

# Fake News Detection Model Detect using Ensemble Machine Learning Techniques

Jyoti<sup>1</sup>, Yogesh Kumar<sup>2</sup>

<sup>1</sup>Ph.D. Research Scholar, GD Goenka University, Gurugram, India

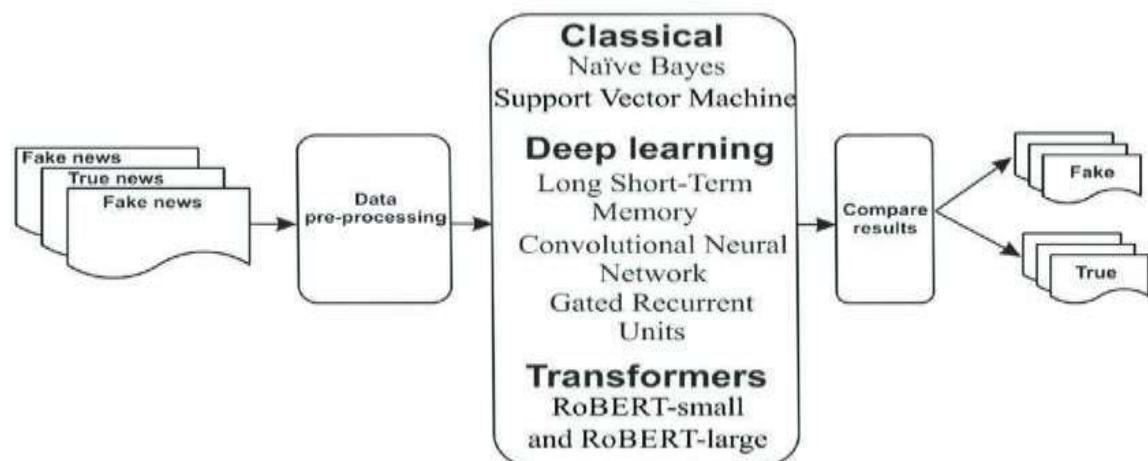
<sup>2</sup>School of Engineering and Sciences, GD Goenka University, Gurugram, India.

**Abstract:** Social media's ability to disseminate information quickly has made it possible for both fake and legitimate news to proliferate, endangering political processes, public confidence, and personal reputations. This paper addresses this issue by putting forth the ensemble machine learning model NDetect, which successfully detects fake news from textual content by combining Decision Tree, Support Vector Machine, Logistic Regression, and Random Forest classifiers. The ISOT Fake News Dataset, which included more than 44,000 news stories with labels, was used to train and test the model. Enhancing the accuracy of fake news identification by utilizing the capabilities of many classifiers through ensemble learning was the main goal of this study. The conventional measures of accuracy, precision, recall, F1-score, and ROC-AUC were used to thoroughly assess NDetect's performance. With a ROC-AUC score of 0.957 and an accuracy of 89%, the suggested model outperformed all baseline models, including Random Forest (52%), SVM (54%), Logistic Regression (53%), and individual Decision Tree (87%).

**Keywords:** Fake news, Fake news detection, Logistic Regression, Ensemble learning, Decision Tree, Random forest, evaluation metrics, Support Vector Machine.

## 1. INTRODUCTION

The growth of the technology and availability of societal networks have significantly influenced the consumption of information. The world is now in the age of information and everything, including news, either goes viral or takes only a few seconds to cover the entire globe. However, this ease of information dissemination has also given rise to a significant challenge: On the subject of external threats, the major factor was identified as false news refers to a story that has been crafted with the aim of passing as news when in real sense it is not news or is actually a lie [1]. The use of what is commonly referred to as 'fake news' was not new, however, the use and spread of such news was enhanced by using the internet and especially, social platform. Currently, Artificial intelligence also has been used as significant weapon in fight against false news. AI tools like natural language processing as well as machine learning are significantly useful and able to examine big amounts of data at single time and pinpoint those that bear certain characteristics of fake news [2]. These systems use different techniques, of which one is the content analysis technique, which involves analyzing the textual contents of each news article for features indicative of false information, the other is context analysis which checks on the reliability of its source and where the information is presented from [3].



**Fig 1: Structure of the detection system of fake news [3]**

Transmit of false news remains a big issue in modern world that threatens democratic institutions, shakes public trust and disrupts social cohesion. Owing to the fact that information is easily shared on social media platforms and other online forums, fake news has also spread quickly making the masses to be misguided [4]. This issue is made worse by the reality that fake news makers are ever in a position to develop fake and

highly complex wrongful characters aided by modern technology. Despite the numerous attempts to address the problem, current approaches to identifying and preventing fake news remain unsatisfactory.

This research is designed to fill these gaps through the specific identification of performance of AI techniques in notification of fake information and its ultimate goal to improve the efficiency of the methods in an effort to better protect information credibility in the context of the contemporary technology world. This paper proposes an ensemble learning model for content-based fake news detection. Decision Tree (DT), Logistic Regression (LR), Random Forest (RF) and Support Vector Machine (SVM) were used for their satisfactory performance in machine learning processing tasks. Ensemble learning combines various learning models to improve the results obtained by each one.

Following are the key points objectives that fulfill the research gaps by demonstrating within research : Creation of ensemble machine learning model (NDetect) that enhances the detection accuracy of fake news. Use of traditional metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC, so that the performance of the suggested ensemble model (NDetect) is assessed and contrasted with that of conventional machine learning models (Logistic Regression, SVM, Decision Tree, Random Forest). Improve model generalization and robustness in identifying false information by utilizing the ensemble approach to overcome the shortcomings of individual classifiers.

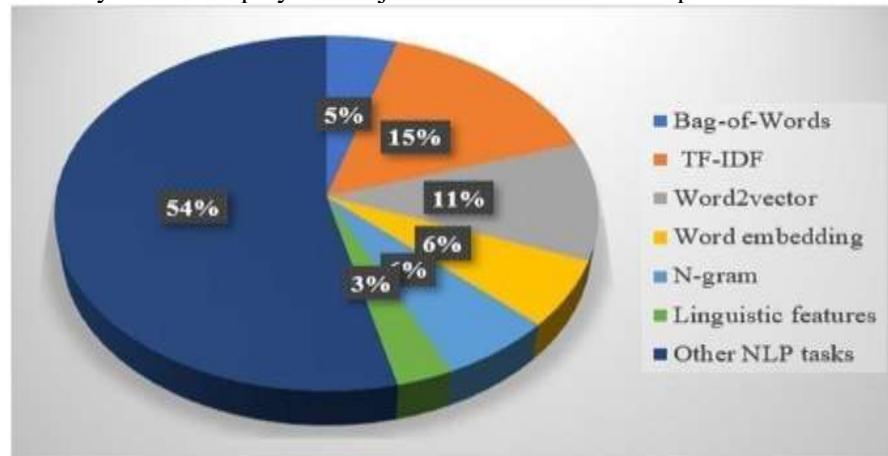
Demonstrate the NDetect model's applicability for fake news recognition in a large-scale social network context and compare it to current state-of-the-art methods.

## 2. RELATED WORK

With the advancement of technology especially the internet, production and distribution of information has revolutionized with increased production of material that could be either reliable or fake. Fake information, which can be illustrated as information which is orally disseminated as news and, at the same time, is clearly untrue and/or those untruths are being provided with the intent to mislead, has become one of many topical issues of today's media and communication. The strengths of the present information encompass its comprehensive nature in relation to the current state of knowledge as well as the ability to mention improvements in technology and indicate the research gaps that should be filled in the future.

## HISTORICAL CONTEXT AND EVOLUTION OF FAKE NEWS WITHIN ONLINE PLATFORM

Fake news might appear to be a relatively recent problem, but its origins can actually be traced back to the initial stages of misleading information and propaganda. The increase in technology especially the introduction of Television also enhanced the spread of such messages [5]. However, the advancement of technology especially the internet and social media in the later part of the 20th up to the early years of the 21st century has ensured that the spreading of information can be done easily and has brought about different dimensions on the delivery of news which includes the negative aspect of spreading fake news. Social platforms as Facebook, and Twitter, and YouTube emerged in early twenty-first century changing the modes of news dissemination. An example is the 2016 United States of America Presidential campaign whereby fake news played a major role in how the voters perceived and voted for the candidates[6].



**Fig 2: Concerns regarding fake news detection models basis on features [6]**

This is necessary to know about history of false news on social platforms to prevent and counteract their negative impact and protect the credibility of the information dissemination in the age of the internet and new technologies.

**Table 1: False news on social platform**

Era	Characteristics of False News	Platforms Involved	Impact on Society
Pre-Digital Era	Limited to print and broadcast media; slow dissemination	Newspapers, TV, Radio	Localized impact, slower spread of misinformation
Early Digital Era	Emergence of online news; increased speed of dissemination	Blogs, Online News Websites	Wider reach, moderate speed in spreading misinformation
Social Media Boom (2000s)	Viral spread through social media; user-generated content	Facebook, Twitter, YouTube	Rapid, global spread; increased polarization and misinformation

The role of history has been effective in explaining how fake news has changed its characteristics regarding digital and social media. The literature is able to pinpoint some of the gaps in the presented studies indicating that there are unresolved issues related to applying the models for new strategies of misinformation. Altogether, this work reaffirms the importance of false news detection and acknowledges the fact that it is a very important and challenging task altogether, and requires continuous research and development.

## LITERATURE GAP

Although a lot of work has been done in ML and AI for fake news detection, some of the major gaps are still opening up in the current literature which suggests a lack of research focus and potential terms for the future work. **Adaptability to Evolving Misinformation Tactics:** The majority of today's models are static and although trained on certain datasets, they may become soon irrelevant due to new types of misinformation. There is also significant research required in creating 'learning' algorithms that may adapt to the new and ever-changing styles of misinformation [7].

**Handling Imbalanced Data:** One of the issues yet poorly discussed in the literature industry is the imbalance of data sets, where the numbers of fake news are many fewer than the real news. Some techniques that have been tried include oversampling and data augmentation but these approaches have not been properly applied in real applications [8].

**Multilingual and Cross-Cultural Detection:** It suffers from giving little attention to multiple languages and the cross-cultural nature of fakes or fake news detection having most of its current research work using materials in the English language. It is stressed that fake news is context-dependent, and hence models that work for one language or culture may not work for the other [9].

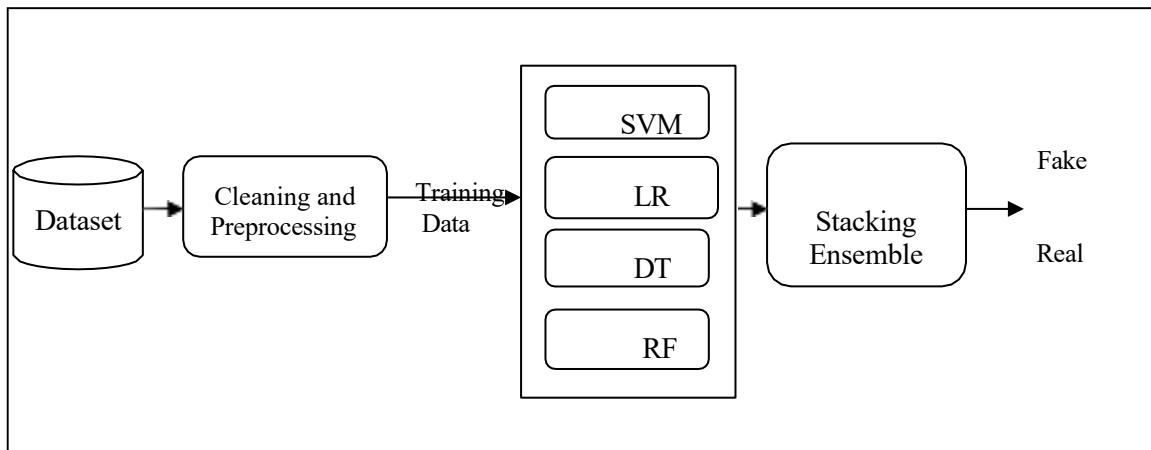
**Integration with Human Judgment:** The combination of reliance on some kind of AI with the integration of human review may increase the chances of catching false positives and broaden the general viewpoint about the situation [10]. Research is to be conducted to know how the knowledge of Artificial Intelligence systems can be combined with the expert's knowledge to have a synergistic approach toward the advancement of AI systems and human experts.

**Real-Time Processing and Multi-Modal Data:** As the frequency and sophistication of fake news increases it becomes more important to utilise multiple data sources and possible to allow for real-time classification of articles [11]. This study has pointed out that future research should also seek to increase performance speed and efficiency of the existing detection system as well as come up with more encompassing techniques of detection that would embrace different types of data.

### 3. MATERIAL AND METHODS

The suggested model for detecting bogus news is described in length in this section. Its design is shown in Fig. 3 and is divided into three primary stages: (1) preliminary data analysis and cleaning, (2) machine learning models,

(3) ensemble model and fake or real decision making. Data cleaning as well as pre-processing done after the data was extracted. Four machine learning models were then constructed: Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Logistic Regression (LR). Clean data was used to train each model. They were then integrated into an ensemble model. At the point, the algorithm is prepared to determine and forecast whether the news was authentic or fraudulent.



**Fig. 3 Architecture of Proposed Model**

#### Data Set Description

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”. The authentic news stories were gathered via Reuters.com, but the bogus ones were from dubious websites that PolitiFact and Wikipedia verified as phony[12]. It contains metadata like publication date, source, author and text content which makes it an informative resource when analyzing patterns related to fake and real news.

#### Data Pre-processing

Raw texts in the dataset are actually news articles from real-life news websites and have plenty of noise in many forms, such as links and stop words, which are not informative, text with lots of different case characters, punctuation, and tags. The data should be preprocessed and cleaned prior to being utilized in the proposed model to enhance its quality. During this stage, various operations are performed on the datasets with the NLTK toolkit, a collection of open-source libraries commonly used to handle human language 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. Removing them will result in reducing file size while indexing and improving the detection mechanism efficiency.

**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 will cause texts to be treated equally. Just think of the word “fake,” and “fake”! are treated equally. All of them removed and replaced with the string “url” to achieve a better visibility of the URL links.

**Lemmatization-** For evaluation, lemmatization is the method of merging a word's multiple inflected versions into only one word. Through lemmatization, the words are examined semantically. 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.

#### Algorithms Used

In this research work, ensemble learning is used by combining the outputs of different candidate or base models to reach at final output. The ensemble consists of four machine learning (ML) models: Support

Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), each has separately trained [22].

These proposed learning models are being implemented by python. In the work, following base models are being taken:

**Table 2: Classification algorithms chosen as Base Models**

Model	Description	Strengths	Weaknesses
<b>SVM [14]</b>	The support vector machine's main objective is to generate the best line or decision boundary for grouping n-dimensional data into different	High interpretability, effective for simple cases.	Prone to overfitting on large or complex datasets.

	categories.		
<b>RF [15]</b>	It is chosen due to their capacity to overcome the problem of instability in the case of using a single decision tree for predicting and balancing the variance by averaging several trees	Effective in some cases, benefits from hyper parameter tuning.	Can be sensitive to the choice of hyper-parameters.
<b>DT[16]</b>	In a different field of study, where the case dataset must be separated into various branches according to the criteria, one of the well-known methods is the decision tree classifier. It makes use of a tree- like structure.	Robust against overfitting, strong for subtle distinctions.	May be less interpretable.
<b>LR [17]</b>	Because linear regression cannot effectively handle categorization jobs and misclassification might have detrimental effects. A more effective method for overcoming this constraint is logistic regression.	Effective for linear problems with normal precision and recall.	Struggles with complex patterns.

### A) Model Performance Evaluation

To evaluate the performance of fake news classification learning models and the use of ensemble algorithms, various metrics are used. These metrics assist in the assessment of the model and its capability to identify false news while at the same time avoiding errors.

#### Definitions of some terms used for evaluations

**True Positive (TP)** - The positive target variables that are accurately expected to be positive should be represented.

**False Positives (FP)** – Show the total number of negative variables that were incorrectly projected to be positive.

**True Negatives (TN)** -Targets for negative variables that are accurately expected to be negative.

**False Negatives (FN)** - Positive variables are goals that are incorrectly projected to be negative.

**Accuracy:** An important statistic for evaluating classification of models is accuracy, quantifies percentage of accurate predictions the model makes. Equation (1) provides a formal definition of accuracy.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

$$\text{TP} + \text{TN} + \text{FP} + \text{FN}$$

**Precision:** When the model produces a favorable result, it is utilized to test its accuracy. Evaluating the model's ability to generate accuracy of predictions requires precision. It assigns a score to the model's capability to produce precise predictions. Equation(2) provides the definition of precision in mathematics.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

**Recall:** Also called sensitivity, recall is the ratio of actual positives also known as fake news that is accurately picked by the model. When compared to all possible positive prediction, it quantifies the proportion of accurate predictions positively. Equation (3) provides the mathematical definition of recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

**F1 Score:** F1 measure is most useful when it is important to pay equal attention to either precision or recall at the same time. Recall and precision are combined using the harmonic mean to create F1 score. Equation (4) used to illustrate the F1 scoring formula:

$$\text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall})$$

$$\text{F1Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

**AUC-ROC score (Area Under the Receiver Operating Characteristic Curve):** The AUC-ROC earned its name because it assesses the model's capacity to differentiate between differ classes. It employs all classification thresholds and as higher the score, better the performance of the model in terms of true positive rate and true negative rate [18]. Equations (5) and (6) represent the TPR (true positive rate) and the FPR(false positive rate), respectively:

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (5)$$

$$\text{TP} + \text{FN}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (6)$$

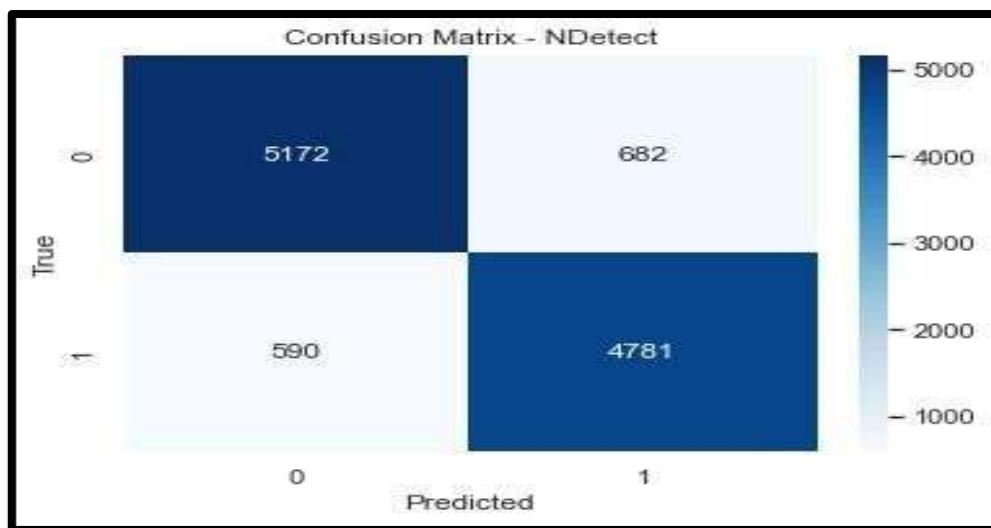
**Confusion Matrix:** In the work, Confusion matrix gives a convenient method of summarizing the performance of the model by presenting the number of true positive, true negative, false positives and false negative cases [19]. Usually, the matrix takes the form of a square table, with rows representing the true classes and columns representing the anticipated classes. In Table, the confusion matrix's mathematical formula is displayed.

**Table 3: Confusion Matrix**

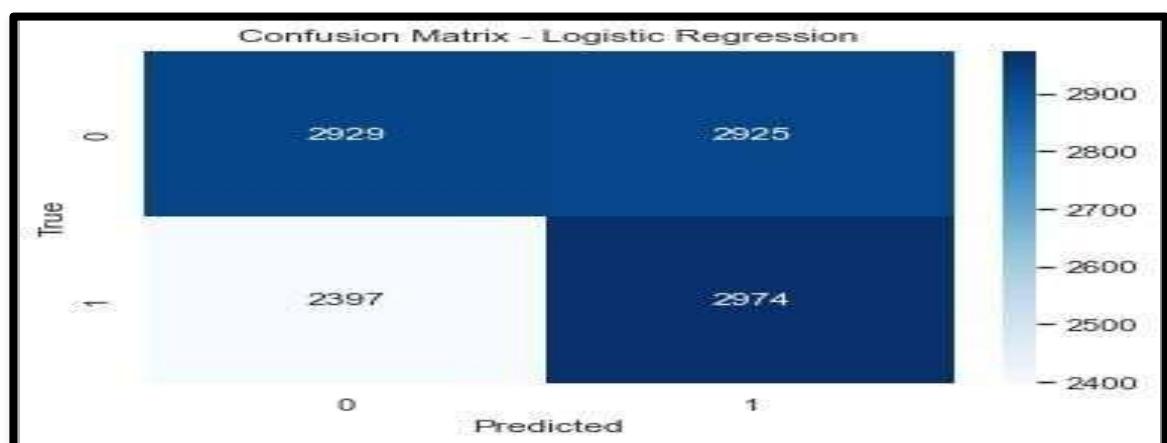
Actual Values				
Predicted Values			Positive 1	Negative 1
			P	P
	Positive 1	Negative 1	N	N

#### 4. EXPERIMENTAL RESULTS

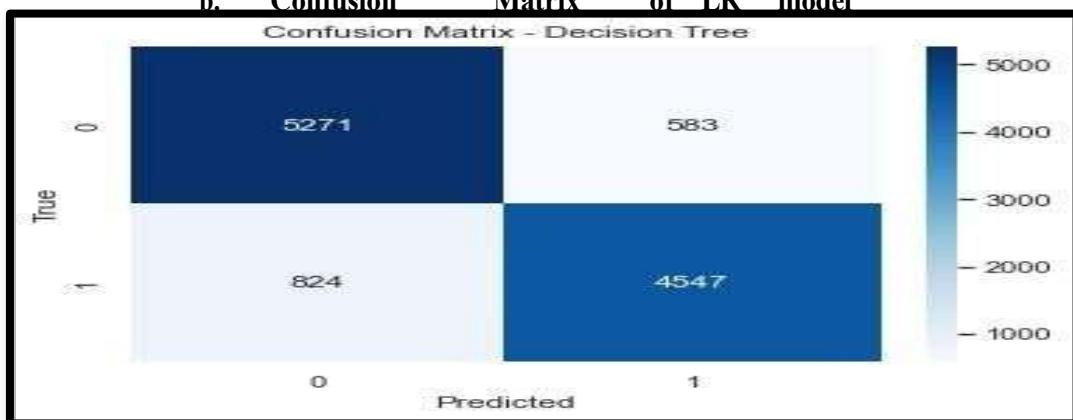
The proposed model in the research gives findings and discussion of the false news detection after trained on “fake news dataset-ISOT” using different machine learning algorithms. Python Jupyter used for environment, alongwith different libraries. There are two datasets used and named a “Fake” dataset and a “True” dataset and each of these datasets contains certain columns like “title,” “text,” “subject,” and “date.” The work aims to analyze the output of four different base models that are Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM) and proposed NDetect Model to differentiate about the true and the false news. For evaluation of models accuracy, precision, recall, the F1 score, and ROC AUC are calculated. Accuracy is used to estimate the percentage of accurate predictions



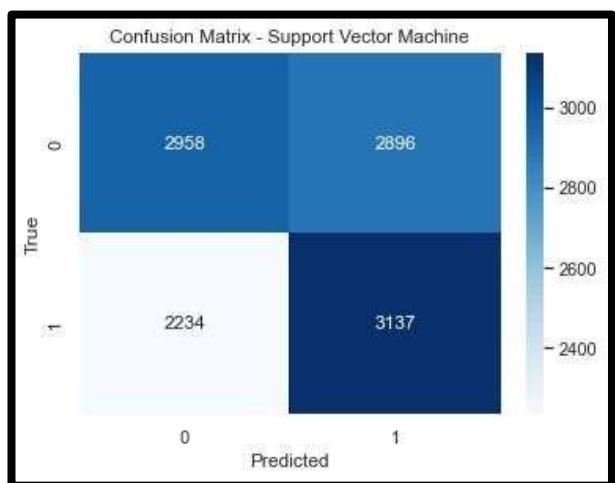
a. Confusion Matrix of NDetect model



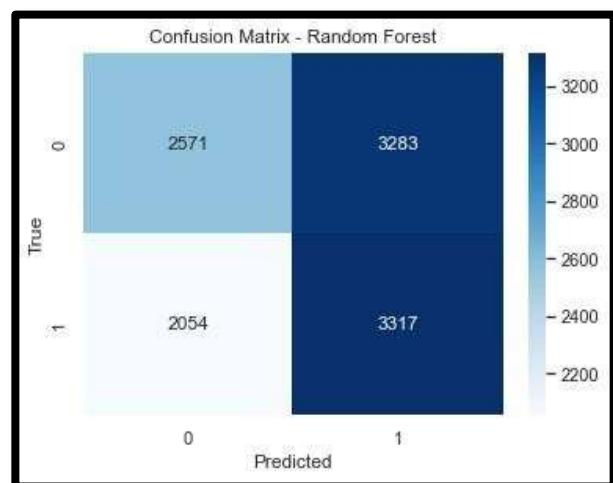
b. Confusion Matrix of LR model



c. Confusion Matrix of DT model



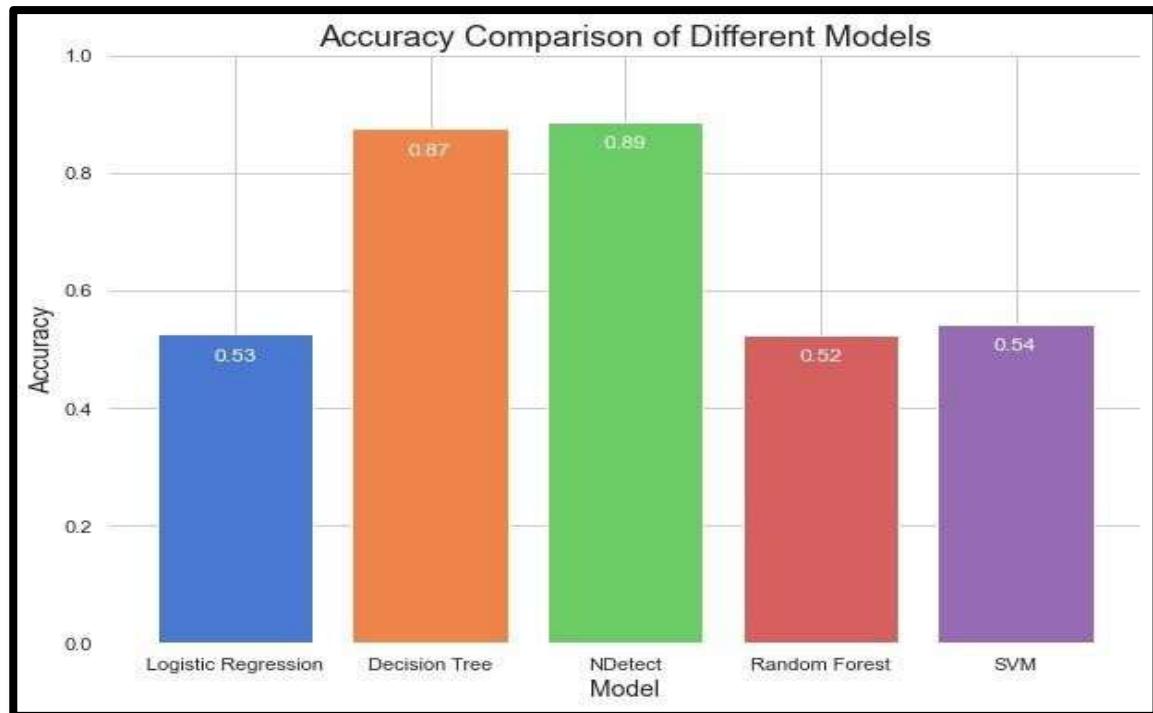
d. Confusion Matrix of SVM model



(e) Confusion Matrix of RF model

**Fig.4 Confusion matrices of base learners and the ensemble model**

The bar chart shows the comparison of different accuracy of different models in fake news detection. NDetect obtained the highest accuracy at 0.89, while Decision Tree is at 0.87. The Logistic Regression, SVM, and Random Forest obtained the lowest accuracy scores at 0.53, 0.54, and 0.52, respectively. Figure 5 presents a comparative analysis for proposed model with related work.



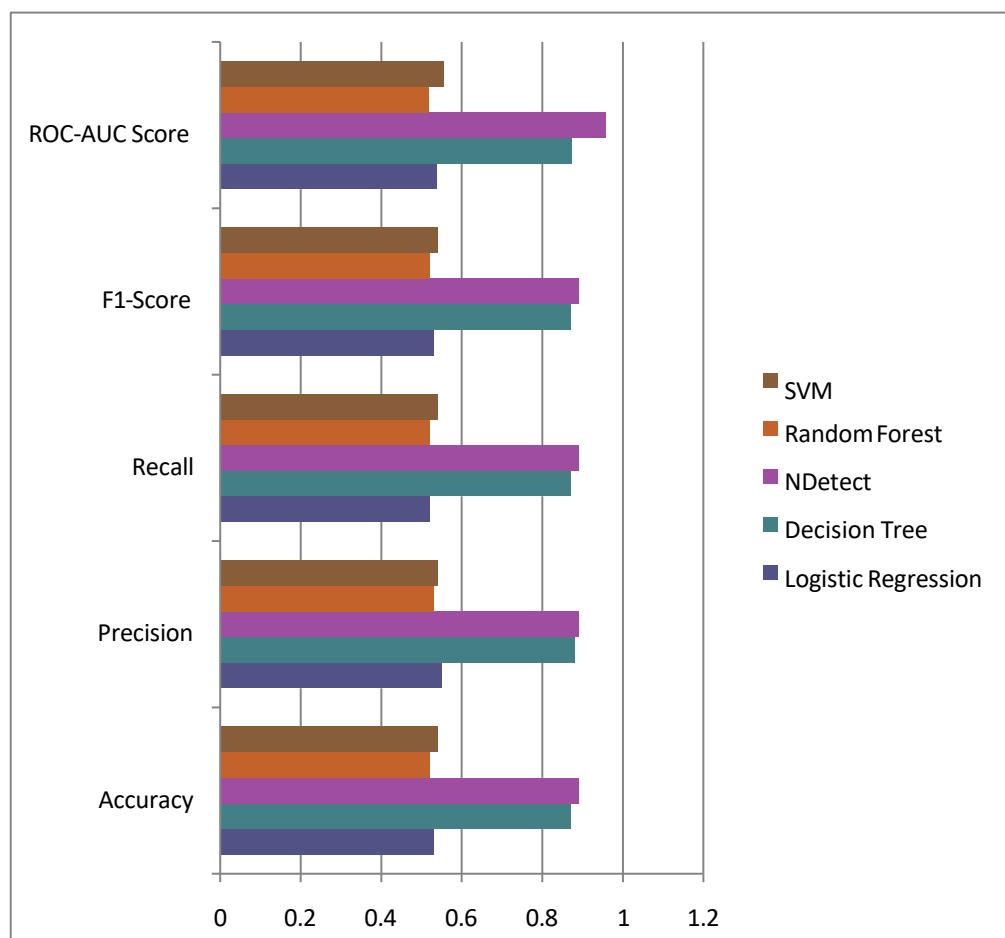
**Fig 5: Accuracy Comparison of Different Models**

Performance of different algorithms were checked and measured by considering another features like accuracy, Area under Curve (AUC), precision, sensitivity/Recall, F1 score generated from the dataset. The overall results that is being obtained is summarized and displaying in the table:

**Table 4: Comparison of proposed model performance evaluation metrics with related works**

Model	Accuracy	Precision	Recall	F1 - Score	ROC-AUC Score

NDetect	0.89	0.89	0.89	0.89	0.957020
Logistic Regression	0.53	0.55	0.52	0.53	0.537171
Decision Tree	0.87	0.88	0.87	0.87	0.873497
SVM	0.54	0.54	0.54	0.54	0.554620
Random Forest	0.52	0.53	0.52	0.52	0.517041



**Fig 6: Result Comparisons through Chart**

## 5. RESULTS DISCUSSION AND IMPLICATIONS

The NDetect ensemble model proved its efficacy in challenging classification tasks such as fake news detection, outperforming all other models in terms of accuracy, precision, and F1-score. NDetect decreased overfitting by combining several decision trees, in contrast to standalone models. Decision Tree models fared poorly on noisy, high-dimensional text data because they overfitted, despite being simple to

understand. Due to its linear character, logistic regression performed mediocrely but was unable to identify intricate patterns.

SVM's performance was inconsistent; while it showed promise in high-dimensional problems, it had trouble with outliers and needed to be carefully adjusted. Misclassifications were prevalent in ambiguous articles, according to confusion matrix analysis, indicating a more widespread difficulty in comprehending textual context. NDetect is the most successful overall, although aspects like scalability, interpretability, and computational cost are still crucial.

## 6. CONCLUSIONS AND FUTURE DIRECTIONS

The findings confirm that the ensemble technique offers a more robust and balanced framework for identifying false information in addition to mitigating problems like overfitting and limited generalization present in individual models. Combining the advantages of Random Forest, SVM, Logistic Regression, and Decision Tree, the model outperformed all of the separate baseline models, achieving 89% accuracy and a ROC-AUC score of 0.957. The ensemble method enhanced classification consistency on difficult textual data.

This paper establishes the foundation for future research combining sophisticated Natural Language Processing (NLP) with transformer-based models for more in-depth contextual analysis while demonstrating the efficacy of ensemble learning in false news classification challenges. Furthermore, in order to make false news detection more flexible and scalable for real-world implementation, efforts should concentrate on real-time processing, multilingual datasets, and managing data imbalance.

## International Journal of Environmental Sciences

ISSN: 2229-7359  
Vol. 11 No. 12s, 2025 <https://www.theaspd.com/ijes.php>

### REFERENCES:

- [1] Abd El-Mageed, A. A., Abohany, A. A., Ali, A. H., & Hosny, K. M. (2024). An adaptive hybrid african vultures-aquila optimizer with Xgb-Tree algorithm for fake news detection. *Journal of Big Data*, 11(1), 41. <https://doi.org/10.1186/s40537-024-00895-9>.
- [2] Naitali, A., Ridouani, M., Salahdine, F., & Kaabouch, N. (2023). Deepfake Attacks: Generation, Detection, Datasets, Challenges, and Research Directions. *Computers*, 12(10), 216. <https://doi.org/10.3390/computers12100216>.
- [3] Abdullah, M. A., Ghaleb, F. A., Mohammed, S. M., Fawaz, J. A., & Asif, I. K. (2023). Web-Informed- Augmented Fake News Detection Model Using Stacked Layers of Convolutional Neural Network and Deep Autoencoder. *Mathematics*, 11(9), 1992. <https://doi.org/10.3390/math11091992>.
- [4] Nkoro, E. C., Njoku, J. N., Nwakanma, C. I., Jae-Min, L., & Dong-Seong, K. (2024). Zero-Trust Marine Cyberdefense for IoT-Based Communications: An Explainable Approach. *Electronics*, 13(2), 276. <https://doi.org/10.3390/electronics13020276>.
- [5] Alyoubi, S., Kalkatawi, M., & Abukhodair, F. (2023). The Detection of Fake News in Arabic Tweets Using Deep Learning. *Applied Sciences*, 13(14), 8209. <https://doi.org/10.3390/app13148209>.
- [6] Arshed, M. A., Stefan, C. G., Dewi, C., Iqbal, A., & Mumtaz, S. (2024). Unveiling AI-Generated Financial Text: A Computational Approach Using Natural Language Processing and Generative Artificial Intelligence. *Computation*, 12(5), 101. <https://doi.org/10.3390/computation12050101>.
- [7] Mohamad Rafad M. M., & Gopika, P. (2024). Fake News Detection Using Machine Learning. *International Research Journal of Innovations in Engineering and Technology*, 8(2), 138-142. <https://doi.org/10.47001/IRJIET/2024.802020>
- [8] Moreno-Vallejo, P. X., Bastidas-Guacho, G. K., Moreno-Costales, P. R., & Chariguaman-Cuji, J. J. (2023). Fake News Classification Web Service for Spanish News by using Artificial Neural Networks. *International Journal of Advanced Computer Science and Applications*, 14(3).
- [9] Shahzad, K., Shakeel, A. K., Ahmad, S., & Iqbal, A. (2022). A Scoping Review of the Relationship of Big Data Analytics with Context-Based Fake News Detection on Digital Media in Data Age. *Sustainability*, 14(21), 14365. <https://doi.org/10.3390/su142114365>.
- [10] SuhaibKh. Hamed, MohdJuzaidin, A. A., & Yaakub, M. R. (2023). A Review of Fake News Detection Models: Highlighting the Factors Affecting Model Performance and the Prominent Techniques Used. *International Journal of Advanced Computer Science and Applications*, 14(7)<https://doi.org/10.14569/IJACSA.2023.0140742>.
- [11] Nadeem, M. I., Ahmed, K., Li, D., Zheng, Z., Hend, K. A., Mostafa, S. M., Mamyrbayev, O., & Hala, A. H. (2023). EFND: A Semantic, Visual, and Socially Augmented Deep Framework for Extreme Fake News Detection. *Sustainability*, 15(1), 133. <https://doi.org/10.3390/su15010133>.
- [12] Abuzinadah, N., Umer, M., Ishaq, A., Hejaili, A. A., Alsubai, S., Ala', A. E., Abdullah, M., & Ashraf, I. (2023). Role of convolutional features and machine learning for predicting student academic performance from MOODLE data. *PLoS One*, 18(11)<https://doi.org/10.1371/journal.pone.0293061>.
- [13] Ali, H., Hashmi, E., Yildirim, S. Y., & Shaikh, S. (2024). Analyzing Amazon Products Sentiment: A Comparative Study of Machine and Deep Learning, and Transformer-Based Techniques. *Electronics*, 13(7), 1305. <https://doi.org/10.3390/electronics13071305>.

[14] Malhotra, P., & Malik, S. K. (2024). Fake news detection using ensemble techniques. *Multimedia Tools and Applications*, 83(14), 42037-42062. <https://doi.org/10.1007/s11042-023-17301-w>.

[15] Alshattawi, S., Shatnawi, A., AlSobeh, A. M. R., & Magableh, A. A. (2024). Beyond Word-Based Model Embeddings: Contextualized Representations for Enhanced Social Media Spam Detection. *Applied Sciences*, 14(6), 2254. <https://doi.org/10.3390/app14062254>.

[16] Bhumichai, D., Smiliotopoulos, C., Benton, R., Kambourakis, G., & Damopoulos, D. (2024). The Convergence of Artificial Intelligence and Blockchain: The State of Play and the Road Ahead. *Information*, 15(5), 268. <https://doi.org/10.3390/info15050268>.

[17] Thompson, R. C., Seena, J., & Adeliyi, T. T. (2022). A Systematic Literature Review and Meta-Analysis of Studies on Online Fake News Detection. *Information*, 13(11), 527. <https://doi.org/10.3390/info13110527>.

[18] Machová, K., Mach, M., & Balara, V. (2024). Federated Learning in the Detection of Fake News Using Deep Learning as a Basic Method. *Sensors*, 24(11), 3590. <https://doi.org/10.3390/s24113590>.

363

### International Journal of Environmental Sciences

ISSN: 2229-7359

Vol. 11 No. 12s, 2025 <https://www.theaspd.com/ijes.php>

[19] Thompson, R. C., Seena, J., & Adeliyi, T. T. (2022). A Systematic Literature Review and Meta-Analysis of Studies on Online Fake News Detection. *Information*, 13(11), 527. <https://doi.org/10.3390/info13110527>.

[20] Kumar, Y., Verma, S. K., & Sharma, S. (2021). An Ensemble Approach of Improved Quantum Inspired Gravitational Search Algorithm and Hybrid Deep Neural Networks for Computational Optimization. *International Journal of Modern Physics C*, 32(08), p.2150100 (SCI).

[21] Machine Learning Algorithms List [2021 Updated] ([simplilearn.com](https://www.simplilearn.com))

[22] Wanda, P., Diqi, M. DeepNews: enhancing fake news detection using generative round network (GRN). *Int. j. inf. tecnol.* 16, 4289–4298 (2024). <https://doi.org/10.1007/s41870-024-02017-3>

[23] Qasem, A.E., Sajid, M. Leveraging contextual features to enhanced machine learning models in detecting COVID-19 fake news. *Int. j. inf. tecnol.* 16, 3233–3241 (2024). <https://doi.org/10.1007/s41870-023-01564-5>.

[24] Das, S. A new technique for classification method with imbalanced training data. *Int. j. inf. tecnol.* 16, 2177–2185 (2024). <https://doi.org/10.1007/s41870-024-01740-1>

[25] Ihsan, R., Khurshid, S.K., Shoaib, M. et al. A technique to forecast Pakistan's news using deep hybrid learning model. *Int. j. inf. tecnol.* 16, 2505–2516 (2024). <https://doi.org/10.1007/s41870-024-01781-6>

[26] Saikia, P., Gundale, K., Jain, A., Jadeja, D., Patel, H., & Roy, M. (2022, July). Modelling social context for fake news detection: a graph neural network based approach. In 2022 international joint conference on neural networks (IJCNN) (pp. 01-08). IEEE.

[27] Liao, Q., Chai, H., Han, H., Zhang, X., Wang, X., Xia, W., & Ding, Y. (2021). An integrated multi-task model for fake news detection. *IEEE Transactions on Knowledge and Data Engineering*, 34(11), 5154-5165.

[28] Mishra, A., & Sadia, H. (2023). A Comprehensive Analysis of Fake News Detection Models: A Systematic Literature Review and Current Challenges. *Engineering Proceedings*, 59(1), 28.

[29] Antoun, W., Baly, F., Achour, R., Hussein, A., & Hajj, H. (2020, February). State of the art models for fake news detection tasks. In 2020 IEEE international conference on informatics, IoT, and enabling technologies (ICIoT) (pp. 519-524). IEEE.

[30] Jiang, T. A. O., Li, J. P., Haq, A. U., Saboor, A., & Ali, A. (2021). A novel stacking approach for accurate detection of fake news. *IEEE Access*, 9, 22626-22639.

[31] Kumar, S., & Arora, B. (2021, August). A review of fake news detection using machine learning techniques. In 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 1-8). IEEE.

[32] Jyoti, & Kumar, Y. (2024). Fake News Detection with a Focus on Sustainability: A Review of the Literature and Research Priorities. *International Conference TALASH-2024*. Book Chapter. Walnut Publications.

[33] Jyoti, & Kumar, Y. (2024). Combating Misinformation: Insights into Datasets, Models, and Evaluation Strategies for Fake News. *IEEE International Conference DELCON-2024*.

[34] Jyoti, & Kumar, Y. (2024). Social media fake news detection using a robust machine learning model and Data-Centric approach. *African Journal of Biomedical Research*, 305–314. <https://doi.org/10.53555/ajbr.v27i6s.6215>.

[35] Jyoti, & Kumar, Y. (2025). Harnessing Ensemble AI Algorithms for Enhanced Fake News Detection on Social Media. *International Conference ICISHME-2025*, ISBN: 978-93-89947-84-7.

363