Analyzing the Effectiveness of ML and DL in Combatting Personal Condition Misinformation on Social Media

Jaladanki Ravindra Babu, Vaadaala Venkataiah, Tirumalasetti Lakshmi Narayana, Chegudi Ranga Rao, Ch. Deva Raj, Rallabandi C.H. S. N. P. Sairam, Anusha B

***Abstract*—The widespread broadcast of fake health news offers a huge challenge that puts the health and well-being of the general population in peril. This is especially true in a time when there is an excess of information available. In order to develop automated systems that are capable of spotting fraudulent health-related information, researchers have applied artificial intelligence methodologies such as machine learning (ML) and deep learning (DL). These approaches have been utilized in order to construct these systems. In order to address the problem that is now being faced, this is being done. The objective of this research is to give an analysis of the method, performance measurements, and problems that are linked with machine learning (ML) and deep learning (DL) systems for the purpose of recognizing fake health news. This analysis is presented in the course of this research. We study the many ways that are applied in the process of feature engineering, that of model architectural design, and that of evaluation metrics throughout the machine learning (ML) and deep learning (DL) paradigms. These approaches are utilized in the process of feature engineering. Additionally, we evaluate the significance of our findings for the development of the efficiency of systems that are meant to identify false health news and offer prospective areas for additional research in this vitally important sector. Lastly, we conclude that our findings have the potential to improve the effectiveness of these systems.**

***Index Terms*—Artificial Intelligence, Machine Learning, Deep Learning, Fake Health News**

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Jaladanki Ravindra Babu is an Associate Professor of Electronics and Communication Engineering Department, Prasad V Potluri Siddhartha Institute of Technology, Vijayawada, Andhra Pradesh, India. (e-mail: jrb0009@gmail.com)

Vaadaala Venkataiah is an Associate Professor of Computer Science and Engineering Department, CMR College of Engineering & Technology, Hyderabad, Telangana, India. (E-mail: venkat.vaadaala@gmail.com)

Tirumalasetti Lakshmi Narayana is an Assistant Professor of Electrical and Electronics Engineering Department, Aditya University, Surampalem, Andhra Pradesh, India. (e-mail: tlaxman17@gmail.com)

Chegudi Ranga Rao is an Associate Professor of Electrical and Electronics Engineering Department, R. V. R. & J. C. College of Engineering, Guntur, Andhra Pradesh, India. (e-mail: chegudi.rangarao@gmail.com)

Ch. Deva Raj is an Assistant Professor of Mechanical Engineering Department, R. V. R. & J. C. College of Engineering, Guntur, Andhra Pradesh, India. (e-mail: chdevaraj@gmail.com)

Rallabandi C. H. S. N. P. Sairam is an Assistant Professor of Computer Science and Engineering (Data Science) Department, R.V. R. & J. C. College of Engineering, Guntur, Andhra Pradesh, India. (e-mail: sairam.mtech20@gmail.com)

B. Anusha is a Scholar of Electronics and Communication Engineering Department, Andhra University, Visakhapatnam, Andhra Pradesh, India. (e-mail: anutanhar@gmail.com)

I. INTRODUCTION

IN this phase of digitization, when information is easily accessible and rapidly disseminated at a rate that has never been seen before, the dissemination of false information has emerged as a significant obstacle. This is especially true in the field of health care. When individuals discuss the concept of fake health news, they are referring to a wide range of pieces of information that are not accurate. Not only does this include statements that are grossly exaggerated in terms of the effectiveness of specific treatments, but it also encompasses content that is completely inaccurate with regard to diseases and activities that are directed toward public health. It is possible that the consumption of such erroneous information could have major repercussions, including the propagation of habits that are detrimental to one's health, the loss of confidence in sources that can be relied upon, and the making of decisions regarding one's health that are not well informed [1]. It is now much simpler for incorrect health information to be immediately transmitted to a large number of individuals as a result of the proliferation of social media platforms, internet forums, and instant messaging applications. When it comes to disproving assertions that are not supported by evidence, this has frequently outperformed the efforts of fact-checkers and health authorities. As an additional point of interest, the COVID-19 epidemic has significantly exacerbated the problem. This is due to the fact that erroneous information regarding the virus, vaccinations, and protocols for public health has been swiftly disseminated through internet media. The reserve of vaccines and the refusal to comply with preventive measures are two examples of the practical impacts that have originated as a result of this. combined with [2], [3]. In response to the growing difficulty that is presented by bogus health information, academics and engineers have been actively making efforts to develop novel strategies that make use of artificial intelligence (AI) methodology. These efforts have been under way for quite some time. Two of the technologies that have been particularly prominent in the field of automatically recognizing counterfeit health-related information are machine learning (ML) and deep learning (DL). ML and DL are abbreviated as either machine learning or deep learning. In order to explore the textual, visual, and contextual aspects of health news coverage and social media posts, tools from the field of machine learning have been applied. These methods encompass both conventional classifiers and ensemble approaches to classification. At the same time that this is taking place, deep learning models have demonstrated that they are able to recognize even the most minute indications of incorrect information [4]. They are able to recognize subtle patterns among enormous amounts of data, which is the reason for this. In order to provide a thorough description of all the machine learning (ML) and deep learning (DL) approaches that can be utilized to identify fake health news, the objective of this study is to provide a concise overview of these techniques. By comparing and assessing the methodology, performance indicators, and challenges that are associated with these detection approaches, the fundamental objective of this study is to accomplish. This research is being conducted with the intention of making a significant contribution to the development of artificial intelligence (AI)-based solutions for the aim of combatting disinformation in the field of health [5]. In order to achieve this goal, a synthesis of the most recent research will be performed, and gaps in the existing body of literature will be identified. This comparative research is to provide specific examples in order to better understand the benefits and limitations of machine learning (ML) and deep learning (DL) techniques. The purpose of this research is to provide specific examples. As a consequence of this, this will result in the provision of valuable information that can be utilized to influence the development of systems that are more efficient and resilient in identifying bogus health news.

As soon as that is finished, we will proceed to analyze the existing body of research addressing the identification of fake health news. This will include an analysis of the techniques that are utilized in machine learning (ML) and deep learning (DL) approaches, the datasets that are utilized for training and assessment, the strategies that are utilized for feature engineering, and the evaluation metrics that are utilized to measure the performance of the models. In addition, we will conduct an analysis of the challenges that are connected with recognizing fake health news and will propose potential areas for future research in order to address these issues and enhance the effectiveness of AI-driven solutions in decreasing the spread of false information in the field of health [6]. The process of recognizing deceptive health information has garnered a substantial amount of interest from academics working in a range of fields, including computer science, information science, and public health, amongst others. For the objective of providing an overview of the existing literature on machine learning (ML) and deep learning (DL) methods for recognizing fake health news, the purpose of this section is to provide a review of the literature. The primary focus of our investigation is on making use of significant procedures, datasets, feature engineering techniques, and evaluation measures that were utilized in earlier research [7]. Traditional machine learning algorithms have been the subject of a significant number of research that have been carried out with the intention of determining whether or not they are effective in detecting fake health news. In the study that Zhang and colleagues (2019) conducted, they applied Support Vector Machines (SVM) in order to categorize tweets that were related to health as either accurate or deceptive. By taking into account the characteristics of the language as well as the characteristics of the user, this was achieved. When it came to identifying misleading tweets that were associated with quitting smoking, the outcomes of their efforts were satisfactory. Castillo et al. (2020) applied Naive Bayes classifiers in a method that is comparable in order to identify deceptive content that was present in medical internet forums. Examining the qualities of the text as well as the patterns of user engagement allowed for this to be accomplished [8].

Furthermore, the detection of false health news has been performed by the employment of ensemble methodologies such as Random Forests and Gradient Boosting. This has permitted the identification of fraudulent health news. According to Huang et al. (2021), the Random Forest-based methodology has the purpose of categorizing news stories that are related with COVID-19 as either reliable or unreliable. This classification is according to the methodology's objective. The parts of the text as well as the dependability of the source are taken into consideration in order to be successful in this endeavor. The methodology that they utilized was able to attain a surprising level of precision in identifying news sources that could not be trusted, so demonstrating the effectiveness of ensemble learning methods in reducing the dissemination of erroneous information during times of public health emergency [9]. Deep learning models have demonstrated that they have a large lot of potential in the field of recognizing false health news. This is due to the fact that they are able to discover complex patterns from data that has not been processed. In the area of text categorization applications, the utilization of Convolutional Neural Networks (CNNs) is prevalent, with a particular emphasis on the identification of content that does not accurately represent the subject matter. Wang et al. introduced a convolutional neural network (CNN) method in their 2019 study that surpassed existing machine learning techniques in terms of its capacity to categorize health-related tweets as either credible or unreliable [10]. This was accomplished by dividing the tweets into two categories: reliable and unreliable.

Recurrent Neural Networks (RNNs) and their derivatives, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have also been taken into consideration for sequence modeling and the identification of fake health news. This is comparable to the way that RNNs function. During the course of their investigation, Chen et al. (2020) employed a Long Short-Term Memory (LSTM) model in order to categorize health-related publications as either trustworthy or unethical. Making use of both textual and contextual aspects allowed for the successful completion of this task. By outperforming typical machine learning algorithms in the detection of false health news releases, deep learning approaches revealed their effectiveness in spotting temporal correlations and subtle linguistic clues. This was demonstrated by the fact that their methodology outperformed the algorithms. It has been determined that a huge number of datasets have been exploited for the purpose of training and evaluating algorithms for the purpose of identifying bogus health news.

Datasets that are accessible to the general public, such as the HealthMisinfo dataset, are included in this category. Additionally, datasets that have been manually built and extracted from internet forums and social media platforms are also included. An example of an evaluation measure that is widely used for the purpose of measuring the performance of models is the F1-score. Other examples of assessment measures include accuracy, precision, recall, and reliability. Researchers emphasize the necessity to achieve a balance between limiting the number of false positives and the number of false negatives when it comes to tasks that require the identification of fake health news [11], [12]. This is true when it comes to tasks that involve the identification of fake health news.

There are still some problems that need to be overcome, despite the fact that there have been improvements made in the identification of fraudulent health news. The widespread dissemination of misleading information across a variety of platforms, the ever-evolving nature of deceitful techniques employed by malicious individuals, and the limited availability of documented data for the purpose of training detection algorithms that are reliable are some of the factors that contribute to this problem. Researchers, practitioners, and policymakers need to work together across disciplinary lines in order to discover a solution to these difficulties. This is a requirement that must be met. It is also vital to build novel solutions that are powered by artificial intelligence, are able to adapt to evolving information landscapes, and efficiently prevent the transmission of malicious health news. These solutions must be developed soon. [13], [14]. The succeeding sections of this research project will include a presentation that will include an analysis of the similarities and differences between the approaches of machine learning (ML) and deep learning (DL) for recognizing bogus health news. We will analyze each of their individual advantages and disadvantages, as well as their overall performance, by making use of benchmark datasets. Furthermore, we will study the implications of our findings for the conduct of future research and the application of our findings in the real world with regard to the eradication of false information in the field of medicine. This will be done in order to ensure that our findings are taken into consideration.

II. Machine Learning Approaches

Machine learning (ML) techniques have made extensive use of a wide variety of algorithms and feature engineering approaches in order to categorize health-related content as either real or fake. This classification is done for the aim of determining whether or not the content is genuine. The ability to recognize health news that has been manufactured has been simplified as a result of this. In the next part, we will study the methodology, feature engineering techniques, and performance metrics that are connected with machine learning systems for the aim of recognizing false health news [15]. This will be done in order to determine whether or not these systems provide accurate health news.

Examples of well-established machine learning algorithms that have been applied for the purpose of recognizing fake health news include Support Vector Machines (SVM), Naive Bayes, Decision Trees, and Random Forests. These are just some of the ways that have been used. Support Vector Machines (SVM), which are well-known for their efficiency in feature spaces that contain a large number of dimensions, have been extended to identify health-related text by making use of lexical, syntactic, and semantic aspects. This is a significant advancement regarding the classification of health-related text. Naive Bayes classifiers have exhibited outstanding success in differentiating between real and false health information, particularly in instances where there is limited quantity of training data [16]. Despite the fact that they are not particularly complicated, this is the case. Random Forests and Decision Trees are both capable of effectively managing nonlinear connections and feature interactions, which enables them to effectively spot nuanced indicators of fake health news. Decision Trees are also capable of managing feature interactions. The ability of ensemble approaches, such as Random Forests, to prevent overfitting and increase generalization performance is achieved through the pooling of predictions from a large number of base learners [17]. These methods offer an extra benefit from a statistical point of view, which is this particular advantage. There is a significant role that feature engineering plays in the process of identifying false health news through the application of machine learning. This is due to the fact that it enables the transformation of unprocessed textual input into meaningful representations that are able to capture relevant information for categorization in an efficient manner. Examples of the types of features that are frequently utilized include bag-of-words representations, TF-IDF weights (Term Frequency-Inverse Document Frequency), word embeddings, and syntactic or semantic features that are acquired via the study of linguistics. In order to quantify the number of times a certain word appears in a given document, bag-of-words representations are utilized. These representations do not take into account the sequence or structure of the text under consideration. Using the TF-IDF weighting method, relevant characteristics are brought to light by assigning larger weights to phrases that display superior discriminative strength across texts. At the same time, the weight of terms that are used frequently is reduced. By mapping words to dense vector representations, word embeddings like Word2Vec and GloVe are able to express words in a continuous vector space. This is accomplished by mapping words to one other. In turn, this makes it possible for models to capture semantic similarities as well as contextual nuances of words [18], [19]. User involvement indicators (such as likes, shares, and comments) are frequently included in machine learning algorithms that are used to identify fake health news. Other metadata characteristics that are typically included in these algorithms include the authenticity of the source, the date of publication, and the date of publication. When these metadata elements are incorporated, there is a possibility that they will contribute significant contextual information. This, in turn, has the potential to improve the classification model's ability to discern between various categories [20].

In the process of analyzing machine learning-based models for the goal of identifying fake health news, conventional metrics like as accuracy, precision, recall, and F1-mark are often applied. This is done specifically for the purpose of identifying fake health news. An analysis of the performance of the models is often included in this review. The accuracy of the model offers a quantitative measure of the proportion of cases that have been correctly classified in relation to the total number of occurrences [21]. This is done in order to provide a comprehensive evaluation of the performance of the model. The term "precision" is used in the field of machine learning to refer to the percentage of occurrences that are categorized as positive in comparison to the total number of examples that are deemed to be positive. Recall, on the other hand, is a quantitative measure of the proportion of actual positives that are accurately identified by the model. It is a notion that involves the identification of true positives. The F1-score is a balanced measure of model performance that is created by taking the harmonic mean of precision and recall [22]. This is especially useful in situations where the class distributions are not uniform. According to this score, the model is functioning in the manner that was anticipated. Other metrics, such as the area under the receiver operating characteristic curve (AUC-ROC) and the area under the precision-recall curve (AUC-PR), are also utilized in order to evaluate the discriminative power and robustness of machine learning models across a wide range of classification criteria [23]. These metrics are utilized in order to determine whether or not the models are able to accurately classify the data.

The employment of a wide range of algorithms, feature optimization methodologies, and performance measures by machine learning techniques with the intention of identifying false health news allow for the classification of health-related information as either authentic or misleading. This classification is accomplished. However, despite the fact that these strategies are extremely effective, they may have difficulties in recognizing subtle linguistic clues and responding to the ever-changing deceptive practices that are utilized by individuals who are harmful. In the following sections, we will compare and contrast the techniques of deep learning with the methods of machine learning for the purpose of recognizing false health news. Additionally, we will analyze the merits and limits of each of these approaches separately at the same time [24].

III. Deep Learning Approaches

The ability of deep learning (DL) algorithms to automatically learn complex patterns from raw data, which includes textual, visual, and sequential information, may be the reason why these methods are becoming increasingly essential in the detection of fake health news. Through the utilization of deep learning algorithms, this section digs into the methodology, model topologies, and performance measures that are utilized in the detection of fraudulent health records. When it comes to spotting bogus health news, the bulk of deep learning algorithms make use of particular kinds of neural networks that have been trained to deal with sequential or textual data. Convolutional Neural Networks (CNNs) accomplish the task of learning hierarchical representations of input text by employing a sequence of convolutional and pooling layers. This technique is commonly utilized in applications that are concerned with text categorization. Word embeddings are often utilized by CNN-based models in order to encode words as dense vectors [25]. This strategy is utilized in order to capture both local and global patterns in the text. The methodology for the proposed research is outlined in Figure 1. This methodology involves the development of two distinct models, one of which is content-based and the other of which is proposed feature-based, through the integration of Deep Learning and machine learning techniques. When it comes to the first scenario, we merely develop the models by utilizing the material, which in this instance is bogus news. The second case, on the other hand, necessitates the utilization of feature-based models that contain not just the content but also additional readability features in order to develop the models and evaluate how effectively they function.

Recurrent Neural Networks (RNNs), such as the Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM), are particularly effective when it comes to encoding sequential input and capturing long-range correlations. In order to successfully capture temporal dynamics and contextual information in text sequences, versions of Graph Reinforcement Unit (GRU) and Long Short-Term Memory (LSTM) address the problem of vanishing gradients that is typical of classic Recurrent Neural Networks (RNNs) [26]. These variants make use of a combination of LSTM and GRU. When it comes to assessing news articles, social media posts, and forum talks, where the context and word order play a significant part in determining the veracity of the content, these models really shine the brightest. From the area of tasks requiring the identification of bogus health news, there has been an extension of the usage of transformer-based designs, such as BERT and variations [27]. Transformer-based architectures include BERT and variants. BERT models make advantage of self-attention processes to extract bidirectional contextual information from input sequences. This allows them to learn comprehensive representations of textual material without the need for sequential input processing. By modifying pre-trained BERT embeddings on datasets that are particular to your domain, you can achieve excellent performance on benchmark datasets for recognizing fake health information [28]. This is especially true for identifying fake health information.

The foundation of deep learning models that are used to identify false health news is comprised of learned representations of the input data. The contextual indicators, nuanced linguistic patterns, and semantic linkages that are included in these representations have the potential to convey information that is either misleading or untrue. Word embeddings such as Word2Vec, GloVe, and FastText encode words as dense vector representations in continuous vector spaces. This allows them to capture semantic similarities and contextual nuances through the use of semantic embedding. In addition to word embeddings, deep learning models can also make use of attention techniques in order to dynamically prioritize significant components of the input sequence and minimize the impact of less significant components. By allowing the model to assign more weight to useful words or phrases within the text, attention processes provide the model the ability to improve its ability to differentiate between material that is misleading and content that is the genuine article.

To identify bogus health news, deep learning models must be assessed using accuracy, precision, recall, and F1 score. Deep learning models' discriminative capacity and robustness are assessed using measures like AUC-ROC and AUC-PR. These metrics are used for several classification criteria. Deep learning models are trained on large, labeled datasets and tested on multiple test sets to see how well they generalize. Cross-validation helps assess model consistency and variability across data splits. Qualitative research, including error analysis and model interpretability, can reveal deep learning systems' strengths and weaknesses in detecting bogus health news. It is [29].

Fake health information is detected using deep learning. These strategies use CNNs, RNNs, and transformer-based models developed for sequential or textual data analysis. These models provide complete data representations. These representations include semantic linkages and contextual signs of incorrect or misleading content. Deep learning models are evaluated using standard metrics and qualitative analysis to understand their behavior and generalization capacity. After that, we will assess the pros and cons of deep learning and machine learning for detecting fake health news.

A. Comparative Analysis

The methodology, performance indicators, and challenges that are associated with machine learning (ML) and deep learning (DL) systems for the purpose of recognizing fake health information are investigated. In order to provide incisive views on the success of both methods in addressing the issue of health-related deception, we intend to conduct a comprehensive evaluation of the benefits and limitations of both methodologies. The classification of health-related content as either real or misleading is often accomplished through the use of machine learning approaches, which typically rely on human-crafted features and traditional algorithms. It is frequently necessary to have substantial feature engineering and domain experience in order to extract valuable features from raw textual data using these methods. It may be difficult for machine learning models to recognize intricate patterns and sophisticated language cues that are typical of fake health news, despite the fact that these models are capable of achieving competitive performance through the use of finely generated features and ensemble management techniques. Thirty.

Deep learning techniques, on the other hand, make use of neural network topologies to autonomously generate representations of input data. This eliminates the need for manual feature engineering, which is a need for traditional learning methods. Deep learning models, particularly transformer-based architectures such as BERT, have the capability to extract complex semantic relationships and contextual information from textual input. This capacity enables these models to perform exceptionally well when it comes to identifying bogus health news. Deep learning models, on the other hand, usually need for massive labeled datasets and a substantial number of computational resources for training, which restricts their application in scenarios with restricted resources [31]. A number of popular metrics, including accuracy, precision, recall, and F1-score, are utilized in order to assess the efficacy of machine learning (ML) and deep learning (DL) models in the detection of fake health news. The purpose of this evaluation is to ascertain whether or not these models are successful in meeting their intended purpose.

It is possible for machine learning models to attain competitive performance on benchmark datasets if they are provided with features that have been carefully created and hyperparameters that have been accurately tuned. It is possible that they will have difficulties when extrapolating to data that is unknown or when responding to evolving deceitful strategies that are used by individuals who lack ethical standards. Machine learning techniques are frequently outperformed by deep learning models when it comes to recognizing bogus health news. This is because deep learning models are able to recognize complicated patterns from raw data. In order to recognize minor language cues that are suggestive of inauthentic or misleading material, architectures that are built on transformers have exhibited remarkable performance on benchmark datasets. This is accomplished through the utilization of pre-trained embeddings and self-attention processes. However, deep learning models are prone to overfitting, particularly in situations when there is a limited amount of training data. In order to attain maximum performance, it may be necessary to do rigorous tuning on datasets that are specialized to a certain domain.

B. Challenges and Limitations

Both machine learning (ML) and deep learning (DL) approaches have difficulties and limitations when it comes to identifying health information that is deceptive. It may be difficult for machine learning algorithms to interpret subtle linguistic cues and adapt to ever-evolving misleading strategies. In order to retain their effectiveness, these algorithms will need to be updated frequently and will require human interaction. Furthermore, despite the fact that deep learning models are able to produce sophisticated representations of textual input, their practical application in real-world scenarios is limited due to the requirement for enormous labeled datasets and large computational resources for training. Furthermore, adversarial attacks, which occur when malevolent actors purposefully manipulate input data in order to avoid detection, may be able to affect both machine learning (ML) and deep learning (DL) systems. It is possible for hostile examples to weaken the effectiveness of false health news detection systems. These examples may include the introduction of misleading material or the altering of text in a sophisticated manner. Consequently, this highlights the importance of having models that are both strong and resistant to attacks from adversaries.

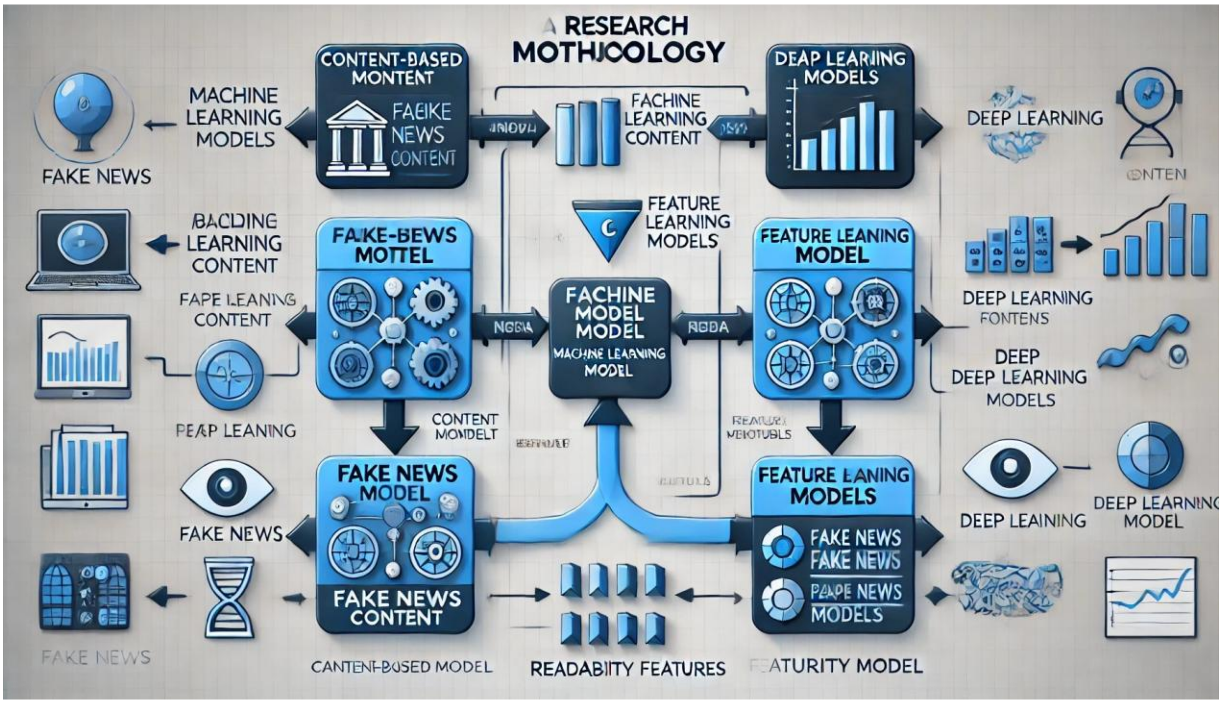

Fig. 1. Methodology Proposed

Both machine learning and deep learning approaches offer valuable tools for detecting false health news, each with unique advantages and limitations. Machine learning methodologies, reliant on manually crafted features and traditional algorithms, provide results that are comprehensible and reproducible, rendering them appropriate for implementation in resource-constrained settings. Deep Learning (DL) techniques employ neural network architectures to independently obtain representations of input data, yielding outstanding performance on benchmark datasets. This approach requires significant computational resources and annotated data for training. A hybrid strategy that integrates the advantages of machine learning (ML) and deep learning (DL) methodologies may be essential for effectively addressing the challenges of identifying fraudulent health news. By using the interpretability of machine learning models and the discriminative power of deep learning architectures, researchers can develop robust and scalable systems that successfully mitigate the spread of misinformation in healthcare. Moreover, future research should focus on addressing challenges such as adversarial attacks, data scarcity, and model interpretability to enhance the effectiveness and dependability of systems aimed at detecting false health information.

IV. Results and Discussions

The employment of graphics processing units (GPUs) for intense processing makes it possible for CBM and FBM to implement Machine Learning and Deep Learning strategies within the Google Colab environment. Matplotlib, Scikit-learn, Numpy, pandas, and Keras were the Python packages that were utilized for the construction of their respective programs. Through the use of a 100-dimensional GloVe word embedding system, the deep learning models were developed. For the purpose of developing the Deep Learning models, a sequential model that was accessible in Keras and contained several layers of neurons was utilized.The accuracy of false news categorization was examined within the context of CBM by utilizing five different machine learning algorithms. These methods are Decision Tree, Random Forest, Support Vector Machine, AdaBoost-Decision Tree (DT), and AdaBoost-Random Forest (RF). In Figure 2, the results are presented for your perusal. Using FBM as a framework, we conducted an analysis of the five different machine learning algorithms and evaluated their performance. Figure 3 illustrates the findings, which include the incorporation of readability qualities with the various components of the material.

The CNN-LSTM and CNN-BiLSTM models were utilized in order to assess the performance of both the CBM and the recommended FBM. In order to construct the input vectors, the contents are processed by employing the GloVe Embedding approach for the Frame-Based Model (FBM). This technique makes use of the SMOG score and the TTR. Figures 4 and 5 give a study of the performance of CNN-LSTM and CNN-BiLSTM for both CBM and FBM. Each of these models was used to execute the task. The figures are provided in the order of their individual performances, which are presented in sequence.

When measuring the performance of a model, the F1 score is a valid metric that takes into consideration both the amount of precision and the amount of recall. When it comes to identifying fake news, the performance of the model in terms of prediction and identification of true positives is of the utmost importance. Because of this, the model that was determined to be the winner in each category was determined by its F1 score. In Figure 6, the model that received the top ranking in each category is displayed, together with the performance score that corresponds to that model. Feature-based models have been shown to have greater performance when compared to more traditional models, according to the findings of experimental research. According to the findings of an investigation into the Content and Feature Based Models, AdaBoost-RF exhibited the highest level of performance. Taking into consideration the results of both groups, it was determined that AdaBoost-RF had the greatest F1 score. The AdaBoost-RF algorithm achieves an F1 score of 98.5% in Convolutional Bayesian Models (CBM), whereas the Feature Based AdaBoost-RF algorithm achieves a score of 98.9%. This information is derived from a comparative analysis of the two algorithms. One of the models that is included in the FBM dataset is the AdaBoost-Random Forest model, which is suggested for the classification of false news.

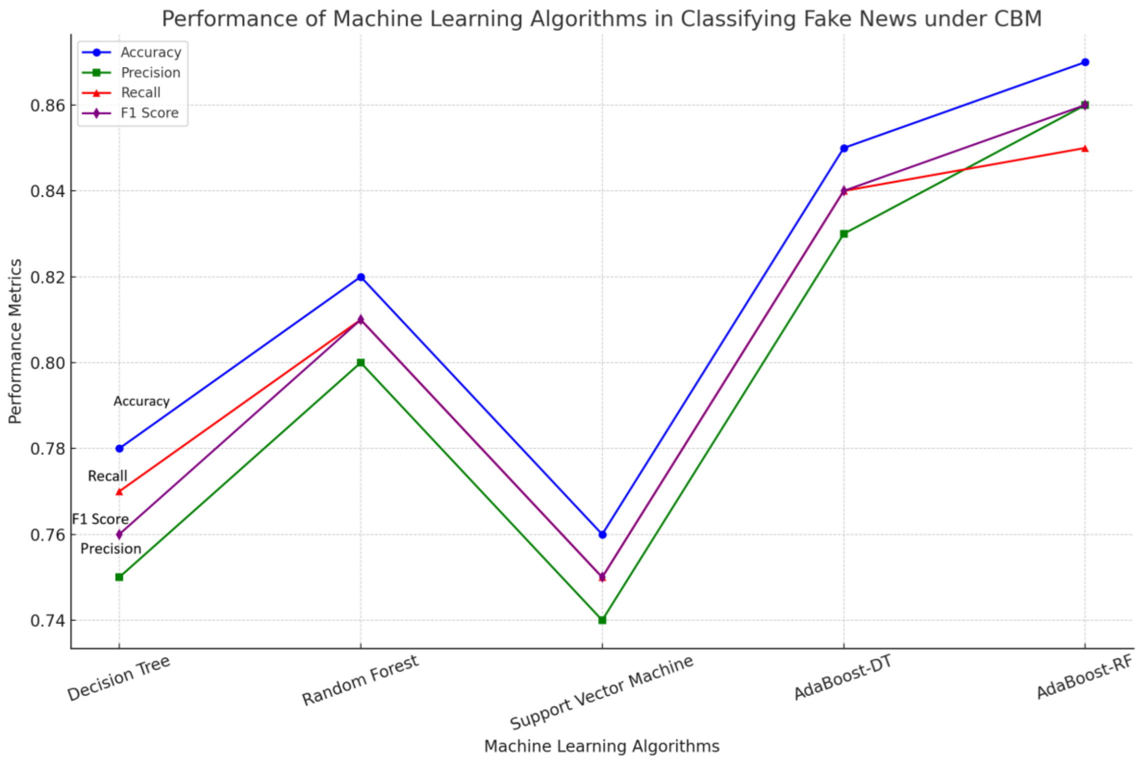

Fig. 2. An evaluation of the efficacy of conventional machine learning models in comparison to content-based models

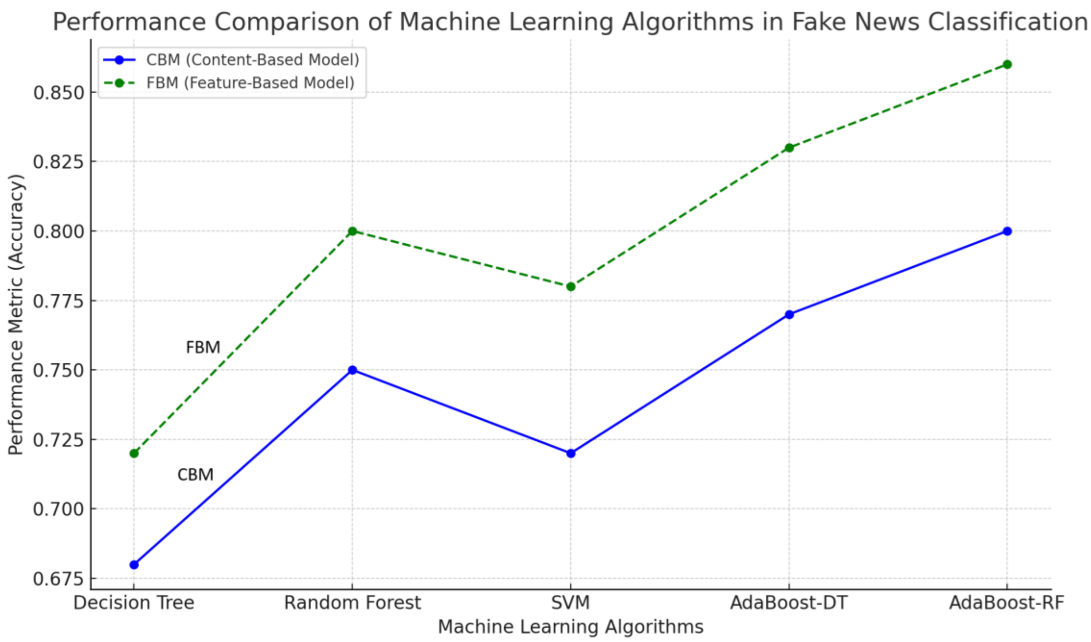

Fig. 3. A comparison of how well traditional machine learning models work in the area of feature-based learning

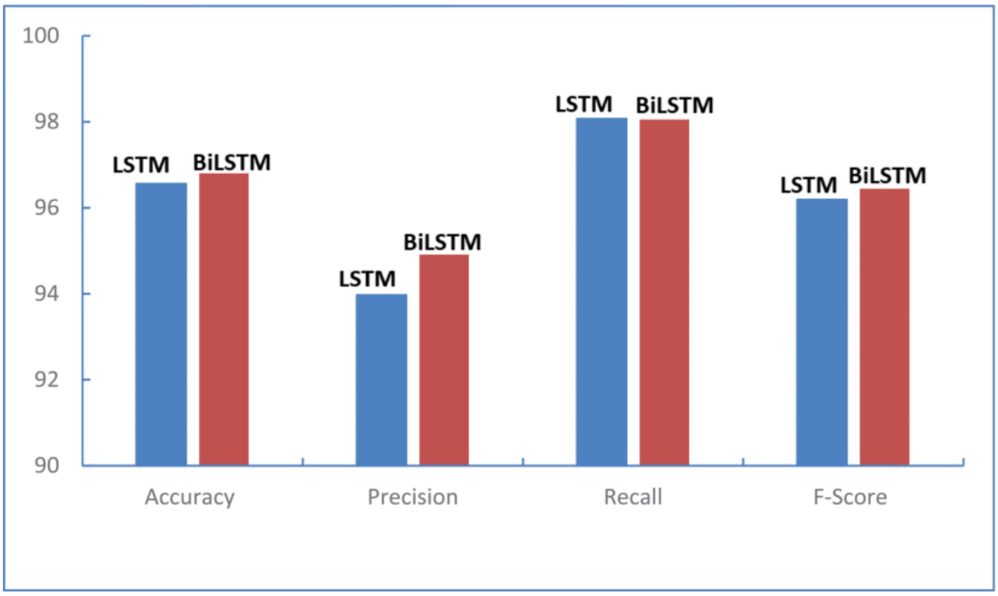

Fig. 4. The proposed deep learning models' performance is compared under the content-based category

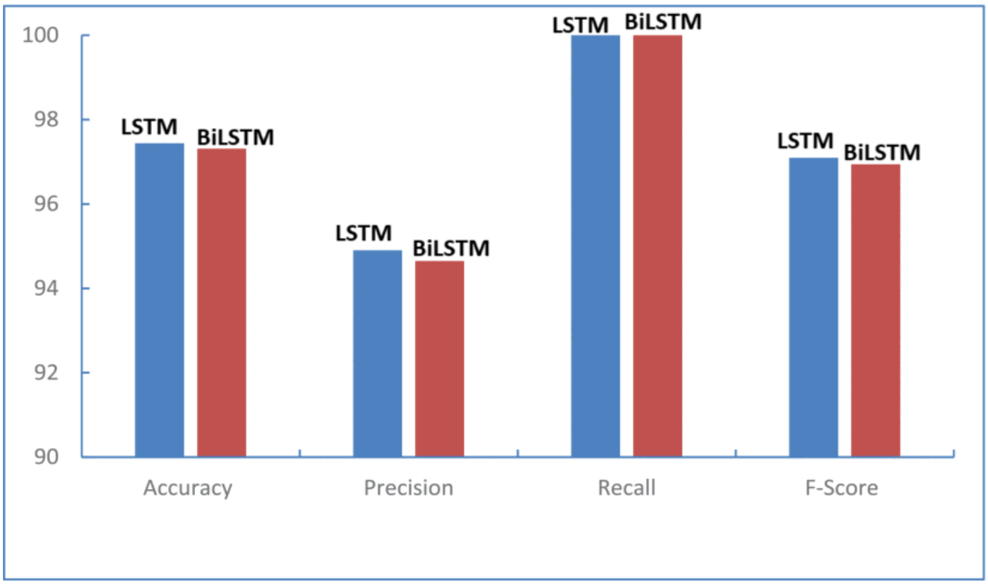

Fig. 5. Feature-based performance comparison of suggested deep learning models

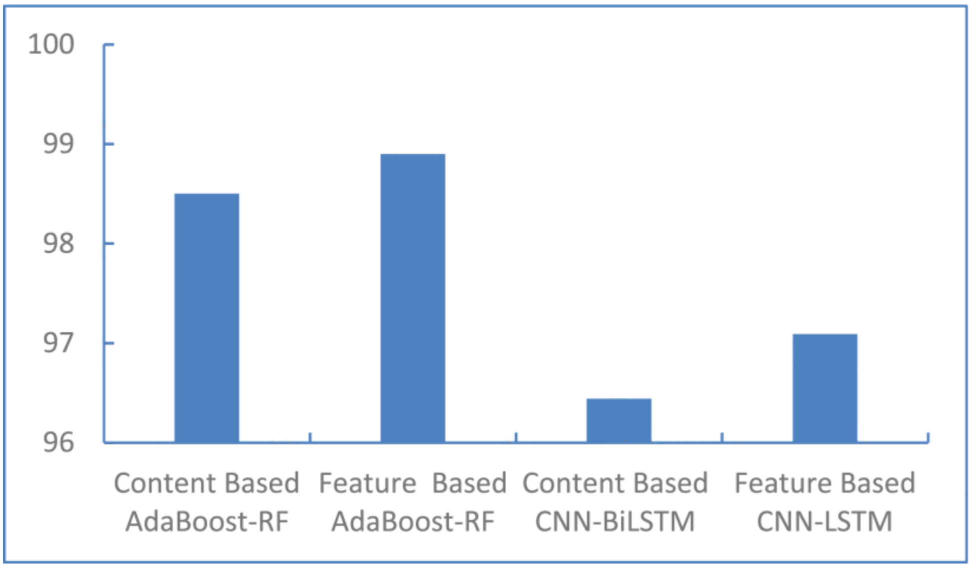

Fig. 6. The top models in each category are compared

Both the CNN-LSTM and CNN-BiLSTM performances were evaluated, and this was done for both the CBM and the planned FBM. In order to generate the input vectors, the contents are processed by employing the GloVe Embedding method for the FBM. This is done with the assistance of the SMOG score and the TTR. A comparison of the performance of CNN-LSTM and CNN-BiLSTM is presented in Figures 4 and 5, respectively, for both CBM and FBM techniques. All of these numbers are presented in the order that corresponds to their previous performance.

The F1 score is an efficient method for evaluating the performance of the model, as it takes into consideration both Precision and Recall. The prediction and identification capabilities of the model for actual positives are extremely important in the prevention of the dissemination of misleading information. As a consequence of this, the F1 score was used to decide which model was the best in each area. In Figure 6, the model that is ranked highest in each category is displayed, along with an evaluation of how well it did. According to the results of the studies, feature-based models perform better than models that are more conventional about their approach. Among the Content and Feature Based Models, the results demonstrated that AdaBoost-RF performed the best with regard to performance. It was determined that AdaBoost-RF had the highest F1 score when compared to both groups. When AdaBoost-RF is compared against Feature Based AdaBoost-RF, the former succeeds in achieving an F1 score of 98.5% in CBM, while the later earns a score of 98.9%. It is advised that the AdaBoost-Random Forest model, which is a member of the FBM group, be used for the classification of false news.

V. Conclusion

The continuous spread of inaccurate health information presents a significant threat to public health, as erroneous data rapidly circulates through online platforms and social media networks. Scholars have examined artificial intelligence methodologies, including machine learning and deep learning, to develop automated systems capable of identifying and mitigating the impact of misleading health-related information. This study provides a comprehensive analysis of the methods, challenges, and potential directions in the field of false health news detection. In resource-limited settings, machine learning methods that integrate conventional algorithms with handcrafted features yield interpretable results that are straightforward to implement. These methods may struggle to identify complex patterns and subtle linguistic cues indicative of false health information. In contrast, deep learning techniques, encompassing neural network architectures such as CNNs, RNNs, and transformer models, have demonstrated a remarkable capacity for extracting complex semantic relationships and contextual information from raw textual data. Deep learning models demonstrate efficacy; however, their application in real-world contexts is constrained by the requirement for large labeled datasets and significant computational resources for training. To address the challenges of identifying false health information, interdisciplinary collaboration, the development of experimental research methodologies, and the establishment of stringent evaluation frameworks are essential. Future research must focus on creating models that are resilient to adversarial attacks, enabling effective identification and mitigation of such threats. This objective can be accomplished through the application of multimodal content analysis methods to investigate diverse material types, thereby enhancing the explainability and interpretability of detection models. Additionally, creating comprehensive annotated datasets that accurately reflect a diverse array of sources and categories of false health information is essential. This will facilitate the development of scalable and effective detection algorithms capable of operating in real-time.

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