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A Smart Model to Detect Hindi Fake News for Social Media Platform using Hybrid Deep Learning

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Abstract*:* As a direct result, erroneous information spreads on those platforms very easily and quickly, leading to improper behaviours and outcomes. Sometimes individuals deliberately spread this erroneous information to upset others in order to advance their own objectives. Due to the rapid expansion of digital news, false information has already created severe hazards to the public's true judgment and trustworthiness. With the growing usage of social networking sites, which provide a fertile environment for its development and transmission, fake news has already put the public at tremendous risk. They made an effort to discover which algorithm was the most effective by contrasting the models they used. According to the results, the naive bayes algorithm may achieve accuracy of 83%, which is maximum. False news worsens the problem it already faces since it harms society as a whole in addition to the negative consequences it has on individuals. Due to the widespread dissemination of erroneous information, the "balance of the news ecosystem" may be upset.

Keywords: *Hybrid Deep Learning, Hindi Fake News, Social Media Platform.*

1. Introduction

Anyone with an internet connection may post content online in the current climate. Unfortunately, bogus news is routinely shared and debated online, especially on websites that emphasize online social networking. People frequently make the error of choosing the improper educational course, going along it all the way to the arrangement's conclusion without pausing to reflect on their choices. These types of actions might promote the spread of false stories and disinformation, which is not good for society as a whole. The negative mindset that a group of individuals, or a subset of those people, has. Preventative procedures must be created in order to cope with such activities at the same dizzying rate as technology progress. Given the importance of this function, it is only natural that some people try to take advantage of the fact that widespread communications play such a huge part in affecting the larger population. On several websites, false information is presented. They try to present the impression that they are covering news while really disseminating false information, outright lies, and PR gimmicks. Maintaining control over the information that provides the public reason to believe in it is their principal duty. Around the world, there are a ton of instances of websites like this. Therefore, the spread of false information affects people's thoughts. The study's conclusions show that experts concur that a sizable amount of artificial computations utilizing brainpower can help in spotting false information.[1-3] Today, the Internet is a necessary component of our daily lives and cannot be separated from it. The amount of audience engagement with the more traditional news media, including newspapers and television, is steadily declining in comparison to the habit of reading and watching the news. One of the most important reasons influencing this trend is without a doubt the growth of various social media platforms. [4-6] Users' time on social networking sites like Facebook and Twitter is now worth more than it ever was. For instance, facebook reported having 2.07 billion active users in November 2017. Concurrent with the increase in internet and social media usage, significant problems emerged. Despite being a great instrument for spreading information that is free and unrestricted and doing so at an exponential rate, social media platforms provide the ideal environment for the creation and transmission of false information. [7-9]

1.1 Deep learning-based approach for automated false news identification

After reviewing several machine learning and deep learning approaches, the authors of this study provide a novel deep learning-based strategy for automatically recognizing fake news. We performed trials with sixteen different machine learning model configurations and assessed the results. Three alternative word embedding strategies were utilized in deep learning model configurations for tests, and then they were compared to state-of-the-art techniques. Convolutional neural network (CNN), long short-term memory (LSTM), bidirectional LSTM (BiLSTM), and CNN-BiLSTM models were used. The use of 12 distinct configurations was the total.

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1.2 WhatsApp Has a Fake News Detection Function

Although false news detection and other security precautions have been added to WhatsApp, these features are not yet available to beta users because they are still in the alpha testing phase. In an effort to stop the spread of false information, WhatsApp took this action. WhatsApp is presently testing the "Suspicious Link Detection" function. This function will alert users, and it will accomplish this by putting a red warning label on any links that it determines are leading to phony or alternative news websites or sources. Additionally, Over 25 forwards from the same device will prevent a message from being transmitted.[10-13]

1.3 CNN Acoustic Model

CNN, a more sophisticated variant of DNN, seeks to uncover the local structure hidden within input data as its main objective. CNN is able to accurately depict the spectral correlations in acoustic features and successfully reduce the spectrum fluctuations. .[14-16].

The ASR system was more resilient to fluctuations brought on by a range of speaking styles and speakers in the past when convolution was simply applied to the frequency axis. Toth, Waibel, and others later utilized convolution along the time axis[17-19].

1.4 CNN-BLSTM Hybrid Architecture

The experimental configuration for the later-discussed hybrid CNN-BLSTM architecture is described in this section.

Figure 1 demonstrates how the suggested design integrates three separate models—CNN, BLSTM, and fully linked layers—rather than just one, two, or even three. A few convolutional layers are first added in order to lower the frequency fluctuation in the input signal to a more tolerable level. The initial combination of each of the two convolutional layers that make up each CNN layer yields 256 feature maps. This results from the comparatively low feature dimension (40) of speech, which explains why this is the case. High-frequency and low-frequency areas exhibit highly diverse activity patterns from one another. The feature map is shrunk by two convolutional layers of processing to a size that is considerably closer to 16. As a result, modeling locality and taking into account invariance are no longer required. According to Sainath et al., The entirety of the frequency-time space will be covered by a frequency-time filter with first and second convolutional layer dimensions of 9 by 9 and 4 by 3, respectively. [20-24].

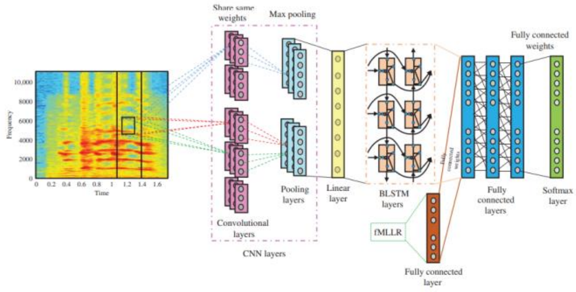

Fig 1: An Example of the CNN-BLSTM architecture used with the speech signal's log-mel features.

2. BERT Model

The BERT model is an open-source machine learning framework with a focus on natural language processing (NLP), to put it briefly.. BERT was created so that computers would be better able to understand the importance of obscure written content by using language itself to establish context. With data that was collected in the form of text from Wikipedia, the BERT framework has already completed preliminary training. Question and answer datasets might be added to this training to make it better. It is a deep learning model that is totally built on Transformers and which connects every output data to every input data. This model is officially known as "Bidirectional Encoder Representations from Transformers," or simply "BERT." In older times, the models could only read the text in one of two directions—left direction to right direction or right direction to left direction—and not both at once. Because it is designed to read the information (text) from both sides, the BERT model stands apart from others. The establishment of this feature, known as bidirectionality, was a byproduct of the development of transformers.[25-28].

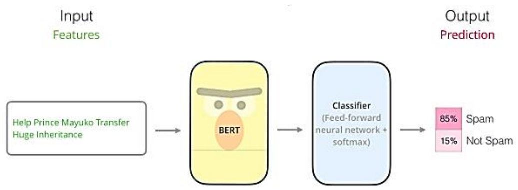

Fig 2. Display input features and output prediction.

The modified BERT language model that we are employing in this study is as follows.:

Contributors of Fake News

While the news is produced by actual people, false news is frequently produced by non-humans. There are three main categories of fake news spreaders:-

- Humans
- Bots
- Cyborgs

Due to how simple it is to create a fake account on social media, these accounts may be bought for very little money and be used to disseminate incorrect and harmful information.

3. Objectives of the Study

1. To study on Hybrid CNN-BLSTM Architecture
2. To study on CNN Acoustic Model and Deep learning-based strategy for automatic detection of fake news

4.Research Method

These responses have all been accurately categorized by the various classifiers that were employed to create them. The medium-sized corpus utilized for the numerous tests on the CNN-BLSTM architecture consists of about 150 hours of spoken Hindi and 200,000 distinct utterances. Each model is given 40-dimensional log-mel FB features to utilize. These properties are calculated once every 10 milliseconds. The asynchronous stochastic gradient descent (ASGD) technique is suggested while trying to improve the network. It works by pre-training all neural networks in accordance with the CE criteria at a constant learning rate of 105. Trials are also done to train the HF sequence using the distributed ASGD. The first weight setting is done using the Glorot-Bengio method. [29-30]

5. Datasets

The news items utilized in this investigation will be divided into two different groups: (i) True news items, and (ii) fake news items. Throughout the course of this investigation, we employed a number of strategies to distinguish between real news and false news. Only a large portion of the report will be gathered from the numerous news sources, including this one, that were used to create the annotated news pieces.

Each dataset has been split into three distinct categories: training, validation, and testing. Training datasets are the first type, while validation datasets are the second type and testing as third type. Table.1 displays how the datasets were divided. The distribution of the training, validating, and testing datasets, as well as the datasets for true and false news, was fairly even.[31-32]

Table 1 Distributions of data

Type of Dataset	Real News	Fake News	Total
Dataset of Training	7731	7731	15463
Dataset of Validation	3858	3858	7717
Dataset of Test	3858	3849	7717
SUM	15448	15448	30898

6. Proposed Architecture Model and Algorithms

One of the numerous applications of machine learning algorithm classifiers is the identification of false news. There are countless uses for it, and this is just one of them. Following initial training on a dataset, the classifiers will be able to detect fake news on their own. Logistic regression will be used as the prediction technique. [33-35] Table 2 presents the LWS and FWS outcomes in various settings. In the experiment, two LWS filters are utilized, and their efficiency is compared to FWS in terms of the number of parameters. In compared to the computational expense, the proportionate increase in WER (less than 0.7%) looks insignificant. The performances that LWS with two filters and FWS offer are very similar. Since the FWS approach is simpler to use, we opt against choosing to predetermine filter positions for each restricted weight. Due to its ability to balance WER and parameter count with 6.9 M parameters, FWS has been chosen to replace LWS as the best technique. This setup will be used for next testing.[36-38].

Table 2: The relationship between WER and full vs. limited weight sharing

Process	Hidden units in the first and second convolutional layers	Parameter	WER on the practice set (%)	Testing set for WER (%)
FWS	256/256	6.8 M	18.3	20.1
LWS		7.7 M	18.2	20.0
FWS	384/384	8.3 M	18.1	20.0
LWS		10.1 M	18.0	20
FWS	512/512	11.3 M	17.8	19.7
LWS		12.6 M	17.6	19.8

6.1 Naïve Bayes Algorithm

It is one of the strategies for categorizing things. The theoretical basis for it is the Bayes theorem. This approach uses automated forecasting and makes the supposition that each forecast stands alone. It starts with the most basic grasp of probability, makes the assumption that each input is unique, and then determines the outcome. The dataset was assembled using news from Facebook, and the Naive Bayes method is the easiest approach to adopt when building a classification model. It has 3500 training articles in addition to 1700 test-related articles (Sunitha R et al., 2021). Three sections—one for training, one for testing, and one for validation—make up the dataset. The "validation dataset" is used to establish the model's overall parameters after the model has been "trained" using the training dataset. We will make use of the testing dataset to make sure that everything is accurate. The accuracy of this model, which in this case used the steaming technique to reduce words to their root forms, is 74%. We will evaluate the accuracy with which the Naive Bayes, Support Vector Machine, and Neural Network classifiers categorize the data. [39-42]

7. Data Analysis

In this experiment, one deep learning model was combined with three conventional techniques. Table 3 displays the outcomes for the validation dataset using each of these techniques. SVM , Logistic Regression, and Naive Bayes algorithms all had F1 ratings of 96.50%, 97.50%, and 94.40%, respectively. Comparing the Naive Bayes algorithm to other traditional techniques, it will produce the highest F1 score. The LSTM F1 score is 96.7 percent using deep learning model. The dataset that will be utilized for testing and validation has 7718 records in total.[43-45]

Table 3 Results of a Validation Dataset

Type	Name	Acc	Pre	Rec	F1	T.P.	TN	FP	F.N.
Classical	SVM	0.943	0.903	0.987	0.943	3651	3656	353	56
	NB	0.975	0.956	0.993	0.974	3671	3772	250	22
	LR	0.964	0.952	0.974	0.964	3884	3591	224	17
Deep learning	CNN	0.938	0.962	0.996	0.966	3672	3742	286	14

In this experiment, three traditional methods were integrated with one deep learning model. The test dataset results from each of these techniques are shown in Table 3 below. The Support Vector Machine algorithm, Logistic Regression approach, and Naive Bayes approach each have F1 scores of 97.50%, 94.70%, and 96.50%, respectively. Among the traditional algorithms,the greatest F1 score will be produced by the Naive Bayes method . The LSTM F1 score for the deep learning model is 99.7%. There are 7718 records in total in the dataset that will be used for testing and validation.

Table 4 Results of a test dataset

Type	Name	Acc	Pre	Rec	F1	T.P.	TN	FP	F.N.
Classical	SVM	0.942	0.9121	0.984	0.946	3751	3555	352	56
	NB	0.973	0.963	0.985	0.974	3771	3672	250	23
	LR	0.962	0.952	0.975	0.964	3783	3691	223	17
Deep learning	CNN	0.978	0.963	0.993	0.998	3772	3642	286	14

Although the LWS model with 512/512 units yields the best results, it has an unacceptably high (12.7 M) number of parameters. However, when employing 256/256 units, FWS only uses 6.9 million parameters. The amount of parameters used by FWS is almost half that of LWS, yet there is only a 2% relative quality loss.[46-48] FWS with parameters of 6.9 M thus seems to be the preferred option. There is little doubt that a rise in the number of hidden units also causes a rise in the rate of recognition; nevertheless, this raises the complexity of the network. Speaking clearly helped the maxout neurons work successfully. A noisy environment may change the results. The feature set is improved through speaker adaption methods, which boosts the system's performance by improving its feature set. Table 8 displays findings from a comparison of CNN-BLSTM hybrid systems' WER to those of CNN, DNN, and RNN. The CNN-BLSTM hybrid has the potential to outperform the Gaussian-based hidden Markov model (HMM), deep neural network (DNN), and CNN, respectively, by 24.24 percent, 10 percent, and 5.8 percent when trained utilizing speaker-adaption and maxout + dropout. This serves to support the claim that CNN-BLSTM hybrid structure outperforms other models in the speech recognition test, and that this advancement is made possible by its unique structure. This development is possible because CNN-BLSTM hybrid structure outperforms other models.

Table 5: Available acoustic models' WER values.

Method	WER (%)
GMM-HMM	22.4

DNN	18.7
Deep belief network	18.6
RNN	18.2
CNN	17.7
CNN-BLSTM	16.5

7.1 Feature analysis of the input

The necessary characteristics are locally correlated for CNNs in terms of frequency and time. Coefficient of Mel-frequency cepstral are the characteristics that are most commonly employed for speech recognition, however since they lack localization in frequency, they cannot be utilized with CNN. This is because of the nature of their data. melFB characteristics provide this quality, which is denoted by the notation "locality in frequency." Numerous researchers have suggested a large number of speaker adaption strategies, which are adapted to increase the performance of ASR systems. The findings have demonstrated spectacular gains in recognition rate as a result of these techniques. Improving a system's performance frequently involves combining more time with dynamic knowledge about its characteristics. The efficiency of the system may be improved further by merging the time-derivative information of features known as delta (Δ) and double-delta (ΔΔ). Experiments with log-mel ΔΔ+Δ characteristics were carried out and addressed in Section 4. By taking the average of the length of the vocal tract, another typical approach known as vocal tract length normalization (VTLN) is able to normalize variances in speech such as disparities across speakers, accents, and stress. Because it applies the warping to the log-mel frequency band of each speaker, it maintains the frequency localization and, as a result, it appears more fruitful. In this part, an analysis of the functionality of complicated features is carried out.[49-50]

Table 6: WER as an Included Feature

Feature	WER (%) on training set	WER (%) on testing set
Log-mel FB	18.1	20.0
Log-mel FB was converted by fMLLR.	18.0	20.0
Warped log-mel FB VTLN	18.0	21
VTLN-warped log-mel FB was modified by fMLLR.	17.8	21.7
Log-mel FB was converted by fMLLR. +Δ+Δ Δ	17.4	21.7
FB Log-mel +Δ+ΔΔ +fMLLR(DNN)	17.2	21.2
FB + fMLLR(DNN) VTLN-warped log-mel	17.6	21.5
Warped VTLN-mel FB +Δ+ΔΔ	17.2	21.0
mel VTLN-warped FB +Δ+ΔΔ +fMLLR(DNN)	17.0	18.8

8. Conclusion

We require a system that can recognize bogus news on its own since it is pervasive in our everyday lives. We are utilizing machine learning models to do this. The model provided here is the first in the Hindi news medium, despite the fact that the issue of spotting false news has been the focus of much study. Since this technology will automatically identify fake news from online news sources, we will be able to exert stronger control over inaccurate information. We employed the Naive Bayes, Logistic Regression, Support Vector Machine, and LSTM models of Convolutional Neural Network classifier algorithms for this particular study subject. The Convolutional Neural Network model that has been proposed has improved accuracy. Utilizing fMLLR characteristics and CNN-BLSTM features, a novel strategy has been devised. Overall relative improvements of 5.8% and 10% were obtained when comparing the suggested design to the best-performing CNN and a DNN system, respectively. Because of the characteristics of the maxout neuron, dropout, and speaker-adapted, the hybrid system was able to attain this incredibly high gain. The study's conclusions state that merging CNN with BLSTM produced a system that is not only computationally efficient but also competitive with the currently accepted methodology.

Author contributions

Vidhya Barpha[1]: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Validation, Field study **Pramod S Nair**[2]: Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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