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ORIGINAL RESEARCH

Identification of Fake News Using Deep Neural Network-Based Hybrid Model

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Abstract
The current era of social digitization and exponential growth of social media decreases the distance between people to connect with each other. Due to increasing the massive information on social media networks such as Facebook, Twitter and Instagram etc., it also increases the fake/incorrect information among users. This fake/incorrect information may cause severe effects on various levels of society, i.e., individuals (depression, increased death rate etc.), political (influenced by some political party for harm/benefit), religion and society etc. In this paper, we initially proposed machine learning models as a baseline and, later, a hybrid deep learning model (CNN + LSTM) for detecting fake/real news on text and image datasets. Finally, a comparative analysis is conducted with state-of-the-art to validate the proposed model. The experimental evaluation reveals that the proposed model achieved 96.1% accuracy on text news and 91.36% on image news data.

Keywords Social media · Fake news · Machine learning · Deep learning

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Introduction

Human society developed multiple ways for communication in 90's such as television, newspaper and radio. These were vital sources of information for people. As technology advances and the use of the Internet gets cheaper, social media network gets popular, i.e., Twitter, Facebook, WhatsApp and Instagram are used by billions of people worldwide. Nowadays, Social media platforms are utilized to share views on various issues, exchange messages, post pictures, and read the news. According to a study, there are 4.31 billion social media users in 2021, constituting more than 50% of the total population [1]. The main reasons behind increasing users on social media platforms are:

- Accessing the Internet is way less costly compared to traditional means.
- A plethora of content and hiding real identity is easier on social media.
- Easy to communicate with people of the same interest.

People tend to spend more time on these social giants and get in contact with different content in which news contributes to 50–60% of the total content on social media networks. With the increasing utilization of Facebook and Twitter, it is easy to convey fake news content. According to

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a survey done in the US in 2016, 60% of the adult population get news from Facebook and other social media platforms. In India, Whatsapp and Facebook are essential means to get news in which 65% of news are fake and misleading. Fake news is not new in the market; it has been spreading since the 90's when television and newspaper were used. Now, only the means to convey fake news is changed: social media networks [2].

Fake news spread on social media through various content that makes it difficult to identify genuine and fake news. Besides fake news, there are fake rumours (mainly for popular personality), satires (parody of actual news for entertainment), and conspiracy theory (forming misconception about the simple concept), and the most common fake news type is astroturfing (used for political and religious gains through sharing the message that looks like shared from genuine organization to target a particular community people) [3]. Furthermore, on social media, misleading news usually contains content different from its headline. Misleading information has higher chances to become viral and causes a negative impact on the reader [4]. The phase changes misleading information from targeting instrumental and critical facts to news that affects emotions and individuality, such as a particular religion or community. According to the study, in India, a lockdown was imposed due to SARS-CoV-2 in March, and with two weeks of lockdown, misleading information about government and virus rose to 60% [5]. There are fake social media posts about the cure for Coronavirus and its origin that mentally affects people. This fake news has a high potential to cause real-time effects.

The exponential increase in social media usage, particularly in low- and middle-income countries, has intensified the spread of fake news, posing a significant threat to implementing evidence-based interventions and the credibility of scientific expertise and ultimately undermining global health [6]. During the Munich Security Conference on February 15th, 2020, the Director-General of the World Health Organisation (WHO) addressed the risk of an "infodemic" of false information surrounding the pandemic. On the internet, incorrect information about the disease's origins, preventions, therapies, diagnostic procedures, and preventative measures frequently adds to widespread ignorance and a lack of trust in scientific expertise. According to a recent study, more than half of the participants were exposed to fake pandemic news [7]. Facebook, the largest social network website in many countries, has collaborated with various fact-checking organisations to tackle mis- and disinformation due to increased demand to govern the "information disorder" on its platform. This is done through warning labels, in which when a piece of content is revealed to be false, its algorithmic recommendation is reduced, and a warning label indicating that fact-checkers have questioned its content is placed on the misinformation. Twitter contains similar warning flags, but when Elon Musk takes over in 2022, he will remove COVID-19 misinformation. Both techniques strive to encourage more systematic material processing by directly linking fact-checks to warning labels [6].

They create fake news using genuine data with tiny threads of non-real statements and gain high prices for this work, and another are fake sites. Usually, mischief people create these fake sites to mislead users and promote falsehood. Another is political and economic related fake news; some platforms propose to give money if they click on a certain game or link that usually attracts unaware users. Furthermore, false news generally causes mistrust among users against all types of information, including information coming from high standard journalism firms [8]. Twitter allows bot accounts and unverified accounts that raises questions on transparency and trust. To avoid an increase in fake news, there are online fact-checking sites such as ad fonts media bias chart that rates the media and their reliability, botometer and hoaxy is used for Twitter that verifies that a user is an actual person or some bot. Another is Tintype for verifying an image is being manipulated or not. The government takes various steps to control the sharing of fake news by blocking websites that promote misinformation and sharing objectionable content [9].

There are various ways to identify fake news, but determining which information is correct and which one is misleading is quite impossible for human beings. There are various ways to identify such fake information like linguistic approach, learning-based or human opinion based through crowdsourcing. Using content-based methods such as analyzing the writing style of news on Facebook and Twitter, use of nouns and manipulation of original news with fake content [10]. As shown in Fig. 2, researchers also consider the social context in which user activity is monitored. User-user relationship, number of likes on a post, number of comments, the relation of user with news publisher and total time spent on reading news on each news channel is analyzed by researchers to understand user behaviour and interaction with news publishers that facilitate how a piece of information is shared online.

Furthermore, another important feature is the echo chamber, a group of people with some interest and perception that plays a significant role in disseminating fake news [11]. These online communities consist of people with the same problems in society, and only those news articles propagate in these groups that match their perception, theory and philosophy. These kinds of groups reject people with views different from them. Currently, researchers consider using the linguistic approach with deep learning to identify fake news that considers both content and context of news articles depending on the dataset provided to the algorithm (Fig. 1).

The main challenge is to develop a system that can classify whether a piece of information on social media is

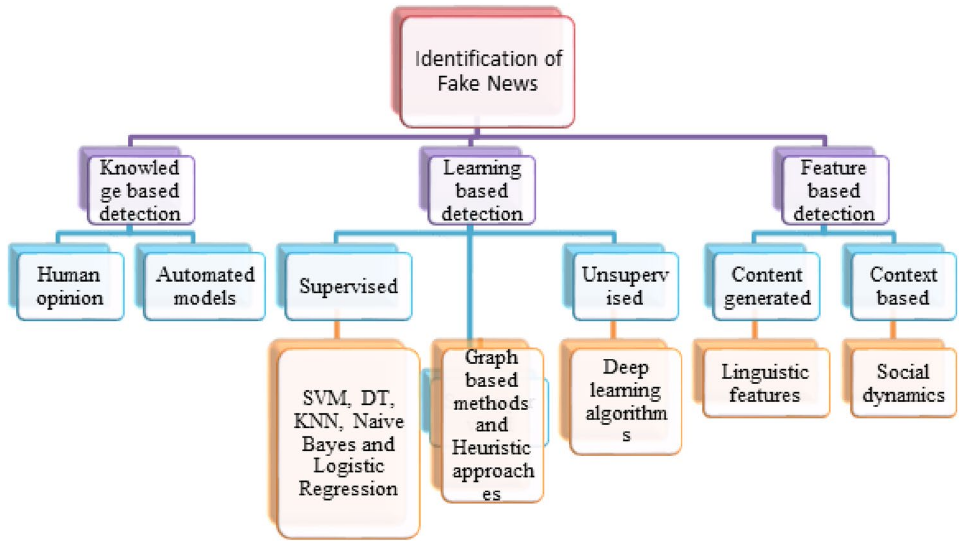

Fig. 1 Various approaches for identification of fake news in traditional media and social media

fake or authentic. The traditional way to detect fake news by expert journalists and organisations never uses social media platforms. So, a computational model is required for analyzing fake news data using different characteristics to determine the correctness of news on Facebook and Twitter. Developing models for this task require an in- depth analysis of social media platforms because news contains text, images and links. Both text and image type data are used in the news to make attractive and reliable user content. Usually, this task requires quality of data and feature set to train a computational model for detecting fake news. Besides fact-finding sites and restrictions from the government, fake news is continuously manipulating and controlling current society. So, to effectively detect fake news, we proposed a framework consisting of machine learning and deep learning techniques that predicts whether a text or image is fake or not on Facebook and Twitter platforms.

In this paper, we collect data from Kaggle and use it to test our model's efficiency. Both fake and legitimate text and images are present in the dataset analyzed using various machine learning models and a hybrid model consisting of convolutional neural network (CNN) and long short-term memory (LSTM). The advantage of using these two deep neural models in the detection task is highly efficient because CNN extracts salient features from each block of input vector precisely while the LSTM model trains on extracted features and forms long-term dependency using cell memory. The significant contributions of the proposed work are listed as follows:

- In the baseline approach, binary classification machine learning algorithms [Naïve Bayes (NB), support vector machine (SVM) and Logistic regression (LR)] are applied to evaluate Fake/Real information on publicly available text datasets.
- To evaluate fake\real images, in base baseline approach, machine learning algorithms [support vector machine (SVM), discrete cosine transform (DCT), scale-invariant feature transform (SIFT) and principal component analysis (PCA)] are applied to evaluate Fake/Real news on the publicly available dataset.
- This study proposed a hybrid CNN and LSTM-based deep learning model to evaluate Fake/Real values of text and images.
- This study evaluates all the popular evaluation metrics for a fair comparison of the results.
- The results of the proposed work are validated with state-of-art methods for fair justification.

The paper is further divided into sections: "Literature Review" describes recent work in fake detection and the effects of fake news on user psychology. "Proposed Approach", the proposed method is described. "Results Analysis of the Proposed Models" discusses machine learning and deep learning models. Results are described and evaluated using the evaluation metric parameter.

In "Conclusion and future scope", the conclusion for this work and future scope is discussed.

Literature Review

This section briefly describes the work done in fake news detection and physiological factors in fake news determination.

Role of Psychology and Sentiments in Fake News Detection

The sharing of fake news on social media platforms such as Facebook and Twitter depends on its impactful content to the user. With time, fake news transforms from textual to visual forms that make news or articles reliable to share to deceive other users. Fake news contains emotionally triggering language that catches the attention of users with low emotional intelligence. Emotional content is one of the prime features of fake news that led to the immediate sharing of news articles without critically assessing the source and core motive [12]. According to a study, people with higher emotional intelligence focus more on whether the news is genuine or fake [13, 14]. On these social networking platforms, every second new content pop up and rapidly changes with another new content from information providers that focus on creating content that satisfies users fear, biased nature and psychological needs, which in turn fuels their emotional connection and beliefs on particular topics such as religion and politics. Users with this type of psychology focus less and rapidly share half-read information [15]. In the paper [16], the author proposed a study to identify the role of emotional intelligence (EQ) in identifying fake news articles on Facebook by providing fake and real news content as Facebook posts to people participating in this experimental study. For evaluating participants' emotional intelligence, a test software named Qualtrics is used. Four types of tests related to fake news detection were done in this. From this study, it was clear that people with high emotional intelligence fall less for fake news than people who are less emotional intelligent (EQ).

The paper [17] focus on the psychological characteristics a piece of text contains on social networking platform. Usually, deceptive people use manipulative language that focuses less on them and changes the core of information. Comparing the use of motion verbs in real and fake news, a fake news article consists of fewer motion verbs.

Language is directly related to a person's psychology. An individual uses words that describe his current mental state, mood, ideas and views [18]. Based on information in textual format, it is easy to manipulate negative sentiment users on social media. So, using linguistics to determine sentiments hidden in natural and fake news articles provides an opportunity to understand the polarity of emotions fake news contains.

In the paper [19, 20], the authors discuss the role of sentiments in spreading fake news on social media. The deceivers feel unconfident about the topic, and so under tension, they create negative sentiment news. Fake news contains more negative emotions than real news that provides many positive sentiments.

In this research, the authors have proposed to analyze the impact of fake news related to coronavirus disease 2019 (COVID-19) on individuals' emotions, motivations, and intentions to share such information. They have applied the appraisal theory to this analysis. Additionally, psychological distance and construal level theory have been used to compare toilet paper shortages and celebrity scandal rumours in the context of fake news. The authors have collected data from 299 Taiwanese respondents who completed questionnaires related to toilet paper shortages and celebrity gossip. They used partial least squares regression and multigroup analysis to process the collected data. The study's findings reveal that surprise is the most intensely felt emotion in both scenarios. However, worry is more prominent in driving altruistic sharing motivation related to toilet paper shortage rumours than in celebrity fake news scenarios. Moreover, the authors have highlighted that emotional attributes, such as basic or self-conscious, concrete, or abstract, can guide how emotions change with psychological distance. However, the degree to which a feeling is relevant to the fake news context is crucial to its manifestation [21].

The authors of this study intend to investigate the mechanisms involved in how individuals believe and spread news postings on social media. They investigated whether the relationship between prior political opinions and rating the correctness of and readiness to spread false and accurate news is mediated by epistemic emotional responses (surprise and curiosity) and perceived credibility (trustworthiness, rigour, impartiality). The authors ran a within-subjects experiment in which they presented 259 Portuguese volunteers with ten articles (five genuine, five fraudulent) containing political information collected from Facebook. They analyzed the findings to understand better how individuals perceive fake and accurate news. The study's findings show that individuals absorb fake and precise information in the same manner. Emotional reactions and perceived credibility are influenced not just by the news content but also by the people's prior views. Negative opinions about the political system have enhanced emotional responses to factual and misleading news, resulting in higher credibility judgements. Increased credibility perceptions have improved accuracy attributions and readiness to disseminate information (true or deceptive). The most notable distinction between participants' interactions with false and authentic.

Participants' readiness to disseminate fake information is partiallyed by emotional responses and credibility assessments. The study suggests that people appear to depend on emotional signals based on past views, as well as emotionally biassed credibility indicators, to determine whether the news is accurate or worth spreading [22] (Table 1).

Table 1 The role of psychology and emotions in detecting fake news

S. no.	Social media	Remark
1	Facebook	Fake news triggered emotion of the users so they share the news without any facts checks
2	Allsocial media	Higher emotional Intelligence people do there facts checks
3	Allsocial media	Social media platforms are filled with constantly changing content to user's psychological needs and can fuel beliefs on sensitive topic like religion and politics
4	Facebook	Finding emotional intelligence in identifying fake news
5	Allsocial media	Focus on psychological characteristics of text on social media and how deceptive people use manipulative language with fewer motive verbs
6	Allsocial media	Highlights relationship between language and psychology
7	Allsocial media	The role of sentiments in spreading fake news on social media is disused in the paper
8	Allsocial media	Focuses on the impact of COVID-19 related fake news on individuals' emotions, motivations, and intentions to share such news
9	Facebook	Study is conducted on the relationship between prior political opinions, emotional responses, perceived credibility, and the willingness to spread false and accurate news on social media

Machine Learning/Deep Learning-Based Approach of Fake News Identification on Social Media Network

The machine learning algorithms are utilized in various fields for classification and detection tasks. These techniques use text, image, video, and links as data from social media platforms to identify fake news are possible. In Ref. [23] author used text-based data. The textual data is extracted from news text. Using supervised learning algorithm KNN, Naïve Bayes, Random Forest, SVM and XGBoost, fake news is best detected using the XGBoost algorithm with 86% accuracy. In another work [24], using logistics regression supervised machine learning algorithm for identifying fake news from Facebook. A model trained using features such as post details and using WEKA machine learning. The model is used as a tool in the browser to filter out clickbait with 99% accuracy. In the paper [25], the author proposed a novel user response generator (TCNN-URG) model for the early detection of fake news. The early detection task helps in detecting false news before it creates any disturbance among readers. CNN model gives an accuracy of 88% with findings suggesting that CNN model collects semantic features from the text that utilized in semantic labelling of data instead of using binary labelling {0, 1} that provides more information why is news fake.

A novel model is proposed in Ref. [26], namely FakeDetector, that builds using a deep diffusive network. The diffusive network model focus on news articles, news creators and news subject representations from the dataset collected from the Politifact website. The findings show that the "health" topic is prevalent in news content with 53% fake news with "economy" as a second popular subject with 46% fake news. A hybrid approach was proposed in [27] for classifying news into a fake and real categories. A deep learning model (CNN-RNN) trained on two different datasets led to RNN learning context features from text data and forms long-term dependency between extracted features and text. In the paper [28], the author focused on the increasing rate of fake news during the Covid-19 pandemic and proposed a supervised text classification model using BERT (bidirectional encoder representations transformers), convolution neural network and long short-term memory models. With SVM used as baseline model and pre-trained and fine-tuned model provide better results from deep learning models showing an increase in fake news during the covid-19 pandemic with 98% accuracy. In the paper [29], the author proposed a bidirectional training technique, namely Fake Bert. It is a deep learning approach trained using fake tweets and authentic news articles about the 2016 US general presidential elections. The classification accuracy improves with long-term dependency between the type of sentence and semantic data type. Usually, authors use context and content data to identify fake news, but in [30], the author used eco-chambers with content information. The author proposed a deep neural network called Deepfake that utilises tensor decomposition formed using news, community/online group information, and user details with social context (user-user relation, user-news provider relation, and social network). The tensor coupled with matrix factorization was used to train the model and tested on a real-world dataset. Fake news is present in various forms, as in text and visual forms, so utilizing both forms provide better chances to determine fake news article. In Ref. [31] author uses both image and text-based data for fake news detection and proposes a TI-CNN. Utilizing psychological and sentiments-based features calculates the lexical diversity of real news, which is more significant than fake news. In the image, data findings show less face in fake news than authentic news images, and image resolution is low with 355 × 228 pixels. In Ref. [32] author utilizes video and text data as news content tensor fused matrix that forms a latent representation of content and context and proposed a neural network model Echo Faked. Analysing video data shows that fake news consists of degraded data frames when a video is compressed. It has been observed that the temporal features of videos are manipulated. In paper [33], the author proposed an automatic fake news detection system using machine learning and deep learning by chrome environment and Facebook. The author uses the LSTM model with various user profile-based features and news content to train and identify fake news by adding it as a tool on a chrome extension.

The authors of this study article explore the issue of false news on social media, namely on Twitter in the Middle East area. The authors present an intelligent classification algorithm that detects fake news in Arabic tweets using transformer-based language and recurrent neural network models. They also give a comparison analysis of deep learning and shallow learning strategies to improve the efficacy of the suggested model. The scientists also created an Arabic Twitter dataset of 206,080 tweets to test their algorithms. The results show that pre-trained deep learning models, such as LSTM and Bert, outperform shallow learning approaches in spotting fake news, with the Bert model obtaining 99% accuracy. Overall, this paper provides essential insights and practical implications for researchers and practitioners seeking to combat the spread of fake news on social media [34].

The authors of this research suggested a method for identifying fake news on social networks that uses the genetic search for neural architecture selection and deep learning. The writers emphasised the difficulties in spotting false information, which may spread through numerous media types. The suggested model has a high detection rate of 89.6% and a low false positive rate of 0.2, making it promising for detecting fake news. Furthermore, the authors did the statistical analysis and discovered that their strategy had low mistake rates compared to input size, supporting the efficiency of their technique. Using sophisticated machine-learning algorithms, the authors presented a viable method for identifying fake news on social media platforms [35].

Based on the study of literature and proposal given by researchers, the following significant points have been identified. First, fake news identification is a primary concern in the current era because it drastically affects our society. Second, it affects different angles at every level of society. Third, no such standard evaluation parameter is available to identify fake/real news (Table 2).

Proposed Approach

Social media users cannot detect whether a piece of information is fake or real by reading text. So, utilizing classification approaches are helpful in this problem. This section discusses the proposed deep neural network-based hybrid model using convolution neural network and long short-term memory algorithms. Machine learning algorithms were used as a baseline method to compare our proposed deep neural model performance. This work used a secondary dataset from Kaggle based on social networking platforms (Facebook and Twitter).

Our proposed approach can detect fake news spread on social media in any form such as advertisement, text-based, images, videos and links. As a result, the model classifies news content as fake or real using a deep neural network-based hybrid model and machine learning algorithms (baseline method). Figure 2a, b describe the fake news detection process using a hybrid CNN-LSTM model for text and image data. The input data is collected from social networking platforms on Kaggle and undergoes pre-processing to convert raw text into numerical representations and split

Table 2 ML and DL-based approach of fake news identification on social media network

S. no.	Technique	Dataset/platform/remark	Result
24	SVM, KNN, NB, RF, XGBoost	Remark: to identify fake news	XGBoost: 86% Accuracy
19	LR	Platform: Facebook	99% Accuracy
20	TCC-URC	Remark: early detection of fake news	CNN: 88%
22	Deep learning modules	Dataset: Politifact	Health topic: 53% Fake news Economy: 46%
25	CNN-RNN	NA	NA
26	BERT, CNN, LSTM	Remark: COVID-19 Fake mews	Increase in fake news with 98% Accuracy
27	Bidirectional training technique	Platform: Twitter	NA
23	DNN	Dataset: social context	NA
24	TI-CNN	Dataset: image and text	NA
29	LSTM	Platform: Facebook	NA
30	LSTM, Bert (bidirectional encoder representations from transformers)	Platform:Twitter (Arabic Twitter Dataset)	Bert models: 99% accuracy

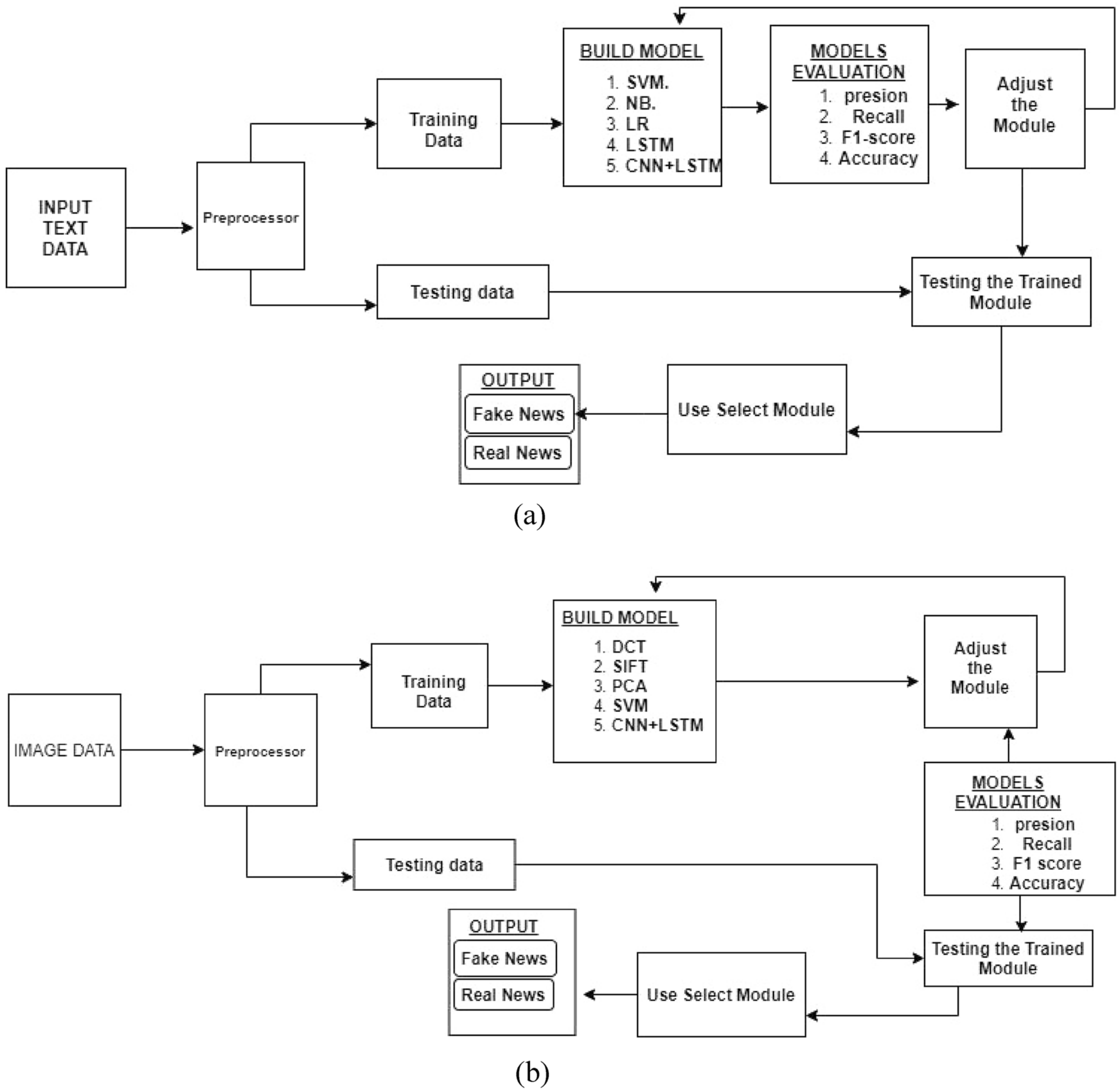

Fig. 2 Proposed framework for fake news detection on **a** textual data, **b** image data

into training and testing datasets. In the modeling phase for text data, ML classifiers and DL algorithms such as SVM, NB, LR, and LSTM classify text data into fake and real categories. LSTM captures long-term dependencies and relationships between words, while CNN extracts local features and patterns from the text. Combining both architectures' strengths can create a more robust model for processing text data. For image data, algorithms such as DCT, SIFT, PCA, and SVM are used. The trained models are evaluated using precision, recall, $F1$-score, and accuracy metrics, and auditing is performed. Testing of the trained models is done using the testing dataset, and the selected method produces results to determine whether the news is fake.

The raw text data is translated into numerical representations that may be utilized as input for machine learning and deep learning algorithms during pre-processing. Several techniques are used in this process, which are described below:

- *Tokenization:* This method includes dividing the text material into smaller components known as tokens. Tokens are often words in natural language processing, although they can also be phrases, sentences, or paragraphs. Tokenization reduces the dimensionality of incoming data, making it easier to process.
- *Stop words removal:* Stop words are words that are regularly used in the language but have little significance, such as "a", "an", "the", "in", "of", and so on. Stop words can be removed from data to minimize noise and enhance classification model performance.
- *Stemming and lemmatization:* Stemming and lemmatization are methods for reducing words to their root

Table 3 Details of distribution of image-based data

Image-based data	
Total images	365
Total clean images	183
Total forged images	182

Table 4 Details of distribution of text-based data

Textbased data (news content)	
Total news content	4276
Total real news	2500
Total fake news	1776

form. Stemming is eliminating suffixes from words to reach their base form, whereas lemmatization is mapping words to their canonical form using a lexicon. Both techniques can reduce the dimensionality of the input data while also capturing the essence of the text.

- *Vectorization:* Vectorization transforms text data into numerical vectors that may be fed into machine learning and deep learning algorithms. Vectorization approaches include bag-of-words (BoW), term frequency-inverse document frequency (TF-IDF), and word embeddings. The boW represents the text as a collection of word frequencies, whereas TF-IDF weights the words depending on their relevance in the document and the corpus. Word embeddings employ neural networks to represent words as dense vectors in a high-dimensional space, capturing their semantic links.

Dataset

The dataset for this work is collected from the Kaggle platform. From Kaggle, we use MICC-F1220 for the image forgery detection task. The dataset contains 183 clean images and 182 forged images, as shown in Table 3. For the news content-based text data, we use William Yang Wang's "Liar, Liar Pants on Fire" dataset, which contains 4276 news content samples. Of these, 2500 are real, while 1776 are fake news, as shown in Table 4. You can download the "Liar, Liar Pants on Fire" dataset using the following command: 'kaggle datasets download -d William Yang wang dataset "Liar, Liar pantson fire"'.

Model Building

This section discusses machine learning classifiers and deep learning algorithms used for image and text-based dataset fake news detection. Machine learning algorithms were used as baseline methods, and the proposed approach used deep learning algorithms that analyse data and fetch features to identify fake content.

Baseline Methods (Text and Image Dataset)

Two types of models used in this work are trained on both image and text-based data (publicly available dataset) for fake news detection. In the baseline method, we used machine learning algorithms to classify data into a fake and real categories. We use seven algorithms, SVM, DCT, SIFT and PCA for image forgery detection and NB, SVM, LSTM, and LR for news content (text) classification. For image forgery detection, SVM, DCT, SIFT and PCA trained on 90 images (forged + clean images) and 93 images used for testing and validating tasks. While for text classification, SVM, NB, LSTM, LR are trained on 2566 news and the rest for testing and validation. In image forgery detection, algorithms such as SIFT identify potential feature points and extract valuable vital points. LSTM connects the previous extracted feature with the current retrieve key point in text-based classification and helps in the prediction task. The final output consists of two labels: FAKE for image and text, identified by the machine learning algorithm as misleading and corrupt; another is REAL, which shows an image and text is genuine and authentic.

CNN-LSTM-Based Proposed Method

The proposed work utilizes the advantages of both: CNN and LSTM for image and text-based fake news identification. The CNN model extracts significant feature points from images and text with LSTM model connects and remembers information extracted from training data to classify between two sets of information. The first layer of the Conv1D model applies a filter on input vectors extracting feature points from each block component. The final output of the CNN model passes to the LSTM model as input; the model processes the features with new extracted one and forms information clusters that remain in memory for an extended period, and classify news content in images and text as fake or real.

CNNs are neural network designs typically used for image processing but may also be used for text processing. The input for text is represented as a vector sequence, and the convolutional layer applies filters to the vector sequence to extract essential local characteristics and patterns. CNNs employ convolutional layers to extract local characteristics from input pictures before using fully connected layers for classification or other tasks. CNNs are adaptable and robust models capable of learning representations that capture crucial input data information and make correct predictions. LSTMs are neural network designs often employed for sequential data processing, such as text. They are good at capturing long-term connections and interactions between

Table 5 Confusion matrix for text model

	Predicted negative	Predicted positive
Actual negative	568	30
Actual positive	15	542

Table 6 Confusion matrix for Image model

	Predicted negative	Predicted positive
Actual negative	517	31
Actual positive	64	488

inputs, which is helpful for natural language processing tasks like text categorization and sentiment analysis. LSTMs may be used for image dataset applications such as video analysis or sequence modeling, in which the LSTM examines a succession of picture frames and records the temporal connections between them.

The CNN + LSTM design combines the strengths of CNN with LSTM networks and can handle both text and picture datasets. In the case of text, the CNN layer collects local characteristics and patterns, which are then passed into an LSTM layer to capture long-term connections between words. The CNN layer uses convolutional layers to extract local features from pictures, which are then fed into an LSTM layer to record the temporal connections between frames or images. Overall, the CNN + LSTM architecture is a robust model capable of capturing both local and long-term information and is helpful for a wide range of natural language processing and computer vision problems.

Deep learning is frequently used in prediction tasks and provides reliable results. Our proposed model is divided into two phases: the first phase consists of convolutional neural network that works on the input images and text individually. For input images, components extracted then feature extraction performed by convolution layer of 1-D CNN, some less useful features removed using pooling layer. The number of channels used is three because of the colour (RGB) component. One image at a time is passed through a filter size of 5×5 with rectified linear unit (ReLu) activation function that converts $-x$ to x and reduces linearity. We use "same" padding and output of pooling layer passed from softmax function that provides labels. For text-based processing using CNN, first input news converts into tokens and passes from feature extraction layer, with 36 filters and kernel size 3. After getting convolved matrix pooling operation is performed that reduces the spatial dimension of input text. After that softmax function is applied and labels assigned, the second phase consists of the LSTM model processing the output of phase 1. Features extracted from images and text moved to the LSTM model. The LSTM model uses features from the CNN phase to develop long-term dependent features for prediction. We use Adam optimizer and sigmoid function [0, 1] at a dense layer that converts the output into 1 and 0.

Confusion Matrix

A confusion matrix is a table that compares predicted and actual class labels for a set of test data to evaluate the performance of a classification model. It summarizes the model's true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The matrix of the proposed approach for text and image is shown below in Tables 5 and 6.

Algorithm for proposed Work:

Step 1: Pre-process the raw text data by converting it into numerical representations using techniques such as word embedding.

Step 2: Data then, split the dataset into training, validation, and testing sets.

Step 3: Implementation of CNN is done and Then Output of the CNN goes to LSTM Step 4: Implementation of LSTM is done to capture the temporal dependencies and context within the text.

Step 5: Merge the outputs from the CNN and LSTM layers using concatenation or addition.

Step 6: Train the model using backpropagation and stochastic gradient descent with a suitable loss function such as cross-entropy.

Step 7: Evaluate the model on the testing set using appropriate metrics such as accuracy, precision, recall, and F1-score.

Step 8: Add a fully connected output layer with a softmax activation function to classify the news as real or fake.

Table 7 Showing results of evaluating image-based data using performance measures on machine learning classifier

Features	Multiple classifiers	Performance measures					
		TPR	Specificity	FPR	Recall	Precision	$F1$-score
Image-based news content	SVM	58	52.2	29	48	68	54
	DCT	78	85	10	88	90	80
	SIFT	90	96	04	94	96	93
	PCA	77	74	17	80	76	75

Table 8 New showing results of evaluating image-based data using performance measures on deep learning classifier

Features	Multiple classifiers	Recall	Precision	$F1$-score
Image-based news content	Deep learning (ensemble)	92	90	89
	CNN	91	95	91
	LSTM	87	89	83
	CNN-LSTM	88	94	91

The confusion matrix section of the research paper presents the evaluation results of a classification model trained on a dataset containing both text and image data. The model's performance is reported separately for text and image data, using various performance metrics based on the confusion matrix. For image data, the model achieves an accuracy score of 91.36%, precision of 94.02%, recall of 88.4%, and $F1$ score of 91.13%. For text data, the model achieves an accuracy score of 96.1%, precision of 94.75%, recall of 97.3%, and $F1$ score of 96%. These results suggest that the model performs well on text and image data but is slightly better at classifying images than text. Overall, the confusion matrix section provides a detailed and informative evaluation of the model's performance, which can help guide future improvements to the model.

Results Analysis of the Proposed Models

The utilization of images and text-based data helps understand how content can be manipulated on social media. Using multiple features to train machine learning and deep learning model provides better accuracy. We evaluated news content using two models, one ML-based and the other using deep neural networks. In ML (baseline method), scale-invariant feature transform (SIFT) with a recall of 94% for images provides better performance than SVM, PCA and DCT. SIFT algorithm extracts features from images by component extraction.

In text-based data, long short-term memory (LSTM) provides satisfactory results with a recall rate of 95%, while logistic regression provides the lowest recall value of 83%, as shown in Table 7.

In the image-based dataset, the highest accuracy achieved is 93% by SIFT algorithm, and in the text-based dataset, the best accuracy achieved is 96% by the LSTM model. We use the evaluation metric parameter to evaluate our model's accuracy, as shown in Table 8. Some of these evaluation parameter formulae are:

$$\text{Sensitivity (TPR)} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})}$$

$$\text{FPR} = \frac{\text{FP}}{(\text{FP} + \text{TN})}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$$

$$F1\text{-Score} = \frac{\text{TP}}{(\text{TP} + 0.5 * (\text{FP} + \text{FN}))}.$$

So, confusion matrix is used to calculate these parameters such as TPR (true positive rate), which calculates that how many predicted correct which are true in real, FPR (false positive rate) shows predicted value true while actual value is false, recall, precision, $F1$-score, sensitivity (true negative rate) and specificity, etc. We observed from these results that text data that contains bold headlines and many links and emoticons are fake news and news which use fewer links and use negations are true news. SVM gives the lowest TPR value in image-based and text-based data given by naïve Bayes of 82% shown in Figs. 3 and 4. The comparison of multiple parameter values in image-based data in Fig. 3 shows that SIFT and DCT perform

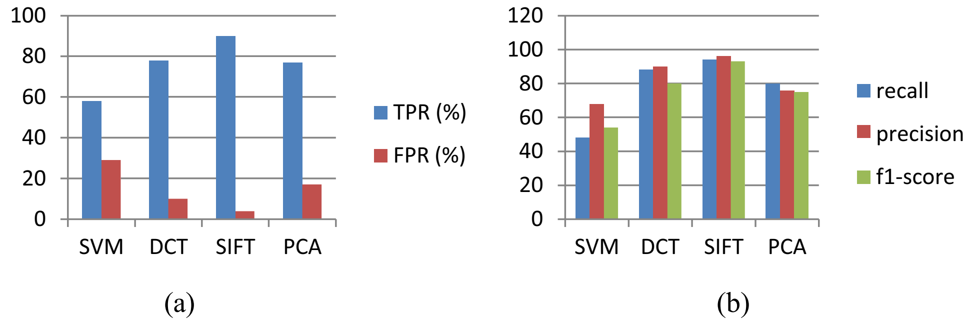

Fig. 3 Results of fake news detection in image **a** TPR and FPR (**b**) recall, precision and *F*1-score

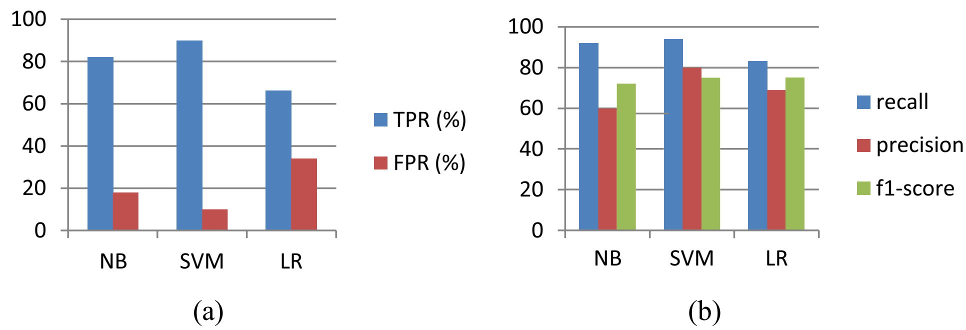

Fig. 4 Results of fake news detection in text **a** TPR and FPR (**b**) recall, precision and *F*1-score

Table 9 Showing results of evaluating text-based data using performance measures on machine learning classifiers

Features	Multiple classifiers	Performance Measures					
		TPR (%)	Specificity	FPR (%)	Recall	Precision	*F*1-score
Text-based news content	Naïve Bayes	92	20	18	92	60	72
	SVM	94	45	10	94	80	75
	Logistic Regression	84	24	34	83	69	75

Table 10 New Showing results of evaluating text-based data using performance measures on machine learning classifiers

Features	Multiple classifiers	Recall	Precision	*F*1-score
Text-based news content	Deep learning (ensemble)	87	91	89
	CNN	90	87	88
	LSTM	95	94	94
	CNN-LSTM	97	94	96

Table 11 Showing accuracy achieved on text and image dataset using baseline method and proposed method

Type of data	Approach	Classifier	Accuracy (%)
Text-based data	Machine learning (baseline method)	Naïve Bayes	60
		SVM	84
		LR	65
Image-based data	Machine learning (baseline method)	SVM	58.7
		DCT	91
		SIFT	93
		PCA	79
Text-based data	Deep neural networks (proposed method)	CNN-LSTM	96
Image-based data	Deep neural networks (proposed method)	CNN-LSTM	91

Table 12 The comparison table consisting previous work and proposed work

Previous work	Dataset	Data type	Method/techn ique	Evaluation metric parameter results			
				Recall	Precision	$F1$-score	Accuracy
Yang Yang et al. [27]	Kaggle	Text	CNN	0.90	0.87	0.88	0.80
		Image	CNN	0.42	0.53	0.47	0.51
Monther et al. [31]	Social Media	Text	Bayes Net	0.97	0.94	0.97	0.99
Njood Mohammad et al. [36]	Instagram Application	Image	CNN	0.91	0.95	0.91	0.93
Jamal Abdul Nasir et al. [28]	ISO and FA- KES	Text	CNN-RNN	0.60	0.59	0.59	0.60
Somya Ranjan Sahoo et al. [33]	Crawler on Facebook API	Text	LSTM	–	–	–	91.1
Jiawei Zhang et al. [26]	https://twitter.com/PolitiFact http://www.politifact.com	Text	Deep learning (ensemble)	0.916	0.913	0.919	0.898
Rohit Kaliyar et al. [32]	BuzzFeedand PolitiFact	Text	Deepneural networks	0.80	0.85	0.82	0.82
Julio C.S Reis et al. [23]	BuzzFace	Text	XGBoost	–	–	0.81	0.86
Proposed model	William Yang wang dataset "Liar, Liar pants on fire"	Text	CNN-LSTM	0.97	0.94	0.96	0.96
	Kaggle	Image	CNN-LSTM	0.88	0.94	0.91	0.91

well, and in Fig. 4, the comparison of recall, precision and $F1$-score on text-based data shows LSTM and SVM perform better in achieving satisfactory results (Tables 9, 10, 11).

Table 12 illustrates the comparison of proposed model with previous state-of-art methods for fake news detection using the image and text-based data. The results show that proposed model received 97% and 95% accuracy on text and image datasets, respectively. It clearly shows that the proposed model using CNN + LSTM method outperforms on both types of the datasets i.e., text and image. Also, the proposed model performs better on other evaluation matrices such as precision, recall and F-score for both types of datasets.

Conclusion and Future Scope

The expansion of social media networks led to different content that included fake news. We proposed a hybrid model to detect fake news using CNN-LSTM models that work on publicly available datasets and label them with fake or real labels. We also use machine learning algorithms that analyze the same dataset and classify them as fake or real. Our deep neural networks model performs better than machine learning classifiers with 96.1% on text data and 91.36% on image data, while the highest accuracy is achieved in text and image-based data by LSTM and SIFT machine learning models. Results show that our model efficiently classifies news content through deep analysis. For future work, explainable AI (XAI) can be used for accessing data sources and what features are manipulated in data to form fake content online. Furthermore, using SIFT with CNN for image forgery detection for better feature extraction.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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