM and Visual Geometry Group 19 (VGG-19). The last step involves classifying and assessing news (real/fake) models using a testing dataset that has not previously been examined.

The DeepFND Model

The purpose of the proposed model is to, given some news complete with text and a picture, evaluate if the news is true or fraudulent. Fig. 2 presents the model’s architecture, which can be broken down into distinct sections. A textual feature extractor and a visual feature extractor are included in the initial section of the system. These two components are accountable for extracting textual features and visual features, respectively. The next step, feature fusion, utilizes scaled dot-product attention to produce a fine-grained combination of textual and visual features. The last component is a false news detector that uses the fused feature to determine whether or not the news is accurate. We came up with an innovative DeepFND model that consists of four separate modules: an input module, a module for feature extraction, a module for feature fusion, and a detector module. Following is a comprehensive explanation of the model’s underlying structure. DeepFND is a suggested approach to identifying false news based on the substance of the story. We must first analyze the phrases that make it up to grasp the significance of the news. Given that various components of a post do not contribute in the same proportions to determining whether or not it is false, we use a technique that automatically focuses on learning the significance weights associated with those components. The model that is being presented is made up of a group of learners who agree on a standard structure to both simplify the model and stop it from becoming too accurate.

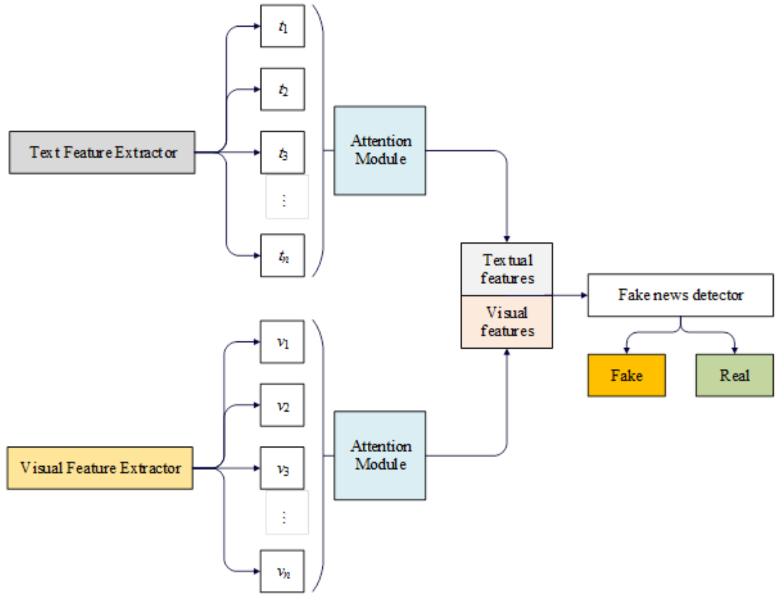

Figure 2. The DeepFND model

The only thing that discriminates against these is the attention modules that they use. We want each one to think about a variety of facets of the post since we know that the effectiveness of an ensemble model is directly proportional to the diversity of the learners. As a result, in the suggested loss function, we strive to make them as unlike one another as is humanly conceivable. Fig. 2 depicts the proposed model's architecture, which uses two simultaneous components to extract information from both the picture and the text of a particular piece of news. After that, the retrieved characteristics are combined and sorted into categories. In the following, more discussion will be provided on various aspects of the model.

Visual Feature Extraction

VGG-19 and Bi-LSTM are the foundation of our ensemble model technique. A statement often linearly presents its data. We use the BiLSTM architecture to record such sequential data. Bi-LSTM is well-known for its ability to record data in both forward and backward directions. Because even a human expert has trouble distinguishing real news from false, it is technically challenging to manually identify appropriate characteristics and separate genuine from fake, especially for binary classification. It is well-known that VGG-19 is effective in capturing concealed characteristics. Our working hypothesis is that VGG-19 will be able to recognize latent elements of the supplied statement and information connected to the claims to evaluate the integrity of each claim.

The use of CNNs has been quite fruitful in the field of computer vision. Multiple feature maps, which may be thought of as visual characteristics of an image, are produced in CNNs by conducting convolutional processes with various convolution kernels over an input picture. We do not employ a single visual representation to stand in for the picture, but rather several visual features, each of which is represented by a feature vector, and completely merge them with textual information. VGG-19, which consists of 16 convolutional layers and 3 feed-forward layers, is used to learn various picture attributes. In contrast to other networks, VGG-19 only produces a single vector of features for each picture, which makes it tough to fuse these data with text at a finer level of granularity. Because of this, VGG-19's last three fully connected layers are deleted, while numerous extra convolutional layers are inserted after VGG-19's 16 convolutional levels (Fig. 3).

Thus, the visual feature extractor is made up completely of convolutional layers and produces a fixed number of feature maps:

$$f = [f_1, f_2, f_3, \ldots, f_k], \quad (1)$$

where k is set by the number of convolution kernels in the final convolutional layer and each feature map

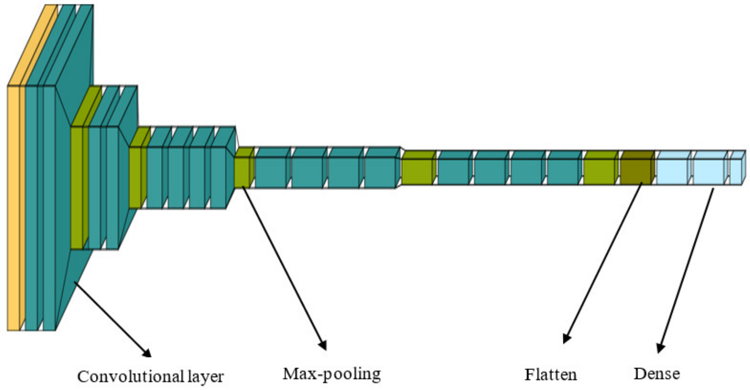

Figure 3. VGG-19 layer architecture.

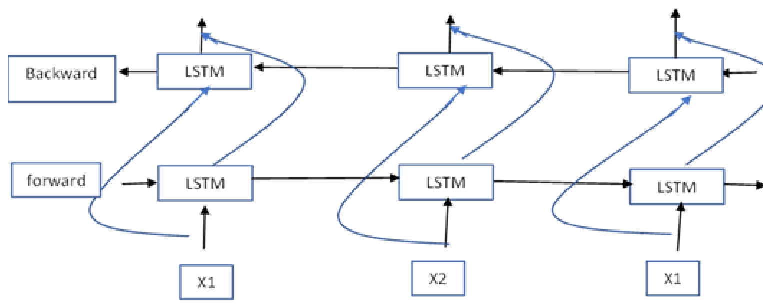

Figure 4. The Bi-LSTM architecture

f_i is a vector with dimensions $(height \times width)$. The visual features are:

$$vf = [vf_1,\ vf_2, vf_3, \ldots, vf_k], \tag{2}$$

where each feature is a single $height \times\ width \times 1$ dimensional vector obtained by compressing the spatial dimensions of each feature map f_i $(i = 1,\ 2,\ \ldots,\ k)$.

Fig. 4 shows the Bi-LSTM architecture. VGG-19 and Bi-LSTM provide superior results by combining their respective representations. Each of the dense networks that follow the Bi-LSTM networks is reconfigured and then passed on to subsequent convolutional layers, where they are prepared with new knowledge about the statement, the speaker's occupation, and the surrounding context. Immediately after each convolution layer is a max-pooling layer, which is trampled before being fed into their respective thick layers. The thick layers of multiple networks carrying distinct attribute information are combined, two at a time, to detention the relations among the various qualities. The resulting network is then nourished into a dense layer of six neurons using softmax as the activation function. Adadelta is used as the optimization method, and the loss function is categorical cross-entropy.

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Algorithm: Fake and Real news detection using VGG-16 and Bi-LSTM model

Input: Collected dataset $d = \{n_1, n_2, n_3, \ldots, n_k\}$

Output: Real and fake news classification

For each i in the dataset d

$$V_i = \{v_2, v_3, \ldots, v_k\}$$

Apply attention mechanism

$$T_i = \{t_2, t_3, \ldots, t_k\}$$

Apply attention mechanism

Concatenate V_i and T_i as f_i
Pass input f_i to the ensemble model
Prediction (feature list)
If predict==1
Result Fake
Else
Result Real
Classified result of fake and real news
Analyze the performance based on the classification

Text Feature Extractor

Essentially, a phrase is just a string of words. Let us say u_{kl} is the lth word in the kth phrase, as determined by a word embedding. This permits us to represent a sentence as $u_{k1}, u_{k2}, \ldots, u_{kl_n}$, where l_n is the total number of words in the phrase. The encoding process for sentences should convert this string into a N_n vector of constant length. It may be represented by a function f such that $E_k = f\left(u_{k1}, u_{k2}, \ldots, u_{kl_n}\right)$, where E_k represents the embedding of the kth phrase.

Attention Module

The attention module's goal is to provide more prominence to the most crucial aspects of every given news item. Let us use a hypothetical five-sentence post to demonstrate this point. A deep network processes these sentences and generates a state variable K at each stage. K_1 mostly covers the sentences se_1 and se_2 (and maybe some of se_3), whereas K_5 concentrates on se_5 and beyond. Attaining the attention weights a_k $(k = 1, 2, \ldots, 5)$ is the responsibility of the attention module, which is typically implemented as a simple two-layer neural network. After that, we build the post embedding PD by averaging the states using a weighted formula:

$$PD = \sum_{k=1}^{5} a_k K_k. \tag{3}$$

To calculate $g(H_i, q)$, multiplicative attention makes advantage of inner product similarity, as shown below:

$$f\left(K_k, p\right) = \left\langle w^1 K_k, w^2 p \right\rangle. \tag{4}$$

Based on the task's objective function, BP is used to learn the weight matrices w^1 and w^2.

Each K_k state in the input post undergoes a linear transformation and *tanh* activation in this procedure. It then performs an inner product of that number with the vector p that serves as its context:

$$f\left(K_k, p\right) = \left\langle K_k, p \right\rangle, \tag{5}$$

where,

$$K_k = tan. \tag{6}$$

The similarity score between H_i and q is calculated using additive attention as follows:

$$f\left(K_k, p\right) = \omega^T \sigma(w^1 K_k + w^2 p), \tag{7}$$

where ω^T denotes the weight vector and the activation *tanh* is denoted by σ.

Customized Loss Function

Here, we focus on the mean squared error (MSE) of each class to create a novel loss function. At the end of the network-training phase, we used the validation data to determine whether a given model had improved upon the loss function's output.

$$E_{MSE} = \frac{1}{M} \sum_{k=1}^{M} \left(t_k - p_k\right)^2, \tag{8}$$

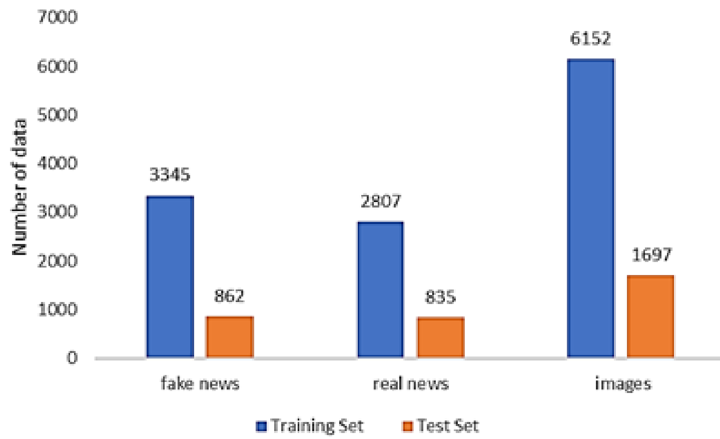


Figure 5. Data distribution of the Weibo dataset

where t_k and p_k are the actual and the predicted values of the kth sample data from our dataset.

$$E_k = \frac{1}{N}\sum_{i=1}^{N}(t_{i,k} - p_{i,k})^2, \tag{9}$$

where E_k denotes the loss value of the kth class.

$$L_d = \frac{1}{k}\sum_{i=1}^{k}(2a_iE_i)^2. \tag{10}$$

EXPERIMENTAL SETUP

Python is used as the testing platform throughout all of the studies. The tests cannot be carried out without the use of the Python libraries known as Keras, NLTK, NumPy, Pandas, and Sklearn. We assess the presentation of the system based on many criteria including accuracy, F-score, precision, and recall.

Datasets

We have used the Weibo, liar, PHEME, fake and real news, and Buzzfeed datasets to analyze fake and real news.

Weibo Dataset

In the dataset compiled by Jin et al.Jin et al. (2017), the actual news was obtained from a reputable news source known as the Xinhua News Agency, and the fake news was validated by Weibo's official rumor debunking mechanism. This dataset was used to evaluate the efficacy of the introduced model. We were solely concentrating on tweets that contained both text and photos to combine the textual characteristics and visual aspects. Consequently, tweets that were missing either text or photos were deleted. The technique for splitting the data is the same as the scheme for the benchmark, and the data are pre-processed in a manner that is comparable to the work of Jin et al. Jin et al. (2017). Fig. 5 contains an in-depth breakdown of the data set's statistical characteristics.

PHEME Dataset

The PHEME dataset includes a collection of tweets, both rumors and non-rumors, that were posted on Twitter when breaking news was occurring as shown in Fig. 6. To be more precise, it includes chat threads from Twitter that are connected to a variety of important events, such as the disturbance in Ferguson, the massacre at Charlie Hebdo, the shooting in Ottawa, the hostage crisis in Sydney, the accident of a Germanwings jet, and others.

The following is how the data are structured. Inside the directory, there are two folders labeled "rumors" and "non-rumors". Both of these folders have subfolders that are named with a tweet ID. The tweet in question may be located by navigating to the directory labeled "source-tweet", whereas the directory

	Unnamed: 0	title	text	label
0	8476	You Can Smell Hillary's Fear	Daniel Greenfield, a Shillman Journalism Fello...	FAKE
1	10294	Watch The Exact Moment Paul Ryan Committed Pol...	Google Pinterest Digg Linkedin Reddit Stumbleu...	FAKE
2	3608	Kerry to go to Paris in gesture of sympathy	U.S. Secretary of State John F. Kerry said Mon...	REAL
3	10142	Bernie supporters on Twitter erupt in anger ag...	— Kaydee King (@KaydeeKing) November 9, 2016 T...	FAKE
4	875	The Battle of New York: Why This Primary Matters	It's primary day in New York and front-runners...	REAL

Figure 6. Collected sample data from the PHEME dataset

Table 1. Primary characteristics of the Buzzfeed news dataset

Parameter	Characteristics
Id	The "Id" that was allocated to the website for the news story. If the article is authentic, the status will be actual; otherwise, it will be phony
Title	This is a reference to the headline that is intended to grab the attention of readers and is relevant to the primary focus of the news story
Text	The "text" of the article, which expands on the news item. The publisher's perspective was shaped by the main claim, which is usually emphasized and elaborated on.
Source	It names a journalist who wrote the news piece or a publication outlet
Images	Pictures help readers understand a news story
Movies	A news article's video or movie clip link helps contextualize the story. Movies are crucial to the news.

labeled "reactions" has the collection of tweets that were written in response to the source tweet. In addition, each subfolder has a file named "annotation.json" that details the reliability of the rumor, as well as a file named "structure.json" that details the flow of the dialogue.

Buzzfeed News Dataset

The Buzzfeed news dataset is constituted of a comprehensive sample of news that was published on Facebook during the week leading up to the 2016 United States presidential election, namely from September 19 to September 23, as well as September 26 and 27. These dates were selected at random. Five BuzzFeed editors went over each post and the linked story, checking each claim for accuracy one by one. There are two different datasets of Buzzfeed news available. One dataset contains false news, while the other has actual news. Both datasets are in the form of CSV files, and each has 91 observations and 12 characteristics or variables. The Buzzfeed news dataset is comprised of two separate datasets, each of which has the following primary characteristics as shown in Table 1.

Fake and Real News Dataset

In this study, we used a dataset that was compiled and made available to the public by Ahmed et al.Ahmed et al. (2018). The data from this dataset is illustrated in Table 2.

The sample data from this fake and real news dataset is shown in Fig. 7. This dataset consists of 23,481 data, which comprises news, politics, left news, government news, US news, and Middle-east news.

Data Pre-processing

During this step, the provided datasets were pre-processed to remove the noise, which included things like stop words, punctuation marks, HTML tags, URLs, and emoticons, among other things. The NLTK toolkit, which is an open-source natural language processing package, was used for the pre-processing.

Table 2. Fake and real news dataset

Data type	Number of data
News	9050
Politics	6841
Left news	4459
Government news	1570
US news	783
Middle-east news	778

	title	text	subject	date
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	December 31, 2017
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017
...	...	...	...	...

Figure 7. Sample data from fake and areal news datasetsAhmed et al. (2018)

Tokenization:

Dividing text/string into tokens is the initial stage in natural language processing before feature extraction.

Word Removal:

Remove stop words after tokenizing. Stop words are minor words that produce noise in text categorization. These words help sentences organize and link words. Stop words include articles, prepositions, conjunctions, and pronouns.

Stemming:

Stemming reduces words to their roots (also known as lemma). Stemming reduces derivative words. The lemma of running ran, and the runner is run. The porter stemmer algorithm, the most used stemming algorithm, was employed.

Extraction:

This research found 26 characteristics. Due to irrelevant features decreasing model accuracy and training cost, fewer features were chosen. Selecting several characteristics also increases model-training time. Thus, we chose less-effective measures like the number of words, characters, sentences, average word length, average sentence length, and Name Entity recognition-based features. For the named entity recognition feature, we retrieved person, org, date, time, facilities (airports, buildings, etc.), geopolitical entities (countries, cities, etc.), product, piece-of-art (book titles, music names, etc.), language, money, and cardinal from the text.

RESULTS AND DISCUSSION

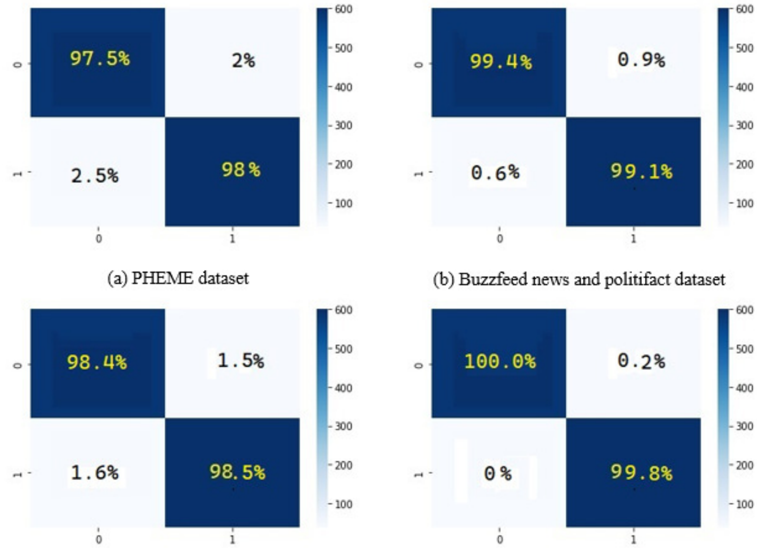
As a means of carrying out an analysis of the findings, we made use of four different metrics, all of which are predicated on the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) in the predictions of the binary classifiers:

1. Accuracy, also known as the proportion of true forecasts (sometimes known as ”right” predictions):

$$Accuracy\,(A) = \frac{TP+TN}{TP+TN+FP+FN}. \tag{11}$$

2. Recall, which measures the capability of the classifier to locate all of the positive samples in the data set:

$$Recall\,(R) = \frac{TP}{TP+FN}. \tag{12}$$



(a) PHEME dataset (b) Buzzfeed news and politifact dataset (c) Fake and real news dataset (d) Weibo dataset

Figure 8. Confusion matrix for the prediction of fake news on the datasets

Table 3. Results on the PHEME dataset

	Precision	**Recall**	**F1-score**
Fake	0.98	0.98	0.98
Real	0.97	0.98	0.98
Accuracy			0.98
Macro avg	0.97	0.98	0.97
Weighted avg	0.98	0.98	0.97

3. Precision is determined as:

$$Precision(P) = \frac{TP}{TP+FP}. \tag{13}$$

4. The values that are computed for the F1-score, which is the harmonic mean of accuracy and recall, fall within the range [0, 1]:

$$Fl - Score\,(F1) = \frac{2*(P*R)}{P+R}. \tag{14}$$

Fig. 8 shows the confusion matrix on the different datasets using the proposed methodology DeepFND.

The statistical significance of the data was determined with the use of a paired t-test. The experiments were carried out five times (with 5-fold cross-validation, meaning an 80%-20% split each time), and the accuracy of the results was determined using 95% confidence intervals.

The results for the PHEME dataset using the proposed DeepFND are shown in Table 3. The overall accuracy of the proposed method is 98%.

The results in the case of the Buzzfeed news and politifact dataset are shown in Table 4. The overall accuracy for this dataset is achieved as 98.43%.

The results for the fake and real news dataset are shown in Table 5.

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The results for the Weibo dataset are shown in Table 6.

The evaluation of our algorithms using cross-validation is not the most illuminating method available. When it comes to determining whether or not a news item is a hoax, there is a cost associated with the creation of the training set. This is because each post may need to be examined individually. The more

Table 4. Results for the Buzzfeed news and politifact dataset

	Precision	Recall	F1-score
Fake	0.98	1.00	0.99
Real	0.99	0.98	0.98
Accuracy			0.98
Macro average	0.97	0.98	0.97
Weighted average	0.97	0.98	0.97

Table 5. Results for the fake and real news dataset

	Precision	Recall	F1-score
Fake	0.99	1.00	0.99
Real	1.00	0.99	0.99
Accuracy			0.99
Macro average	0.99	0.99	0.99
Weighted average	0.99	0.99	0.99

intriguing issue is not how accurate of a level we can get when we know the ground truth for 80% of the postings; rather, the more relevant question is how big of a training set we need to have to get to a specific degree of accuracy. Our methods need to be able to create an accurate classification while depending on a small portion of posts that are already known to belong to a certain category for us to be able to scale up to the extent of the information sharing that occurs inside social networks.

For the fold-2 phase, the values of our proposed model DeepDND's training loss and training accuracy are shown in Fig. 9 and Fig. 10, respectively. When the loss values for the multi-class classification were analyzed, the model showed a very quick decline in the loss value, and it got very close to the zero value (Fig. 9). On the other hand, it was found that our model had a more expedient procedure for learning new information.

All the approaches' Receiver Operating Characteristic (ROC) curves on both datasets are displayed as well, for thoroughness' sake. The True Positive Rate (TPR) and the False Positive Rate (FPR) are plotted to produce the ROC curve, which is then used to diagnose a binary classifier. Fig. 11 shows the receiver operating characteristic curves for the overall dataset.

We compared our technique with the baseline models. According to the results depicted in Fig. 12, our model produces the highest accuracy in classifying real and fake news.

CONCLUSION AND FUTURE WORK

Deception detection on social media is a very young field of study, and scientists are still trying to figure out how to do it effectively in the face of a rapidly expanding fake news industry. This study has the potential to inform future investigations on the best methodological blends for identifying disingenuous posts on social media.

A more precise false news detection algorithm is a goal of the approach presented in this research. A new fine-grained ensemble network called DeepFND is presented. It completely fuses textual characteristics with visual data to detect false news. DeepFND utilizes a VGG-19 and Bi-LSTM ensemble model to combat the spread of false information on social media. This system extracts features from the article's

Table 6. Results for the Weibo data set

	Precision	Recall	F1-score
Fake	1.00	1.00	1.00
Real	1.00	0.99	0.99
Accuracy			0.99
Macro average	1.00	1.00	0.99
Weighted average	1.00	0.99	0.99

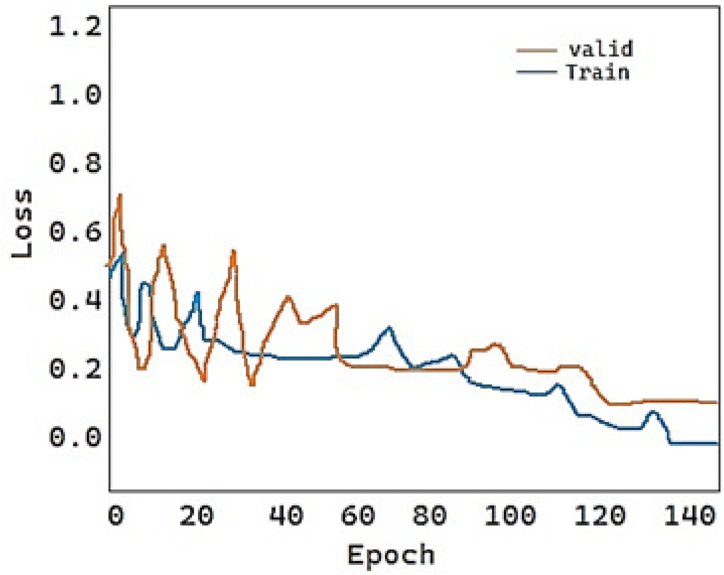

Figure 9. Train and validation loss of the proposed model

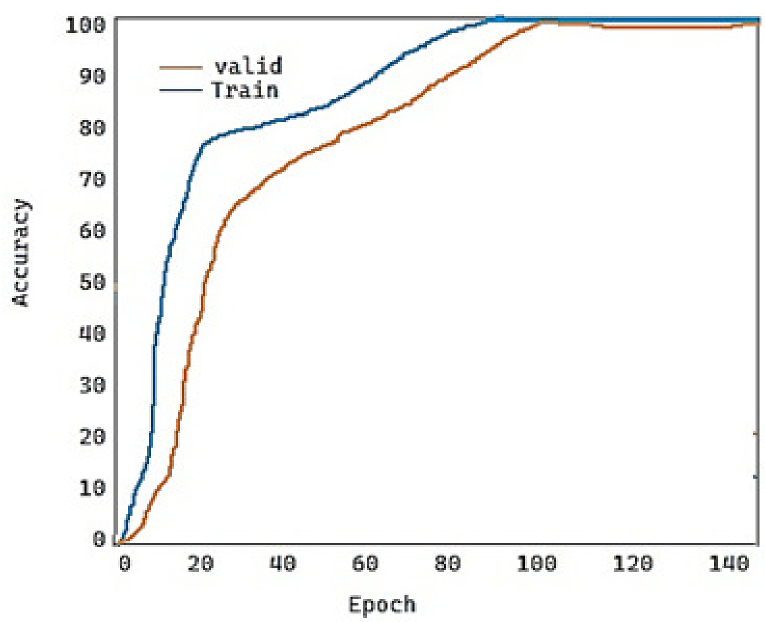

Figure 10. Train and validation accuracy of the proposed model

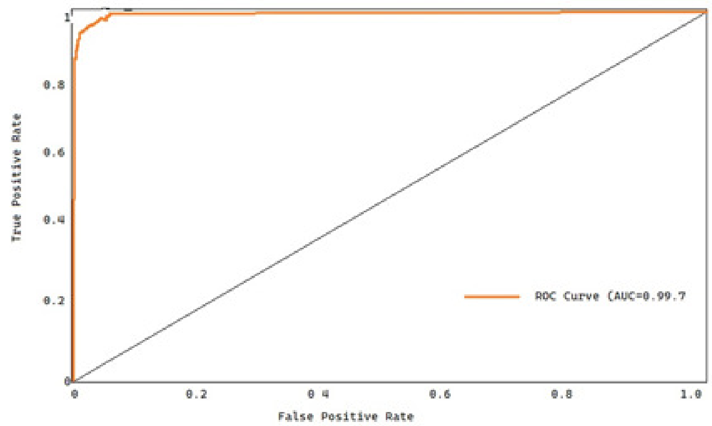

Figure 11. ROC curve of the proposed model

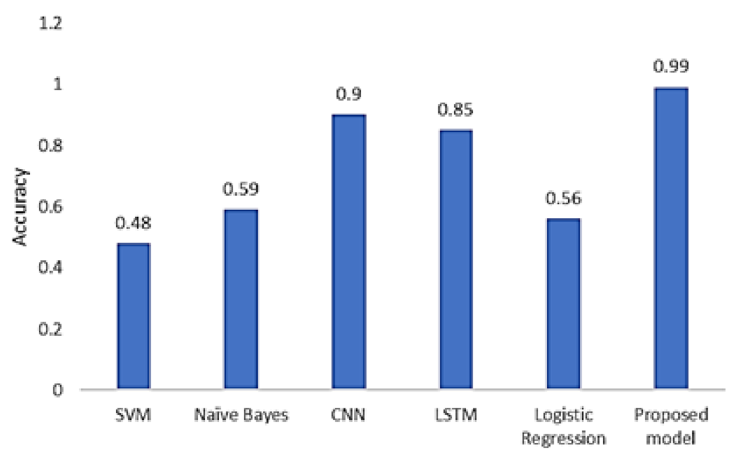

Figure 12. Model comparison with existing models

text and images using an ensemble DL approach. Using a pre-training phase and a fine-tuning phase, the ensemble method employs the joint feature extractor and the attention modules. A novel tailored loss function is utilized in the current study. Automatic approaches for identifying online fake news are investigated. The fusion is both fine-grained and sufficient since it takes into account the interdependencies between various visual characteristics and textual data. DeepFND is found to be effective by experiments done on publicly available datasets. When compared to other approaches for merging visual and textual representations, DeepFND performs well. It is demonstrated that the DeepFND's joint representation, which combines visual and linguistic characteristics, outperforms the joint representation created by fusing a visual and textual representation.

Future work will include not just textual and visual information, but also elements based on social context. The frequency domain visual characteristics will be also evaluated to further boost the efficiency of false news identification.

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