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CONFERENCE PAPER

A MACHINE LEARNING FRAMEWORK FOR DETECTING FALSE NEWS USING EMBEDDINGS AND DIMENSIONALITY REDUCTION

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Abstract

widespread dissemination of knowledge in human history was made possible by the creation of the World Wide Web and the rapid adoption of social media platforms like Facebook and Twitter.Because social media is so widely used, consumers are creating and sharing more information than ever before, some of it is false and unconnected to reality. Automatically classifying a written article as misinformation or disinformation can be challenging. Even a subject-matter expert must take several aspects into account before determining the authenticity of an article. In this work, we propose a machine learning approach for automatically classifying news articles. Our study looks into a variety of linguistic traits that can be used to distinguish between genuine and fake content. Using those qualities, we train a range of machine learning techniques and deep learning models. Using the Long Short term memory (LSTM) model, we eventually achieved 97% accuracy.

Introduction:-

Fake news contains false information that is verifiable. This can cause instabil- ity in some countries, as the Arabic Spring, by spreading incorrect information about a nation's statistics or inflating the cost of particular services. Concerns like author responsibility are being addressed by groups like the Crosscheck effort and the House of Commons. However, their reach is severely limited due to their reliance on human manual detection. In a world where millions of items are either published or withdrawn every minute, this is neither realistic nor accountable. One solution could be to develop a system that provides a trustworthy automatic index score system, or rating for the dependability of different sources and news context. There have been numerous cases of people being killed or seriously in- jured as a result of online rumors. In most cases, the production of fake news rises during a nation's election season. In 2014, the BBC news broadcast con- ducted study on the Indian general election. The researchers examined roughly 16,000 and 3,000 accounts and sites on Facebook and Twitter, respectively, to understand how fake news polarizes Indian society. While networks that spread fake news based on left-wing ideology were found to be less well-organized and successful, this research shows a "strong and coherent" expansion of right-wing ideology.

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Nearly 72% of Indian individuals are unable to distinguish between factual and fictional information, according to another BBC study . All things considered, they indicate that in order to combat the effects of fake news in In- dia, we must educate the populace about digital literacy. Prior to presenting the POLITIFACT dataset[7] and describing the feature extraction process carried out on it, we first examine the previous research in this study. In order to identify whether an article is authentic or fake based on its words, phrases, sources, and titles, this study offers a method for creating a model that applies supervised machine learning algorithms on an annotated (labeled) dataset that is manually classified and guaranteed. The best match features are then tested and chosen using feature selection procedures in accordance with the confusion matrix results in order to get the highest precision. To create the model, we propose to use different categorization strategies. The product model will be able to detect and classify fake articles and be incorporated with any system for future use when the unseen data has been tested and the findings plotted. The model that is suggested First, we take a dataset of fake news and ex- tract four features from sentences: sentence embedding vectors, word-level TF- IDF, character-level TF-IDF, and word-embedding vectors. Principal Compo- nent Analysis (PCA) was then used to maximize the normalized features in the second set of studies. We then employ a variety of deep learning and machine learning methods. With 97% accuracy, the LSTM model was the most accurate of all those models.

The overall contribution of the paper is summarized as follows:

- Extraction of five different feature sets such as word-level TF-IDF, Google 50-dimension, 100D GloVe embedding, 300D GloVe embedding, Sentence BERT for the text document.
- Principle Component Analysis (PCA)-based feature optimization.
- Using a variety of machine learning and deep learning techniques, classify the fake news data while comparing the accuracy, recall, and F1-score.

The remaining sections are structured as follows: A list of possible clustering- related works is provided in Section 2, a detailed discussion of the suggested methodology is provided in Section 3, the results of the suggested model are listed in Section 4, and the suggested model is concluded with some future directions in Section 5.

Related work:-

Studies on automatic false news identification have been ongoing for a few years. A hybrid methodology was presented by Rubin et al.[4] in that blends the net- work analysis method with a language's linguistic properties. Given the possi- bility of network information being unavailable or restricted, this approach may never be appropriate. According to Rubin et al.[4], examined rhetorical struc- tures and the connections between the several false and real news sample struc- tures from NPR's "Bluff the Listener." With the use of clustering, they were able to attain 63% accuracy. As demonstrated by Mihalcea and Strapparava in[5], deep learning can be used to distinguish between accurate and misleading information to a certain extent. Fernande et al. in [1] employed syntactic stereometry to classify deceptive writing by identifying statistical or syntactic trends, whereas older studies mostly relied on lexical patterns of the language.

Due to the well recognized techniques for text analysis, text analysis is the primary resource for detecting fake news. According to Veronica Perez-Rosas et al.[3], linguistic variables play a more significant role in identifying fake news than authentic news. They conducted this linguistic-based categorization for the purpose of detecting fake news. These methods are fairly restrictive and significantly skewed toward language-based analysis[2], so we must incorporate additional news-related aspects to get over this. have combined metadata from Google and incorporated that to boost the classification by 3% in F1-score for 6-label classification problem. However, as was the case with the Nepal earthquake [8][2], some scholars contend that fake news is the result of inadvertent occurrences like educational shock or inadvertent activities. False health information was so common in 2020 that it put the world's health at danger. Early in February 2020, the WHO issued a warning that the COVID-19 pandemic has caused a massive "infodemic," or an increase in both true and fraudulent news, including a lot of false information.

Methodology:-

This section covers the suggested methodology in detail. False reports The first dataset utilized to validate the suggested model is the fake news dataset. Dataset information supplied by [6] In total, there are 21417,23481 samples in this dataset of 44898 statements with the class labels Real-news and Fake- news. Among the eight categories of world-news, politics-news, government- news, middle-news, us-news, left-news, and news, fake news data came in second with 10145,11272,1570,778,783,4459,6841,9050. The overall data statistics for the dataset are shown in Table 1.

Feature Extraction:-

The extraction of features from text sources is essential for machine learning models. A robust feature representation has a major impact on the models' per- formance. This work uses four different features that were extracted from an Odia text document: the TF-IDF word-level feature, the TF-IDF char-level feature, the Gensim sentence embedding feature, and the iNLTK sentence embedding feature.

– **TF-IDF feature at the word level:** Using word combinations ranging from one to three grams, a bag-of-word is constructed. The TF-IDF value is then determined for every word, and a TF-IDF vector is then produced based on the bag-of-word to represent every Odia phrase.

Table 1. Distribution of Real and Fake News Articles Across Categories

News Category	Total Articles	Subcategory	Count
Authentic News	21417	World Affairs	10145
		Political Reports	11272
Fabricated News	23481	Government-Related	1570
		General Interest	778
		United States News	783
		Ideology-Based	4459
		Political Content	6841
		Miscellaneous News	9050

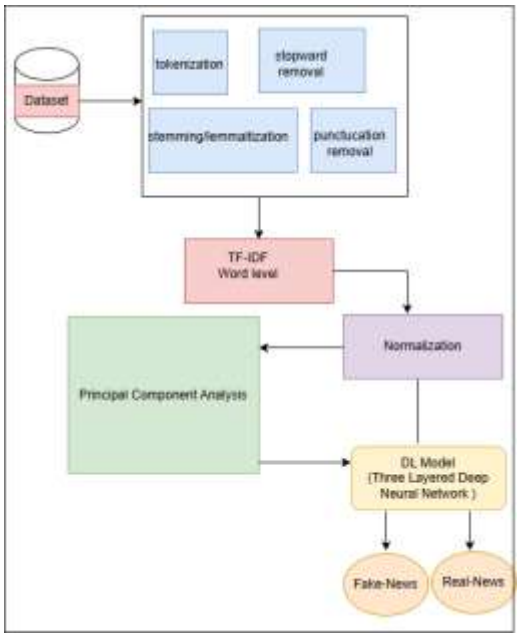

Fig. 1. Work flow of the DL based Fake-News Detection

Feature Normalization:-

Each obtained textual characteristic is normalized by scaling to unit variance and removing the mean. Since many machine learning estimators may perform badly if the individual features do not approximately represent standard nor- mally distributed data, standardization of a dataset is a typical prerequisite. Each feature undergoes independent centering and scaling by calculating the relevant statistics on the training set's samples.

Feature Optimization using PCA:-

A set of observations of possibly correlated variables can be converted into a set of values of linearly uncorrelated variables using a statistical method called principle component analysis. The primary components were chosen to explain the majority of the residual variance since they are orthogonal to one another. Of all the major components, the first principle component has the highest variance. The dimensionality of PCA is decreased in this study by using the normalized features that are produced via feature normalization. The normalized features' dimension was decreased using ten main components. In other words, each nor- malized feature's dimension was lowered to 10 by the use of PCA.

Classification Module:-

The suggested model consists of identifying posts that contain only textual data as either fake news or real news. A dense embedding vector is created from the considered text data by applying the TF-IDF word level feature extraction algorithm. After that, a three-layered dense neural network was trained using the produced embedding matrix to classify the data into two groups: fake news and authentic news. The whole architecture of the suggested model employed in this study is depicted in Figure 1.

LSTM based classification:-

Long Short-Term Memory (LSTM) is a special type of Recurrent Neural Network (RNN) designed to overcome the vanishing gradient problem and capture long- term dependencies in data. Long Short-Term Memory (LSTM) is a specialized type of Recurrent Neural Network used in Deep Learning to model and analyze sequential data such as text, speech, and time-series signals. Unlike traditional RNNs, LSTM is designed to overcome the vanishing gradient problem, enabling it to learn long-term de- pendencies effectively. It achieves this through a unique internal structure called a memory cell, which is controlled by three gates: the input gate, forget gate, and output gate. These gates regulate the flow of information by deciding what to store, what to discard, and what to output at each time step. Due to its abil- ity to retain relevant information over long sequences, LSTM is widely used in applications such as language modeling, sentiment analysis, speech recognition, and sequence prediction tasks, making it a fundamental architecture in modern artificial intelligence systems.

Results and Discussion:-

Experimental Setting:-

The Python experiments were conducted on a Windows workstation with an i7 processor and 32 GB of RAM. The Keras package with TensorFlow was used to construct the deep learning module. Our model was evaluated using the perfor- mance metrics mentioned in the next section.

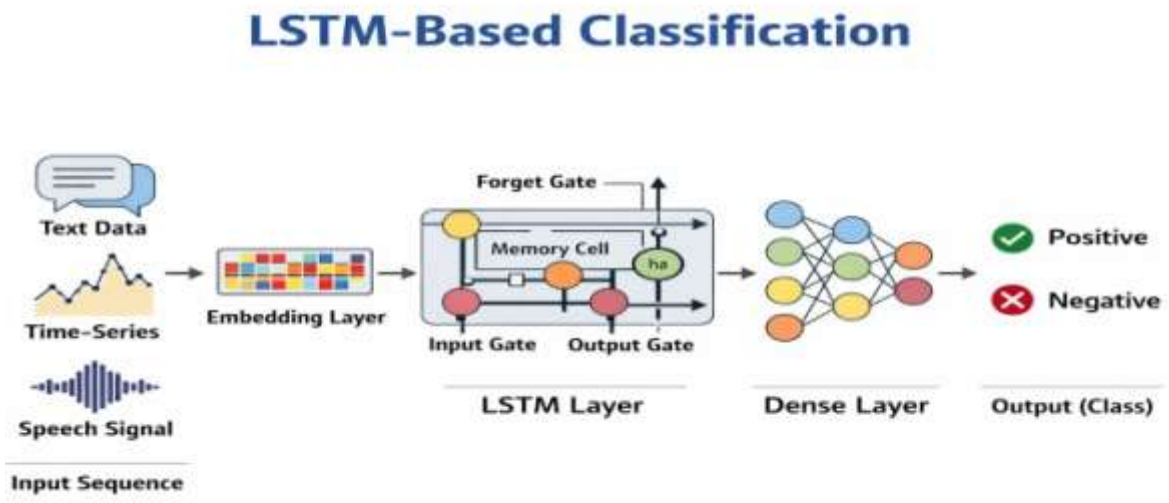

Fig. 2. LSTM based classification

Results of Clickbait Classification:-

Embedding plays a major role in the text classification task we are performing in this study, which impacts the overall performance of the classifiers. Statement We tested five distinct text embedding algorithms: BERT, GloVe-100 Dimen- sion, Glove-300 Dimension, TF-IDF, and Google's pre-trained 50-dimensional embedding. These embedding techniques were used to test the three-layered, fully connected neural networks covered in the previous section. Table 2 shows the network classifier's performance using several embedding techniques, with the result in bold letters indicating the best performance. According to Table 2, the best approach for the three-layered dense neural network classifier was Google's TF-IDF Wordlevel algorithm. The next round of trials focused on choosing the best classifier for the given task. Seven machine learning classifiers have been used in our experiments: (i) SVM, (ii) LR, (iii) Adaptive Boosting (AdaBoost), (iv) GaussianNB, (v) RF, (vi) KNN, (vii) DT, and the three-hidden-layered dense neural network. Table 3 shows the accuracy, precision, recall, and F-1 score of various classifiers. With an accuracy of 0.70, the three-hidden-layered neural network fared better than all other machine learning classifiers, as indicated in Table 3. The proposed three-hidden-layered neural network with Google 50-dimensional embedding has weighted precision, weighted recall, and weighted F-1 scores of 0.78, 0.78, and 0.78, respectively.

Table 2. Classification performance of LSTM model with different embedding tech- niques.

Methods	Class	Precision	Recall	F1-Score	Accuracy
Google 50-dimensional	Fake-news	0.88	0.36	0.44	0.64
	Real-news	0.82	0.84	0.74	
	Weighted avg.	0.79	0.79	0.79	
TF IDF char level	Fake-news	0.88	0.36	0.44	0.62
	Real-news	0.82	0.84	0.74	
	Weighted avg.	0.79	0.79	0.79	
100D GloVe embedding	Fake-news	0.88	0.36	0.44	0.72
	Real-news	0.82	0.84	0.74	
	Weighted avg.	0.79	0.79	0.79	
300D GloVe embedding	Fake-news	0.88	0.36	0.44	0.73
	Real-news	0.82	0.84	0.74	
	Weighted avg.	0.79	0.79	0.79	
Sentence BERT	Fake-news	0.88	0.36	0.44	0.75
	Real-news	0.82	0.84	0.74	
	Weighted avg.	0.79	0.79	0.79	
TF-IDF word level	**Fake-news**	**0.88**	**0.50**	**0.44**	**0.97**
	Real-news	**0.92**	**0.93**	**0.93**	
	Weighted avg.	**0.94**	**0.93**	**0.97**	

Conclusion:-

In this study, we attempt to identify a sample of fake news using a deep learning technique. Therefore, after preprocessing the dataset, we extract the features, normalize them, and then apply PCA to them using the TF-IDF word level embedding technique. After that, we developed a deep neural network model with an accuracy rate of 97% to differentiate between real-news and fake-news data. We intend to perform equivalent analysis on completely different datasets, such Facebook and Twitter, in order to build on our study. We want to find fake news on social media platforms in order to get closer to creating an auto- mated false news detection software. This study creates a baseline for subsequent research and broadens the scope of methods for identifying fake news. The lin- guistic differences will be addressed using the social media data. We would like to investigate further and evaluate how readers are impacted by the distribution of such content in order to make predictions more rapidly.

Table 3. Different classifiers performance with TF-IDF Word level embedding.

Methods	Class	Precision	Recall	F1-Score	Accuracy
Support vector machine	Fake-news	0.71	0.35	0.47	0.69
	Real-news	0.69	0.91	0.78	
	Weighted avg.	0.72	0.80	0.82	
Logistic Regres-sion	Fake-news	0.50	0.93	0.65	0.60
	Real-news	0.90	0.40	0.55	
	Weighted avg.	0.70	0.72	0.54	
AdaBoost	Fake-news	0.72	0.86	0.44	0.78
	Real-news	0.90	0.40	0.55	
	Weighted avg.	0.70	0.72	0.54	
Gaussian NB	Fake-news	0.88	0.35	0.44	0.65
	Real-news	0.67	0.84	0.74	
	Weighted avg.	0.70	0.80	0.76	
Random Forest	Fake-news	0.76	0.63	0.69	0.78
	Real-news	0.79	0.88	0.83	
	Weighted avg.	0.78	0.78	0.76	
KNN	Fake-news	0.00	0.00	0.00	0.61
	Real-news	0.61	1.00	0.76	
	Weighted avg.	0.50	1.00	1.00	
Decision Tree	Fake-news	0.74	0.78	0.76	0.78
	Real-news	0.86	0.82	0.84	
	Weighted avg.	0.78	0.78	0.80	
DNN	Fake-news	0.73	0.76	0.75	0.76
	Real-news	0.86	0.82	0.84	
	Weighted avg.	0.78	0.78	0.80	
Bi-LSTM	Fake-news	0.74	0.78	0.76	0.77
	Real-newsa	0.86	0.82	0.84	
	Weighted avg.	0.78	0.78	0.80	
LSTM	**Fake-news**	**0.71**	**0.94**	**0.92**	**0.97**
	Real-news	**0.83**	**0.81**	**0.82**	
	Weighted avg.	**0.92**	**0.93**	**0.94**	

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