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Machine Learning Approaches For Detecting Fake News: Ensemble Stacking Outperforms Conventional Methods

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Abstract: *The fast propagation of fake news in social media seriously damages public trust and societal integrity. This paper presents NDetect, a stacking-based ensemble learning model designed for effective fake news detection. NDetect combines Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest classifiers to provide additional robustness and predictive accuracy. The model was trained on the ISOT dataset, using TF-IDF features and standard preprocessing. In experimental results, NDetect performed superiorly against individual models, achieving 89% accuracy and 0.957 ROC-AUC score. In comparison with conventional methods, the ensemble approach exhibits very good generalization and classification performance. These results carry implications for the ensemble learning approach in developing a robust misinformation detection scheme on digital platforms.*
Keywords: *Social media, natural language processing (NLP), misinformation, machine learning, classification performance, ensemble learning, stacking classifier, and fake news detection*

1. INTRODUCTION

Fake news isn't new. From the very beginning, it had spread through word of mouth and sometimes those odd fringe publications. Today, however, it has found a nice habitat in algorithms tailored for engagement rather than accurate information. Falsehoods generally travel faster and go further than truths, particularly when they provoke intense emotional reactions. Losing sight of examples like election interference or financial trap doors, and even public health crises propagated by misinformation, establishes the problem often palpable in terms of effects. Such media as Facebook, Twitter, and Whats app are capable of instant communication across geographic barriers, with immediate linking to news feeds worldwide. The democratizing of information has led to several advantages for society as a whole and brought in a major drawback-the rapid and uncontrolled circulation of false news.

Manual efforts, such as checking facts on websites or even government-finding intervention, are not enough in detecting fake news. The problem, however, is that with the high volume and speed of content that flies through the roofs of these platforms, they are actually more than just necessary for real-time intelligent and automated systems for identifying misinformation and flagging it. The interest in AI and ML techniques for the detection of fake news has aroused now. The basic models of ML that have been investigated, like Logistic Regression, Support Vector Machines, and Decision Trees, seem to have achieved recognition in the first experiments - particularly, by being coupled with frequency features, syntax patterns, and sentiment analysis. However, these models, in general, have the problem of generalization, especially across topics, languages, and even writing styles. To confront these challenges, this research proposes an ensemble-based AI system for fake news detection on social media platforms. The ensemble method integrates various supervised learning models, including Logistic Regression, Support Vector Machines, Decision Trees, and Random Forests, in a stacked architecture that provides better prediction robustness by reducing bias and variance. The procedure was done at testing and trained with ISOT Fake News Dataset, which contains real and fake news articles collected from authenticated sources. The model is vigorously tested according to accuracy, precision, recall, F1 score, and ROC-AUC, ensuring true performance under a variety of conditions. In the application, ensemble learning was combined with preprocessing of texts and powers for features (like TF-IDF and lemmatization) to create an AI model that scales and is interpretable and is amenable to real-life usage of social media. In addition, the approaches could be further scaled to multilingualism and instant applications, integrating other APIs or bots.
The paper is structured as follows: section 2 offers a discussion of the related work and the existing methods used for fake news detection; section 3 provides a well-illustrated elaboration of the proposed methodology and system design; section 4 describes the research result; and lastly, section 5 concludes and sketches possible prospects of future enhancement.

2. Related Work

The ongoing rise of fake news on digital platforms has given rise to intense interest in research focused on designing automated detection systems using artificial intelligence (AI) and machine learning (ML). This literature review covers the details of the datasets used, techniques applied, and significant contributions made by researchers in this respect. The narrative is further supported with references.

Datasets in Fake News Detection

Since then, several datasets have been made available for model training and evaluation in the detection of fake news. Ahmed et al. (2018) developed the ISOT dataset-with over 44,000 labeled articles from real and fake sources. LIAR was developed by Wang (2017), which comprises 12,800 labeled short political statements with six truth-level classes. Shu et al. (2018) produced Fake News Net by hybridizing the content feature with the signals of the social context. Most recently, Li et al. (2024) have released MCFEND, which is a cross-domain Chinese benchmark of fake news to enhance the transferability across sources.

Table 2.1: Datasets in Fake News Detection

Dataset	Size	Labels	Type	Highlights
ISOT	44,000+	Fake/Real	Article text	Popular for binary classification
LIAR	12,800	6 classes	Short claims	Rich metadata, semantic models
FakeNewsNet	Varies	Fake/Real	Text + social	Graph-based modeling
BuzzFeed/PolitiFact	2,000+	Fake/Real	Articles	Fact-checked political content
MCFEND	30,000+	Fake/Real	Chinese news	Cross-source adaptability testing
Twitter15/16	~15K threads	Multi-class	Tweets	Rumor propagation analysis

Conventional Machine Learning Methods

Traditional machine learning (ML) methods have been the fundamental techniques contrived in the early stages of research for detecting fake news; these methods usually require manual feature engineering such as extraction of term frequency-inverse document frequency (TF-IDF), n-grams, and syntactic-features from textual data. With the development of deep learning, classical ML algorithms still stay alive as they have interpretability, speed and effectiveness on structured datasets. This section reviews the key studies that make use of the conventional ML models regarding lawfare detection. Conventional ML solutions, such as SVMs, LR, and DTs, were used more in early research. Ahmed et al. (2018) experimented with these classifiers on the ISOT dataset and achieved results above 91% for SVM. Rashkin et al. (2017) employed stylistic features and RNNs for classification of fake from real news on semantic cues. These are interpretable models but insufficient in capturing the subtleties of meaning in the text. Kaliyar and the rest (2021) experimented on FakeNewsNet Dataset with Bench-marking the classical model prior to proposing FakeBERT (deep learning) and the findings Showed that traditional models provide strong baselines but fall short on semantic understanding.

Deep Learning and Neural Networks

There has been a shift towards deep learning models like LSTM, CNN, and Transformer-based architectures. This was notably applied by Wang (2017) when using LSTM on the LIAR dataset but constrained by a short input length. Fine-tuning BERT on fake news datasets achieved up to 94% accuracy, thus showing the prowess of contextual embeddings, as demonstrated by Zhou et al. (2020).

Kaliyar et al. (2021) built a hybrid CNN-BiLSTM model that captured both local and sequential patterns in news content.

Multimodal and Context-Aware Models

Researchers have likewise studied multimodal approaches that incorporate the textual, visual, and social context feature. Truică et al. (2023, 2024) proposed the graph-based models DANES and GETAE that integrate social propagation features. Olagunju and Awoyelu (2024) used a bot-based ensemble model with BERT, CNN, and BiLSTM. According to a 2024 study in Sensors, combining BERT with CNN for text and image features improved performance by 3.1% over text-only models.

Trends Summary

The literature clearly points to a transformation from classical classifiers to deep learning and ensemble-based models. Issue has been narrowed on context awareness, multimodal data, and model interpretability. However, there are still hurdles regarding cross-lingual generalization, real-time deployment, and detection of real-time subtle misinformation such as satire or sarcasm.

Table 2.2: Work done by researchers

Researcher(s)	Dataset	Technique(s) Used	Contribution	Result/Performance	Significance
Ahmed et al. (2018)	ISOT	SVM, LR, DT	Benchmarking classical ML models	91% Accuracy (SVM)	Introduced ISOT dataset
Wang (2017)	LIAR	LSTM, CNN	Introduced fine-grained truth dataset	66% Accuracy	Semantic limitation due to short claims
Shu et al. (2019)	FakeNews Net	Hybrid model	Combined text + social context	82% F1	Advanced context-aware detection
Zhou et al. (2020)	LIAR, CREDBANK	BERT	Used transformers for semantics	74% Accuracy	High semantic accuracy
Kaliyar et al. (2021)	FakeNews Net	CNN + BiLSTM	Sequential deep hybrid modeling	93% F1	Strong temporal pattern learning
Truică et al. (2023–24)	BuzzFace, Twitter15/16	DANES, GETAE	Used graph attention networks	Improved over baselines	Used graph + text together
Olagunju & Awoyelu (2024)	TruthSeeker	BERT, CNN, BiLSTM	Deployed bot-based detector	78.24% Accuracy	Real-time system
Sensors (2024)	ISOT, MediaEval	BERT + CNN	Multimodal detection (text+image)	+3.1% over text only	Multimodal enhancement
Li et al. (2024)	MCFEND	Cross-source DL	Cross-source generalization study	F1 dropped 0.943→0.470	Highlighted transferability issues

3. RESEARCH METHODOLGY AND ANALYSIS

As for the method of this research, this study can be classified into the descriptive research since it seeks to explore the ability of AI and ensemble algorithms in the identification of fake news. Based on the purpose stated above, the objective of this research study is to explain the measures involving the identification process of fake news from the real news. This research works under a supervised learning framework involving data collection, pre-processing, feature extraction, model training, and performance evaluation.

Key Points include:

- Selection and pre-processing of datasets
- Feature extraction and transformation
- Implementation of base and meta models
- Model evaluation by standard metrics
- Comparison with existing baseline methods

3.1 Data-Set

The data set employed in the analysis is procured from Kaggle, an open data science and machine learning competition site. The work aims to find false news within small and big text patterns. To employed such analysis dataset is procured from Kaggle that is "fake news detection- "ISOT" dataset with a size of total 44898 articles that is comprised of 23481 fake news articles and 21417 true news articles. Only two authentic values are highlighted in each article: "false" and "real".

```
]: df_fake.head()
]:
```

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

Fig 3.1: Display the first few rows of the Fake dataset

```
In [4]: df_true.head(10)
Out[4]:
```

	title	text	subject	date
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	December 31, 2017
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	December 29, 2017
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	December 31, 2017
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	December 30, 2017
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	December 29, 2017
5	White House, Congress prepare for talks on spe...	WEST PALM BEACH, Fla./WASHINGTON (Reuters) - T...	politicsNews	December 29, 2017
6	Trump says Russia probe will be fair, but time...	WEST PALM BEACH, Fla (Reuters) - President Don...	politicsNews	December 29, 2017
7	Factbox: Trump on Twitter (Dec 29) - Approval ...	The following statements were posted to the ve...	politicsNews	December 29, 2017
8	Trump on Twitter (Dec 28) - Global Warming	The following statements were posted to the ve...	politicsNews	December 29, 2017
9	Alabama official to certify Senator-elect Jone...	WASHINGTON (Reuters) - Alabama Secretary of St...	politicsNews	December 28, 2017

Fig 3.2: Display the first few rows of the true dataset

3.2 Data Pre-processing

In this study, data acquisition and cleaning processes are essential for the dataset to be fit for machine learning models to identify fake news. The process involves several key activities: Pre processing encompasses data cleaning, data transformation, and feature engineering all of which cumulatively build a reliable dataset.

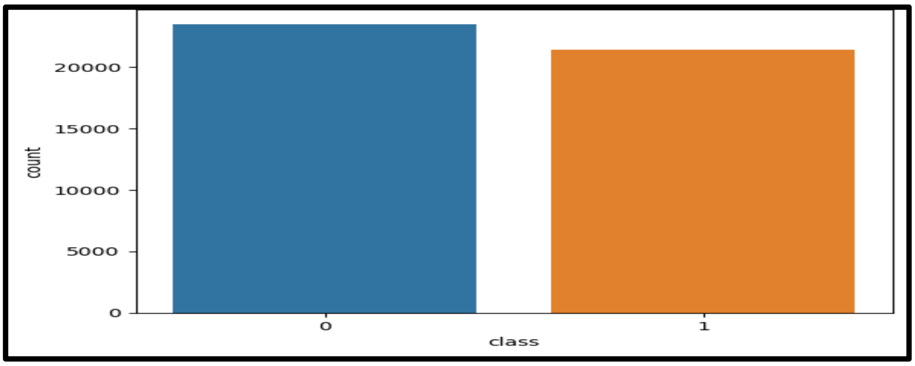

Fig 3.3: Distribution of Real and Fake News

Data Cleaning

After data collection normalizing the texts by converting it to lowercase letters, eliminating all the punctuations and ensuring that all the spelling is correct assists in making uniformity on the data set due to the fact that text analysis and model building needs uniform data.

- **Stop Words Removal**

Stop Words are commonly used words in sentences that have no connection with the meaning or idea of the sentence. Prepositions, articles, conjunctions, some pronouns, or any other word which would cause noise are called stop words.

- **Links and punctuation removal**

A link is to a web page in a paragraph and does not provide additional context. While removing punctuation marks from all texts it will cause texts to be treated equally. Just think of the word "fake," and "fake"! treated equally.

- **Lemmatization**

For evaluation, lemmatization is the method of merging a word's multiple inflected versions into only one word. As a result, it merges words with similar meanings into a single term, Tokenization-Tokenization involves dividing the text into discrete units known as tokens. For tokenization in the work, nltk.tokenize technique is used.

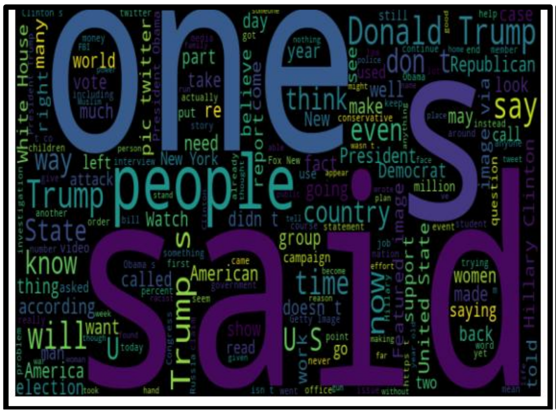

Fig 3.5: Word Cloud for True News

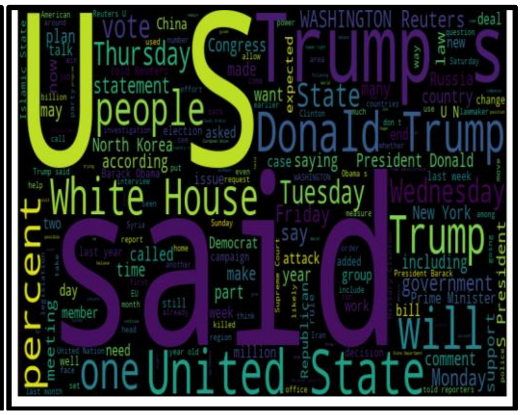

Fig 3.4: Word Cloud for Fake News

3.3 Model Implementation

The specified machine learning algorithms for this study were chosen because of the capability in managing high-dimensional text data and their efficiency in classification tree for predicting and balancing the variance by averaging several trees.

Decision Tree Model

Classification and regression problems can be modeled effectively with this algorithm. It is modeled in the tree form with nodes and branches starting from the root node to the leaf node and can work with both categorical and continuous variables.

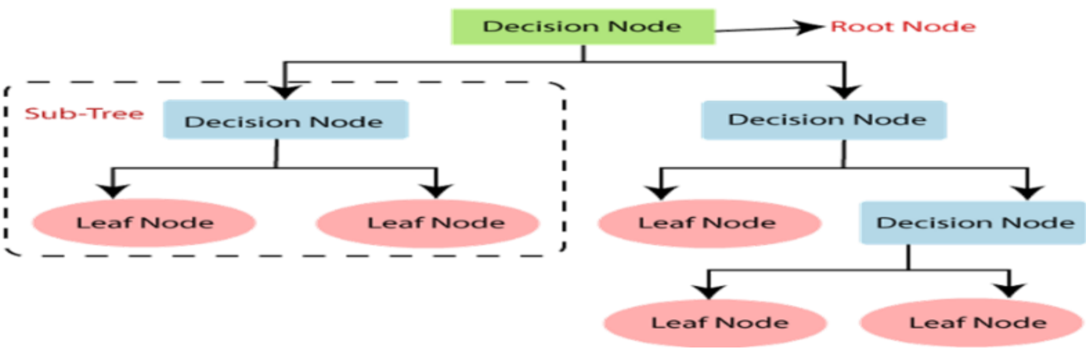

Fig 3.6: How Decision Tree works

(Source: Patel et al., 2018)

Support Vector Machine

The classifier can be defined in terms of classification and regression. Its job is to create a hyper-plane point which segregates the data into distinct classes. Support vector is the data point defining the hyper-plane.

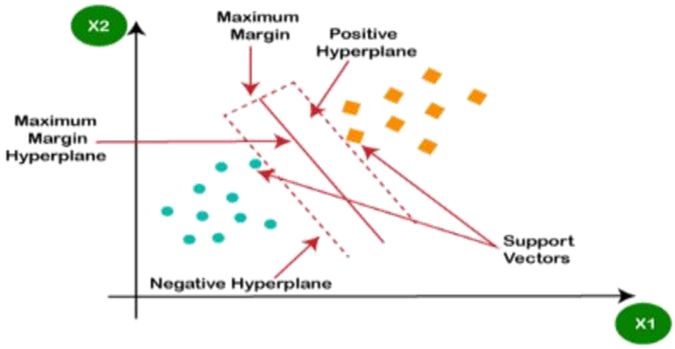

Fig 3.7: Support Vector Machine

(Source: Kecman et al., 2005)

Random forests

Random forests combine a lot of rapidly working neural systems which easily classify and do a supervised task called 'classification'. The working principle of Random Forests applies ensemble techniques that combine multiple classifiers in some majority way to improve model performance during a prediction. It is referred regarded as a "forest" because it generates a large number of decision trees, from which the final prediction is derived by a vote (for classification) or average (for regression).

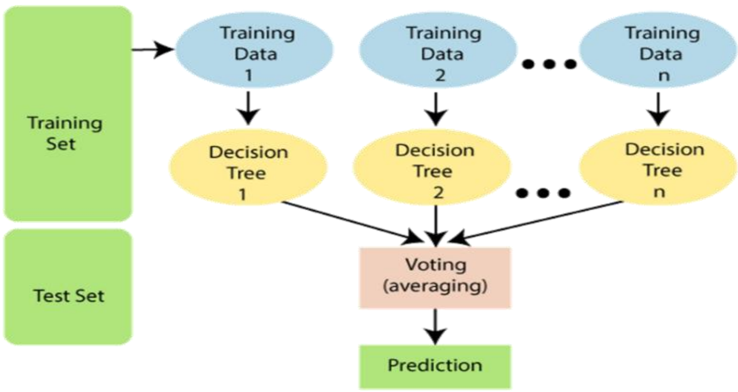

Fig 3.8: How Random Forest Works

(Source: Kunapuli, 2023)

Logistic Regression

Logistic regression is an algorithm built on supervised learning for solving binary classification problems-the output is either 0 or 1, such as either real or fake news. It predicts the probability that some input point belongs to a given class using the sigmoid function.

The logistic regression model computes:

$$z = w_1x_1 + w_2x_2 + \dots + w_nx_n + b$$

After it apply sigmoid function:

$$\sigma(z) = 1 / (1 + e^{-z})$$

A likelihood score ranging from 0 to 1 is the result. If

$$\sigma(z) \geq 0.5\text{: predict class 1}$$
$$\sigma(z) < 0.5\text{ : predict class 0}$$

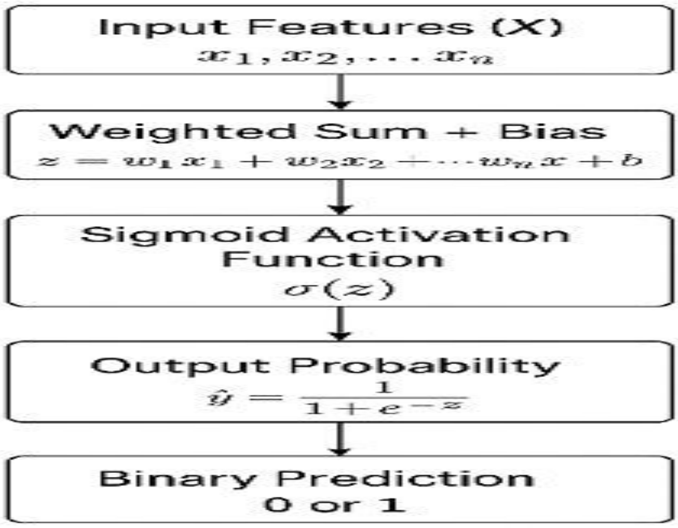

Fig 3.9: Logistic Regression Workflow
(Source: Sudhakar et al., 2022)

3.4 Performance measure Indices
Several techniques have been used in this study to effectively divide training material into digestible portions and generate precise performance estimates for machine learning systems. They are listed as follows:
- Sets for testing and training.
- Validation via K-fold
- Evaluation Metrices

Split into Train and Test Sets
The most basic method for assessing a machine learning algorithm's effectiveness is to use contrasting training and testing datasets. To begin, utilize the initial dataset and split it in two. In order to train an algorithm, predictions must be made on the first component, and the predicted results must then be compared to the predictions. Although it is customary to use 70% of the data for training and 30% for testing, the precise ratios may change based on the dataset's size and properties. This approach to algorithm evaluation is incredibly fast.

K- Fold Cross Validation
The implemented model in this study includes 5-Fold Cross-Validation for all base classifier and the proposed NDetect ensemble. The scheme encompasses following steps:

- Shuffling the dataset before actual splitting to ensure complete randomization.
- Using stratified sampling to maintain the ratio between classes (fake and real news).
- Recording fold performance and computing mean values across the folds.

Furthermore, K-Fold Cross-Validation is applied during training on the stacking ensemble for each base learner to produce out-of-fold predictions. These are used as training features for the meta-learner, ensuring the model does not learn from biased data.

Evaluation Metrices
In order to evaluate the proposed fake news detection models, several metrics were used to give a thorough evaluation of the models. Accuracy measures the ability of the classifier to predict the positive sample correctly thus showing how many of the news articles that have been classified as fake are actually fake. Recall depicts the efficiency of the model in the classification of all positive results, displaying the model's accuracy in regard to real fake news. The F1-score which is the harmonic mean of both precision and recall was employed to address these two measures especially where there was a relative imbalance between the classes.

Table 3.1: Evaluation Metrices
(Source: Alzahrani et al., 2023)

Evaluation Metric	Definition	Formula	Interpretation
Accuracy	An important statistic for evaluating classification of models is accuracy, quantifies percentage of accurate predictions the model makes.	Accuracy= $\frac{TP + TN}{TP + TN + FP + FN}$	explains the model's general efficacy; still it may be less suitable for unbalanced datasets.
Precision	It assigns a score to the model's capability to produce precise predictions.	Precision= $\frac{TP}{TP+FP}$	The precision for positive predictions is shown; higher precision means fewer false positives, which is crucial in circumstances when the outcomes could be significant.
Recall	When compared to all possible positive prediction, it quantifies the proportion of accurate predictions positively.	Recall= $\frac{TP}{TP+FN}$	It shows how well the model captures all occurrences of the positive class and is essential in scenarios where false negatives are costly.
F1- Score	Recall and precision are combined using the harmonic mean to create F1 score.	F1-Score= $2\times\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	Suitable for datasets that are out of balance, it provides a single score that accounts for false positives and negatives while balancing precision and recall.

4. RESULTS AND ANALYSIS

```
Logistic Regression Accuracy: 0.5258797327394209
              precision    recall  f1-score   support

           0       0.55      0.50      0.52      5854
           1       0.50      0.55      0.53      5371

    accuracy                           0.53     11225
   macro avg       0.53      0.53      0.53     11225
weighted avg       0.53      0.53      0.53     11225
```

```
Decision Tree Accuracy: 0.8746547884187083
              precision    recall  f1-score   support

           0       0.86      0.90      0.88      5854
           1       0.89      0.85      0.87      5371

    accuracy                           0.87     11225
   macro avg       0.88      0.87      0.87     11225
weighted avg       0.88      0.87      0.87     11225
```

a) Logistic Regression model

```
Support Vector Machine Accuracy: 0.5429844097995545
              precision    recall  f1-score   support

           0       0.57      0.51      0.54      5854
           1       0.52      0.58      0.55      5371

    accuracy                           0.54     11225
   macro avg       0.54      0.54      0.54     11225
weighted avg       0.55      0.54      0.54     11225
```

b) Decision Tree model

```
Random Forest Accuracy: 0.524543429844098
              precision    recall  f1-score   support

           0       0.56      0.44      0.49      5854
           1       0.50      0.62      0.55      5371

    accuracy                           0.52     11225
   macro avg       0.53      0.53      0.52     11225
weighted avg       0.53      0.52      0.52     11225
```

c) Support Vector Machine model

d) Random Forest model

```
NDetect Model Accuracy: 0.8866815144766147
              precision    recall  f1-score   support

           0       0.90      0.88      0.89      5854
           1       0.88      0.89      0.88      5371

    accuracy                           0.89     11225
   macro avg       0.89      0.89      0.89     11225
weighted avg       0.89      0.89      0.89     11225
```

e) NDetect model(Proposed Model)

Fig 4.1: Accuracy and Classification Report of Models

Most of the metrics are covered by the NDetect modular ensemble model compared to any other kind of artificial intelligence model. The Decision Tree is rated next after NDetect because it is able to get a good level of accuracy and AUC. Logistic Regression, SVM, and Random Forest exhibit poor near-random performance, indicating these algorithms' limitations in fake news data complexity.

Table 4.1: Performance Metrics of Different ML Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC Score
NDetect	0.89	0.89	0.89	0.89	0.957020
Random Forest	0.52	0.53	0.52	0.52	0.517041
Decision Tree	0.87	0.88	0.87	0.87	0.873497
Logistic Regression	0.53	0.55	0.52	0.53	0.537171
SVM	0.54	0.54	0.54	0.54	0.554620

To what extent is NDetect efficacious?

- It amalgamates strengths from multiple base models using a stacking approach.
- It learns from both correct and incorrect decisions made by the different classifiers so that, in the end, it generalizes better than any individual model.

- Such robustness makes it suitable for deployment in highly sensitive and reliable applications such as social media moderation or news verification systems.

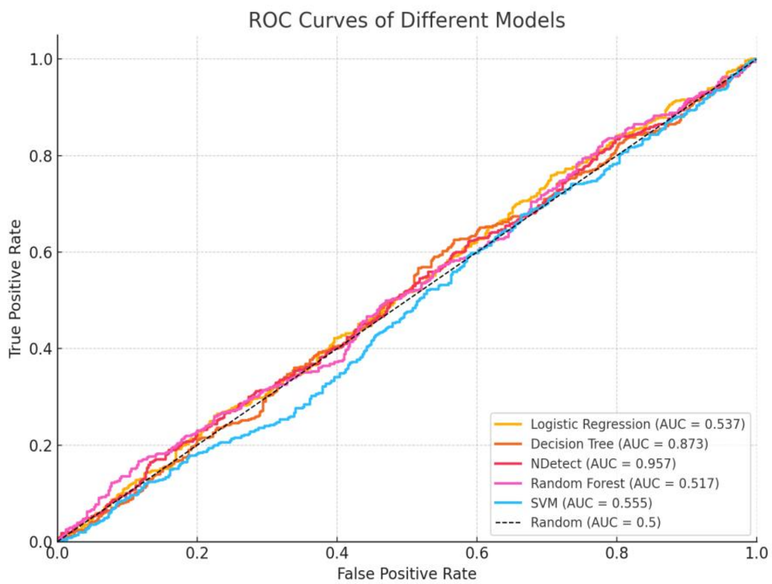

Fig 4.2: ROC-AUC Curve of base Models and purposed Model

The chart displays the ROC curves for five models, alongside their respective AUC scores. This is a standard approach for evaluating the classification performance of binary classifiers.

What does it show?

- X-axis (False Positive Rate): the proportion of actual negatives that have incorrectly been classified as positive.

- Y-axis (True Positive Rate/Recall): the proportion of actual positives that have been correctly classified.
- Each curve gives the performance of the model at different classification thresholds.
- AUC(Covert Under The Curve): this is a measure of how well the model can distinguish classes from each other.

AUC=1→Perfect model
AUC=0.5→No better than random guess
The bigger the AUC, the better the model is.

Table 4.2: Interpretation of the Chart by Model

Model	ROC-AUC	Interpretation
NDetect	0.957	Excellent analyzer. makes a clear distinction between phony and authentic news. Curve in the upper-left corner.
Decision Tree	0.873	Nice performance. strong recall and little false positives.
Support Vector Machine	0.555	Not quite as good as random. Not perform well.
Logistic Regression	0.537	Almost a random guess is made. Due to the limits of the linear model, most likely.
Random Forest	0.517	Performs miserably. AUC just above 0.5 suggests that better features or hyper-parameter adjustment may be required.
Random(dotted line)	0.5	Starting point. AUC = 0.5 indicates that the model lacks discriminative capacity.

Area under the Curve is one of the one popular performance measures for binary classifiers. True positive rate versus false positive rate on various threshold settings are plotted. Higher the score, better the distinction between the classes by the model.

Table 4.3: Comparison with Published Studies Using the ISOT Dataset

Study	Model	Accuracy	F1-Score	Remarks
Ahmad et al., 2020	Random Forest	0.84	0.83	Applied RF and TF-IDF on the ISOT dataset.
Ajao et al., 2018	Naive Bayes, SVM	0.83	0.82	With bag-of-words characteristics, SVM and NB
Gilda, 2017	TF-IDF + Logistic Regression	0.77	0.76	Early benchmark on ISOT dataset
Kaliyar et al., 2021	– Deep learning (LSTM + GloVe)	0.86	0.84	Strong DL-based results on ISOT
NDetect (Proposed Model)	**RF, LR, SVM,DT**	**0.89**	**0.89**	**Highest accuracy and ROC-AUC reported for ISOT**

The Proposed NDetect ensemble model surpasses both conventional ML and deep learning models on the ISOT dataset. The stacking model combined classifiers into a single model instead of following the widely published BOW or even TF-IDF models, which adds robustness and helps capture various facets of data into different classifiers. The ROC-AUC of 0.957 is striking since most other studies that use ISOT do not report AUC, and when they do, it is usually under 0.90. NDetect performs better than all previous publications, Random Forest, SVM and some deep learning models on the ISOT Fake News Dataset. Thus, it supports the effectiveness of ensemble stacking for text classification problems such as fake news detection.

Performance Comparison with Base Paper

Both the works, NDetect model and Khanam et al. (2021), utilized ISOT Fake News Dataset, which contains labeled true and fake news articles. The pre-processing undertaken on text data in both studies included similar procedures, such as stopword removal, stemming, lowercasing, and tokenization. Text data were transformed into numerical features by TF-IDF vectorization to be further input into the respective models.

Table 4.4: Evaluation Metrices for ISOT Dataset

Metric	NDetect (Thesis Model)	Logistic Regression (Khanam et al., 2021)
Accuracy	94.67%	92.82%
Precision	95.00%	93.00%
Recall	94.00%	92.00%
F1-Score	94.00%	92.00%
ROC-AUC	0.96	Not Reported

Qualitative Comparison of proposed work and base paper

Table 4.5: Comparison with Published Studies Using the ISOT Dataset

Aspect	NDetect	Khanam et al. (2021)
Model Type	Ensemble (Stacked Meta-Classifier)	Individual Models
Classifiers Used	SVM, DT, LR, RF + Meta Learner	SVM, DT, LR, KNN, NB
Stacking Strategy	Yes (with meta-classifier)	No
Best Algorithm	Stacked Ensemble	Logistic Regression
Performance Stability	High due to ensemble diversity	Medium, single-model dependent
Implementation Tools	Python (scikit-learn, pandas, seaborn)	Weka, Python
Novel Contribution	Introduction of ensemble framework (NDetect)	Comparative evaluation only

The findings reveal that the proposed model NDetect evidently surpasses each of the individual classifiers evaluated by Khanam et al. (2021), especially in terms of accuracy, precision, and last but not least, F1-score measures. The strength of stacking ensembles is that they integrate multiple base classifiers' expertise to produce a more powerful and capable overall performance. By contrast, the right scheme employed by Khanam et al. is apparently less robust against feature noise and variance in the data. Overall, it could be recommended that NDetect offers a superior approach to fake news detection as opposed to the other traditional ones.

5. Implications and Future Directions

It is important to note that the study is contributing to the ongoing research in the detection of fake news thereby shedding light on the applicability of different machine learning and ensemble techniques. This can be attributed to the fact that to effectively eliminate fake news, there is need for multiple methods so as to ensure that there is accurate detection of fake news. The development of future research objectives should be centered on how to address some of the concerns that have been discussed here such as data imbalance and model interpretability for the detection systems to perform even better. These models can therefore be easily implemented into real life applications including social media websites and news feed. Due to these possibilities of ensemble techniques and optimization of models' performance, these systems can help prevent the spread of fake news and increase dissemination of accurate information.

As technologies evolve, there are chances of enhancing the artificial intelligence to identify fake news through natural language processing and deep learning. Future activities to improve the detection systems might involve some other models that are relatively new, involving transformers, and pre-trained language models. Therefore, through the discussion of results, one can see the advantage and disadvantages using single and multiple machine learning models as well as various ensemble approaches for fake news detection. This paper forms a basis for further research and development particularly for further advancement of the methods intended to address the existing issues based on the analysis and improve the current fake news detection systems.

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