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ADVANCED MACHINE LEARNING FRAMEWORK FOR IDENTIFYING AND MITIGATING FAKE NEWS AND MISINFORMATION PROPAGATION ON SOCIAL MEDIA PLATFORMS

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Abstract
Fake news has become such a serious problem to everyone of all ages and backgrounds as it can deceive. The demand for accurate and reliable methods to detect misinformation has increased due to the rising reliance of individuals on digital platforms for entertainment, news, products, and services. Recent research efforts have tackled this problem, by focusing on developing actionable tactics to prevent the spread of false- information. This paper therefore proposes an ensemble machine learning method by combining Multinomial Naive Bayes, Random Forest, and Logistic Regression to enhance the accuracy and performance of false news detection. The ensemble model to take advantage of each special method and minimize its shortcomings. At a very high false positive rate accuracy of 96% and an F1 score of 95%, experimental data show that our suggested approach performs noticeably better than individual classifiers and other models already in use.

INTRODUCTION

Social media plays a pivotal role in modern society, serving as a primary source of information for countless users worldwide [1]. While it enables quick access to news and real- time updates, it also acts as a conduit for the rapid spread of misinformation and fake news, especially during times of crisis, where the consequences of misinformation can be severe and far-reaching.[2]. The rise of fake news can be attributed to a variety of political, economic, and technological factors, with the explosive growth of online social networks being the most significant driver. Individuals active on social platforms are often exposed to manipulative or misleading language, making them susceptible to misinformation [3].Though its exact meaning varies depending on the disciplinary environment and the topic of each study, the phrase "fake news" has been used by several academic publications. Currently, there is no widely agreed-upon definition; instead, interpretations are changing in response to new information and study [4-5]. Nonetheless, material that is purposefully and demonstrably untrue is typically referred to as fake news. The creation of methods to recognize and handle such content is facilitated by this working definition,

Fake news may take many different forms in the current digital age, from state-sponsored propaganda and purposefully produced stories to humorous articles that are mistaken for the genuine thing [7-8]. These false narratives have caused a great deal of societal strife and increased widespread mistrust in conventional media. Although fake news is typically understood as intentionally deceptive reporting, social media rhetoric has broadened the term's usage, with some individuals now labelling inconvenient truths as fake news to discredit opposing viewpoints. The term has become widely used, particularly to denote false and misleading articles designed to generate revenue through high web traffic [9].This paper aims to propose a predictive model capable of assessing the probability of a news article being fake [10]. Platforms like Facebook have faced intense criticism and scrutiny, prompting them to introduce features that allow users to flag suspicious content. Additionally, the company has publicly committed to developing automated tools to better detect fake news. However, implementing such a solution remains a complex and ongoing challenge [11].

Figure 1 Fake news image on social media platform

The rapid expansion of social media communities and the perceived credibility of established news organizations have inadvertently empowered misinformation creators to boost their visibility and gain followers' trust. These individuals often exploit attention- grabbing headlines and emotionally charged captions to ensure their content is widely shared and rapidly disseminated [12-13]. Their ultimate objective is sometimes to use sensationalism, which works well on advertising systems like Google AdSense, to monetize such material. Because authors are compensated for producing the most interaction, regardless of truth or accuracy, this financial incentive encourages the ongoing propagation of false information. The effects of this tendency, however, are extremely worrisome and potentially harmful [14].

RELATED WORKS

In past years, several research works have been done on fake review detection. These studies were primarily attired at the English language and other popular languages such as Chinese for detecting fake reviews. However, there was no effort for Roman Urdu reviews. Some research work has been done in past years on fake reviews detection for several languages, which are discussed below [15].The syntactic stylometry for deception detection was proposed by Feng in. Xu et al. used a few deep language variables in their study to distinguish between spam and real reviews. Ott et al. combined work from computational linguistics and psychology to identify spam reviews. [16] Mukherjee took advantage of the numerous adverse behavioral imprints of reviewers and developed an unsupervised model. The reviewer behavior-based approaches can occasionally lose their effectiveness due to spammers' best efforts to evade detection. For instance, to escape IP address inspection, they can utilize a proxy server [17].

Two novel datasets were presented in the Automatic Detection of Fake News research to aid in the creation of fake news detection tools. Authentic news stories from reputable media sources in six key domains made up the initial dataset, whereas comparable false pieces were created by crowdsourcing utilizing Amazon Mechanical Turk (AMT) workers [18]. The second dataset obtained from multiple online tabloids included both real and fabricated celebrity news articles. The research used vector space representations of n-grams with Term Frequency-Inverse Document Frequency (TF- IDF) metric as one of several characteristics for classification purposes [19]. The identification accuracy received improvement through the addition of stylometric features which included syntactic structure and readability metrics and punctuation patterns and psycholinguistic markers from the LIWC vocabulary. The Support Vector Machine (SVM) model was used to complete the classification task. The second dataset showed positive results with both the entire LIWC lexicon and TF-IDF-based vector representations, but the first dataset achieved its best results using stylometric criteria including punctuation and readability [20].

Its predecessor models based on human feature engineering and traditional machine learning methods on the widely used Samsung fake news dataset. The FNDNet model is different from prior work in the following aspect: it utilizes only the vector-based word representations [21]. The GloVe method projected words onto 100- dimensional vectors prior to processing through the deep learning model. This architecture was based on a modified Convolutional Neural Network (CNN) with three parallel convolutional layers, along with dense (fully connected) layers [22][40]. FNDNet achieved superior performances to basic machine learning classifiers and advanced deep learning models such as CNN and Long Short- Term Memory (LSTM). The amalgamation of modeling effective neural architecture with efficient word embedding represents the power of deep learning in falseness detection [23][41].

The authors suggest researchers looking to optimize false news identification algorithms should focus on multi-model word embeddings in the future. In Defending Against Neural Fake News, the authors introduce a natural language generation model, Grover, which emulates the subtleties of actual news articles very well. Grover is based on neural networks, like FNDNet, and employs a different technique and architecture, Generative Adversarial Network (GAN) [24][42].

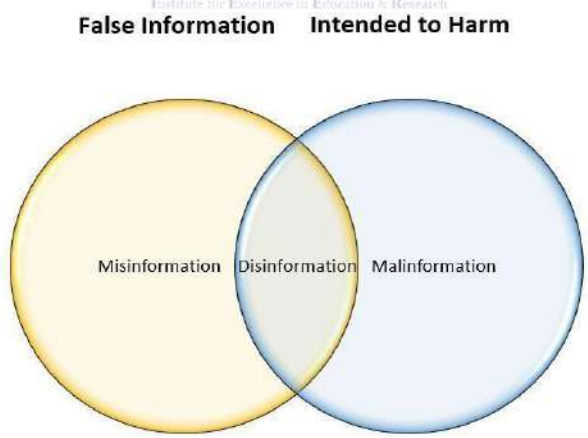

Figure 2 Misinformation Disinformation Malinformation

The GAN includes two parts: a detector, to detect fake news, and a generator, which generated material that appears real. The detector is learning and developing at the same time as the generator learns to create believable content [25]. Since both detectors and generators continually learn in concert through this feedback loop from adversarial learning, detectives should be developed that are reliable and adaptable in the future actions as detecting neural fake news, such as that generated by Grover, is increasingly difficult to reliably or accurately detect using traditional methods [26]. To assist with this development, the team developed a dataset called the Real News dataset, which contains a large, diverse corpus of news stories sourced from the Common Crawl dataset [27].

METHODOLOGY

In this research, we are detecting fake news on social media platforms using the ensemble method. Data is collected from Kaggle which is open source. Dataset will be in English language which includes both real and fake news. After collecting, data is pre-processed to enhance results [28]. For preprocessing, data will be cleaned first by removing stop words, punctuation, and any special characters. Then, the data is normalized to prepare it for further processing, as shown in figure no.3

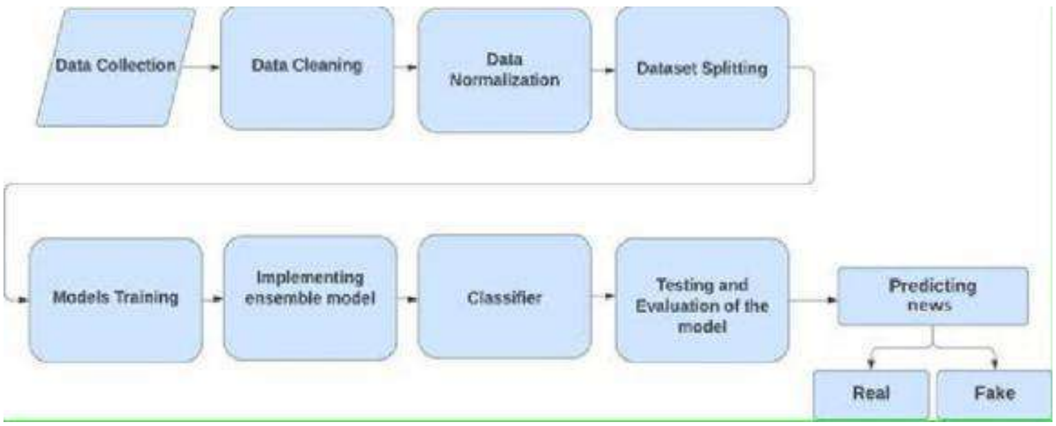

Figure 3 Research framework diagram

- Data Collection
- Data Cleaning
- Data Normalization
- Ensemble Method
- Test and evaluate the model.

The Anaconda platform is being utilized in this research for implementation purposes. Anaconda is ideal for data science and machine learning applications as it presents an integrated environment that contains easier package management and deployment [29]. In addition, it comes with many libraries already installed, including NumPy, Pandas, Scikit- learn, and Matplotlib, which are all needed for data analysis and model preparation. It also provides better control of versions and compatibility across many packages than other applications. Python is used in the coding stage due to its usability, readability, and powerful libraries specific to data processing and machine learning. Python is a popular selection for research and development in data science and machine learning as it provides a flexible environment with a strong community for support. In this research, the Jupiter Notebook from Anaconda will be utilized to provide interactive coding, documentation, and visualization platform [30][43]. This protects the clarity and organization of the implementation phase. Together, Anaconda and Python provide a reliable and organized environment for development and evaluation of the modeling of false news detection systems [31].

RESULTS

The division of dataset is categorized in real and fake news. Visual representation of graphs clarifies the division of data in real and fake news. This graph gives the ratio of splitting of the dataset into two labels.

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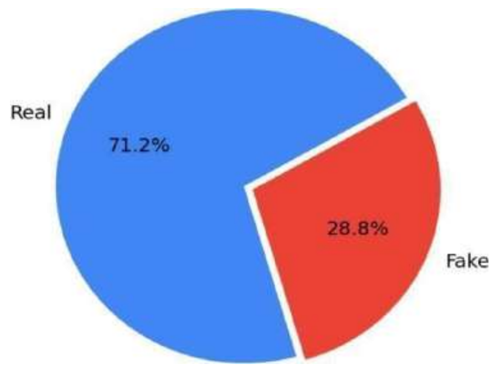

Figure 4 Real vs fake new in dataset

This word cloud is generated from the dataset that is given in the English language. Words collected in the word cloud are taken from the dataset. Words that are used more frequently are displayed in word cloud and words that are highlighted in large size means they are mostly used in news as compared to words that are in small size. These words displayed in clouds identify that they are important and mostly used in news.

Figure 5 Word cloud of constant words

Model training

In the implementation process, the first step was data collection which was collected from open- source websites. The second step was data preprocessing in which data was transformed to train and test models accurately and get better results. In pre-processing, we removed duplication from the dataset, removed most common stop words, and removed punctuation and lower-case letters from the dataset. Furthermore, we check the transformed dataset to detect any problems. The next step is to split the dataset which is split into a train set and a test set. The train set is taken maximum while the test set is taken 20%. Now, the main step is to train the model with algorithms. In this step, we are implementing an ensemble learning technique. Ensemble learning is a method in which multiple independent models are generated using different algorithms to train them, and then these models are combined to give improved accuracy and results. We have created three models named

```
model1 = MultinomialNB().fit(X_train, train_label)
model2 = LogisticRegression().fit(X_train, train_label)
model3 = RandomForestClassifier().fit(X_train, train_label)
```

model 1, model 2, and model 3 and we train these models by giving them a training dataset as shown in the code below.

Ensemble Method working

The ensemble technique works as a single model, which involves different algorithms. Each model is trained separately. Then, each model's prediction is combined to produce a single improved result by neglecting each model's weakness. In our proposed model, we used three algorithms: Naïve Bayes, Logistic Regression, and Random Forest. Algorithms are taken in odd numbers because when the results are combined, it can produce bias in results when the ratio of outcomes is 2:2, so to get accurate results, an odd number of models is used, which gives a 2:1 ratio. Ensemble learning is used from complex and noisy data [32]. We have applied the ensemble technique to our dataset because the dataset is a bit tricky and creates noisy data and the ensemble technique neglects the weaknesses of each model and combines them to make a robust model. The main purpose behind implementing an ensemble is to cluster weak learners together to create a strong learner. The ensemble technique basically neglects the weaknesses of each model and combines them to make a strong model. It improves the results by combining each model prediction and generating single result. Fig 5 is the architecture of the ensemble method and how it works.

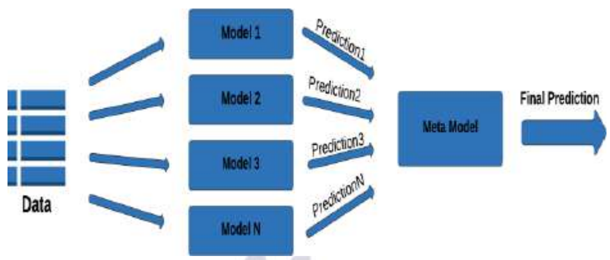

Figure c Training and testing dataset splitting ratio

Multinomial Naive Bayes (MNB) is a common choice for text classification tasks because it works well with sparse input data and can handle many features. It is simple and efficient and often performs well even with relatively little training data. It works by assuming the presence of a specific feature in a class that is not related to the presence of another feature. Nave Bayes is scalable algorithm, a fast algorithm, and can be used for the classification of multiclass and binary classes in [24].

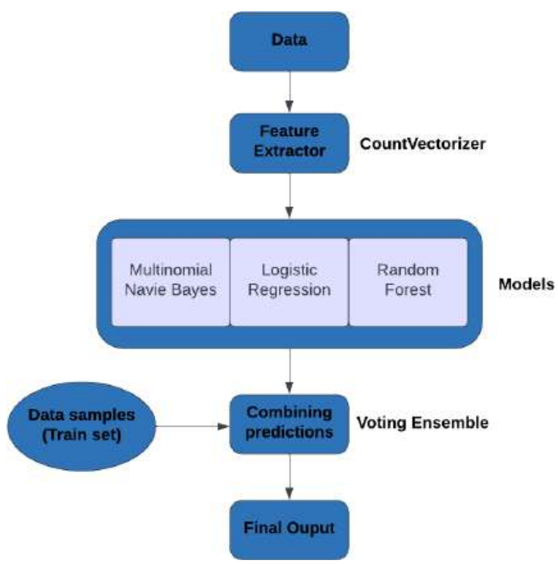

Figure 7 Voting classifier architecture.

Hard voting classifier is a type of voting classifier in which the input data is classified build on the mode of all the outputs made by different models. In hard voting, the outputs are combined to reciprocate the mode [33]. It works when output made by different models is equal to what it is considered in majority voting based on equal outputs. Its phenomena work on majority voting, and the mode is taken of all the predictions [34].

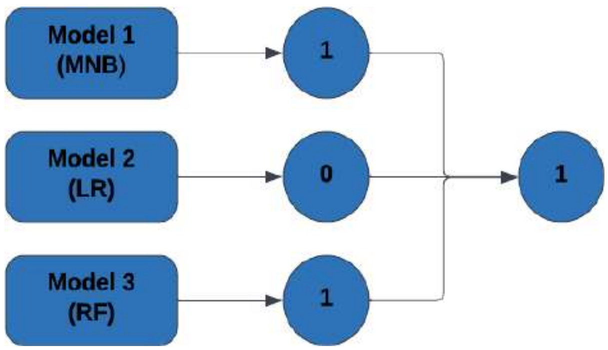

Figure 8 Hard voting classifier architecture.

In these lines of code, **ensemble = VotingClassifier** initializes the classifier with three base models model1(nb), mode2(lr), and model3(rf). **Voting=hard** instruction describes that the ensemble will make predictions based on majority voting. **(X_train, train_label)** is fitting the voting ensemble to the training dataset. In soft voting, the classifier returns output based on probabilities of all the outputs made by different models. Its phenomena work on the probability method in which weights are given to each model and are applied properly based on the given equation [35].

m1= [0.5, 0.8], m2 = [0.2, 0.6], m3 = [0.7, 0.9].

Probability of class 0= 0.33*0.5 + 0.33*0.2 +0.33*0.7 = 0.462

Probability of class 1= 0.33*0.8 + 0.33*0.6 +0.33*0.9 = 0.759

The probability calculated by the soft voting classifier is 46% and 75%. Class 1 has greater value, so the classifier will consider class 1. Below the image shows the working of soft voting classifier.

Comparison between Hard and Soft voting classifiers

The hard Voting classifier ensembles majority voting and generates the mode of the output, while the soft ensembles give average predicted probabilities of output taken from models [36]. Both perform very well on the models. We compare classifiers and the results are almost the same, there is just a difference in point values. The result generated by both classifiers is shown below in the form of precision, recall, and f1- score. Moreover, we have taken support vector machine classifier (SVM) in this model. SVM is a classifier that is used for regression and classification tasks. SVM works very well with sparse data and can hold non-linear relationships between features. In the line of code, we are splitting data into features and labels. Features are taken from the data frame of news, and labels are taken from dataset labels. Then, we are applying feature extractor which is TF-IDF. It is fitting the TF-IDF to feature data of the training dataset. When the model is tested, it will show the result report in which precision, recall, and f1score will be calculated. Below the image shows the results of the SVM model using the TF-IDF feature extractor. The results show that SVM works well on the model and gives better accuracy in detecting fake news.

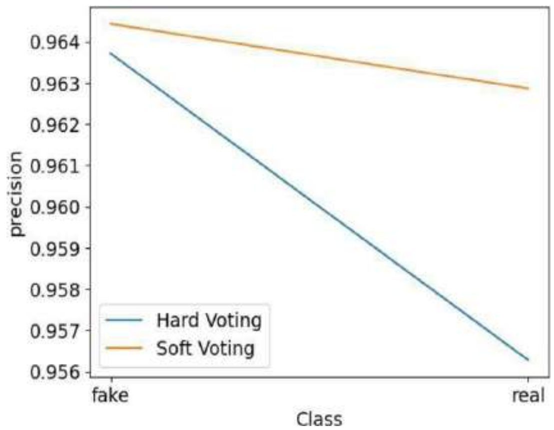

Figure S Comparison of precision for hard and soft voting.

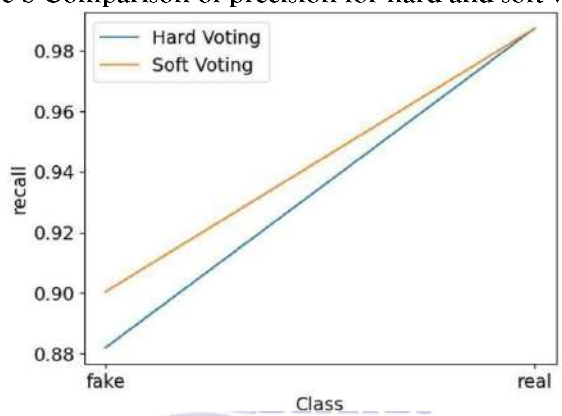

Figure 10 Comparison of recall for hard and soft voting

SVM model to detect fake news using different feature extractors

We have implemented another model in which we have taken TF-IDF as a feature extractor. TF- IDF is a feature extractor that transforms a raw document collection into a matrix document text of TF-IDF features. Term frequency-inverse document frequency (TF-IDF) is an algorithm that takes the frequency of words from the text to identify how those words are related to the document that is given. It is used for text summarization, classification and filtering of subjects [38].Moreover, we have taken support vector machine classifier (SVM) in this model. SVM is a classifier that is used for regression and classification tasks. SVM works very well with sparse data and can hold non-linear relationships between features [39].In the line of code, we are splitting data into features and labels. Features are taken from the data frame of news, and labels are taken from dataset labels. Then, we are applying feature extractor which is TF-IDF. It fits the TF-IDF to feature data of the training dataset [37].

Comparison of Ensemble Model and SVM model: Validation of proposed model

In this research, the count vectorizer is used as a feature extractor in ensemble model while in SVM model TF-IDF is used for feature extraction. The following table and graph show both model results and compare the results. The ensemble model used to detect fake news performs better than the SVM model because it achieves an accuracy of 96%, while SVM has 95% accuracy.

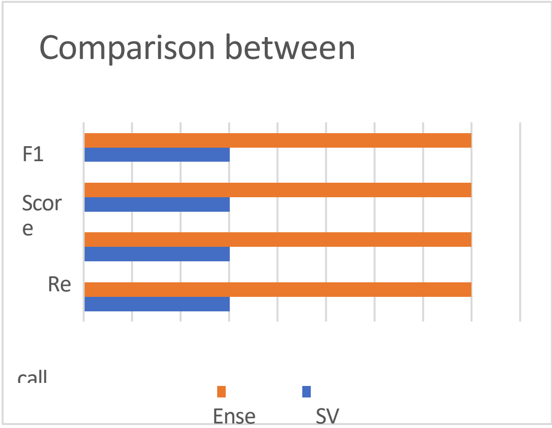

Figure 11 Ensemble model comparison with the

SVM model

The ensemble model to detect fake news works much better than the SVM model because its results are 96% while SVM has 95% accuracy.

Comparison of the Ensemble model with other literature

A comparison table represents the comparison between the proposed model and the state of the art. Below; the table and graph show the models with their outcomes compared with our model results. This table shows the machine learning algorithms taken from literature. These algorithms or classifiers were used by different researchers to detect fake news in different languages, and their results are shown in the given table.

Table 1 Deep learning model evaluation results

Classifier	Accuracy	Precisi on	Recal l	F1 Score
LSTM [14]	94	92	85	88
RNN [15]	91	91	84	86
GRU [16]	92	91	86	88
Bi-LSTM [17]	92	91	86	88
ANN [18]	94	92	90	93
SVM [19]	95	89	93	94
RF [20]	87	87	89	88
NB [21]	70	58	85	67
Proposed Model (Ensemble)	**96**	**90**	**92**	**95**

This table shows the machine learning algorithms taken from literature. These algorithms or classifiers were used by different researchers to detect fake news in different languages, and their results are shown in the given table.

Table 2 Machine learning models evaluation results.

Classifier	Accuracy	Precision	Recall	F1 Score
SVM [19]	95	89	93	94
RF [20]	87	87	89	88
NB [21]	70	58	85	67

After all the implementation steps, the result of the ensemble model is calculated in terms of precision, recall and f1-score. The ensemble model detects fake news gives 96% f1-score and accuracy. It works well and performs well in training, testing, and in runtime detection of fake news. The following image shows the classification metrics or results reports generated by the model in the form of a graph.

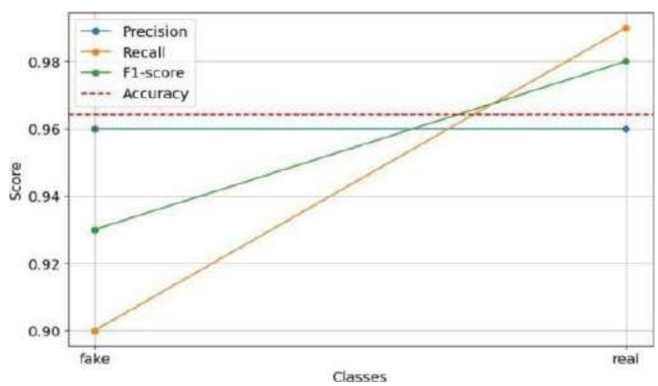

Figure 12 Classification metrics graph.

Conclusion

In this work we propose an ensemble-based system for identifying false news, which includes three well-known machine learning classifiers: Logistic Regression (LR), Random Forests (RF), and Multinomial Naive Bayes (NB). To remain open and accessible to any reader, the training data used for our solution was open-source data that was publicly available. The benefit of our ensemble classifier is that we can derive an ensemble classifier that increases your false news detection coverage, by averaging on the various individual classifiers and reducing the individual shortcomings of each classifier. We also introduced a framework based of seven consistency criteria for assessing the consistency and contradiction of news information to improve the ensemble false news detection system. To promote the pragmatic usability of our implementation, we created a user interface that allows end users to easily enter and evaluate stories of news. To evaluate performance across several performance measures, we made use of experimental comparison of our ensemble approach, along with performance in comparison to several baseline models. Our results indicated that our ensemble classifier is preferable to individual classifiers and performed at 96% accuracy when evaluating U.S. based English- language news stories.

Limitation & future work

With an eye on advancing detection skills with these novel techniques will include architecture based on convolution, graph-based machine learning, and transfer learning. The future work will include these directions in efforts to capture contextual relationships and semantic details such that more accurate and more advanced false news detection systems can be created that are missing from standard models.

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