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A REVIEW AND COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR DEPRESSION DETECTION

Nimisha Raval, Assistant Professor, Department of Computer Engineering, Sankalchand Patel University
Shilpa Serasiya, Assistant Professor, Department of Information Technology, Sankalchand Patel University
Hitarth Patel, Assistant Professor, Department of Computer Engineering, LDRP Institute of Technology and Research

ABSTRACT

Depression can be considered one of the most severe mental disorders which may negatively impact individuals' mood and productivity. Therefore, early diagnosis of depression is required to prevent any further complications of this disease, such as suicide attempts. Owing to the growing interest in machine learning and deep learning-based technologies, many automated approaches have been proposed in recent years aimed at determining whether an individual is suffering from depression. These automated approaches employ different kinds of data, such as audio, video, and textual data. The primary purpose of the proposed research study is to examine different approaches to the problem of detecting depression based on AI technologies during 2021-2025.

As far as potential ways of detecting depression, the following techniques may be applied: SVM (support vector machines), Naive Bayes, and Random forest, which belong to the machine learning area. In addition to the above techniques, we may suggest applying deep learning neural networks such as CNN (convolution neural networks), RNN (recurring neural networks), and LSTM (long short-term memory networks). What is more, we have the possibility of combining several approaches together to achieve better results. Last but not least, we should mention natural language processing as another way of analyzing the information obtained.In spite of all those advancements, many difficulties remain that need to be addressed, specifically concerning data privacy, class imbalance, absence of labeled datasets, and the difficulty in explaining deep networks. Conclusion As can be seen from the above discussion, while deep learning and hybrid techniques perform better than traditional approaches in terms of efficiency and scalability, much remains to be accomplished regarding explain ability and privacy.

Keywords: Detection of Depression, Machine Learning Techniques, Mental Well-being, Academic Settings, Data Preparation, Classification Algorithms, Ensemble Methods, Interpretable AI, Social Media Evaluation, EEG Signals

INTRODUCTION

Depression is one of the most common psychological disorders prevalent worldwide. This condition leads to considerable disruptions in emotional states, cognitive functions, decision-making mechanisms, and interpersonal interactions. Individuals experiencing symptoms of depression exhibit low moods and a lack of interest in usual hobbies. These individuals fail to function effectively, which can make them engage in suicidal tendencies that might cause them to commit suicide in case of undiagnosed depression [1], [2]. Various types of people exist, amongst whom students and youths become vulnerable victims of depression due to academic pressure, professional insecurity, and societal challenges.The standard procedures employed in diagnosing depression involve clinical evaluation, psychiatrist's assessment, and self-report questionnaires. Though such procedures have been proven highly successful and clinically valid, they require vast amounts of effort and professional intervention from mental health experts. Additionally, these procedures cannot be expanded to accommodate larger populations, especially those having limited access to psychological services [3], [4].

Because of rapid progress in digital technology, people now communicate with each other through many different online mediums, including social networking platforms, blogs, and applications. These digital media tools provide opportunities for collecting a huge volume of data created by the users of these platforms. It can be argued that the above-mentioned data contains important knowledge regarding the behavioral and psychological processes of people. According to scientists, linguistic cues, sentiment analysis, and behavior can serve as valuable indicators of the likelihood of having depressive symptoms [5], [6].

The ML algorithm, which is one of the branches of AI, is a relatively novel technique that may be applicable to examine behavioral and psychological data in large volumes. It has been reported that ML-based techniques exhibit strong potential in detecting correlations among different features within large sets of data. Classical machine learning algorithms like SVM, Naïve Bayes, Decision Trees, and Random Forest have produced remarkable outputs in the context of classification problems involving structured data regarding depression recognition.However, considering the increasing volume of unstructured and high dimensional data created through social media and sensors, more sophisticated techniques such as DL have been adopted. In DL algorithms, which include CNN, RNN, and LSTM, the feature extraction process is automatically performed, thereby removing the requirement of manual feature extraction in data. Deep learning algorithms are quite efficient in recognizing patterns, being aware of context, and temporal dependency of data [7], [8].Therefore, the employment of the DL algorithms becomes very appropriate in relation to classifying people based on the three mentioned attributes.Latest developments in deep learning algorithms like neural networks and transformers have enabled the process of simplification of complex data analysis [7], [8]. Moreover, the integration of multiple types of data including text, voice, and physiologic data has led to accurate predictions [9],[10]. However, although there have been many developments, some challenges still exist. For instance, data privacy and data bias issues have remained [11], [12].

Nevertheless, some challenges still remain unresolved even though considerable progress has already been achieved. Firstly, the question of privacy and ethics is important because most of the available depression diagnosis algorithms use sensitive information gathered either from social media platforms or medical trials, which should be secured against any illegal usage. Additionally, the issue of the imbalance in the labeled dataset is faced by the researchers, as well as the lack of enough examples labeled appropriately. These challenges restrict the generalization capabilities of such models and lower the level of reliability. Furthermore, sophisticated approaches based on deep learning may suffer from poor explain ability [11],[12].

Taking into account the mentioned above concerns and achievements, the present review paper aims at conducting an elaborate analysis of the application of machine learning and deep learning for diagnosing depression. The current research will pay particular attention to examining different methods, datasets, preprocessing, evaluation metrics, as well as potential limitations and perspectives in this domain. Analyzing innovative developments within this sphere, this paper will attempt to make an essential contribution to designing efficient and ethical depression diagnosis tools.

LITERATURE REVIEW

In the last few years, the topic of depression detection has attracted many researchers due to the mental health crisis and the availability of digital information. Scientists have developed various methods related to computational intelligence; however, from simple machine learning approaches, they have reached much more advanced techniques like deep learning or even hybrids of different algorithms.Traditionally, a majority of these models used classical machine learning approaches like SVM, Naïve Bayes, Decision Trees, and Random Forest. The use of such approaches was widespread because of their simplicity, ease of interpretation, and reduced costs. However, they perform best on structured data like clinical or survey data where there are clear features to consider. Nevertheless, their performance is often constrained by complex and unstructured data that arise in real-world situations [3], [15]. Furthermore, the performance of these models has been noted to highly depend on feature engineering and data pre-processing.In tandem with the fast-paced growth of social media applications, the research interest started to change direction and concentrate on the analysis of the unstructured texts. Social media offers an excellent resource that contains up-to-date information when people convey their feelings, ideas, and routine activities. The use of NLP methods became popular to derive valuable insights from this data. The empirical results have proved that the linguistic markers, sentiment changes, and behavioral aspects contained in the content may indicate one's proclivity towards depression [13], [14]. The main benefit of this approach is the possibility of continuous monitoring, which makes it extremely appropriate for early diagnosis purposes.In addition to the analysis of text, physiological measurements have also been recognized as a trustworthy basis for recognizing depression in individuals. One example includes the use of techniques based on electroencephalograms (EEG), which allow for obtaining signals related to a person's depression. Such techniques allow analyzing objective features of the work of the brain. The research conducted in this sphere has proven that deep learning algorithms can be used for the analysis of EEG signals and distinguishing between depressed and healthy people [9], [10]. However, their use requires specific conditions..

The incorporation of deep learning technology into depression detection research is a major milestone that has brought many advantages to research work. The difference between traditional machine learning technology and deep learning lies in the fact that the former cannot learn features on its own without human assistance. On the other hand, deep learning technologies such as CNN, RNN, and LSTM are highly efficient at working with different data inputs such as text data, voice input, or behavioral data, owing to their ability to capture context and temporal data [8].

More recent advancements in the domain include transformers which have improved the ability to detect semantically related and context-related information present in the text. The usage of attention mechanisms in these models has made it possible for them to detect correlations and dependencies between words and phrases even in cases where there is a long gap between the words and phrases of interest. Studies comparing the effectiveness of transformers and other traditional

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methods of classification reveal that transformers are significantly more efficient in analyzing social media data compared to the two [7].
Furthermore, hybrid approaches to classification have proven to be very effective in terms of improving the efficiency of the prediction process. Hybrid approaches use combinations of different machine learning algorithms in order to leverage the strength of each individual model while avoiding their weaknesses. For instance, a combination of a classifier from the realm of machine learning and an algorithm based on optimization has proven to work quite efficiently when applied to the problem of depression detection [5], [19]..Another significant milestone achieved in this area is using multimodal data. In contrast to using only one input, multimodal methods combine different sources of data, for instance, text, voice, and physiological signals. As a result, this technique allows us to gain a more complete picture of the mental condition of people, since depression affects humans in various ways. Several works suggest that using multiple types of data enables better prediction results and higher accuracy [9], [20], [10].Nonetheless, several issues should be considered and resolved to ensure a more effective and practical use of deep learning methods for depression detection. One of the major concerns is associated with the quality of the dataset. The authors of the latest papers note that some of the recently published works have applied relatively small datasets, where the data lacks appropriate annotations, which might reduce the precision of prediction [11]. Moreover, the privacy and ethics issues must be taken into account, especially when processing sensitive data collected from social networks or clinical trials. The importance of securing data and ensuring confidentiality cannot be underestimated in creating reliable systems. Lastly, one of the critical concerns associated with the application of machine learning models is the problem of interpretability, which is especially important for black-box methods, such as deep learning algorithms and transformer models [11], [20].Moreover, diversity in languages, cultures, and human behavior among various populations also makes it difficult to formulate general models because what might work well with one group of data is likely to produce disappointing results when tested against another. This further emphasizes the importance of having more inclusive datasets and designing models that are flexible enough to account for such diversity.To conclude, it is evident from literature that there has been an evolution from conventional machine learning algorithms towards sophisticated deep learning techniques, transformers, and hybrids thereof. Although the latest technologies have many advantages over their predecessors, including increased accuracy and computational capacity, these solutions are associated with certain risks that need to be addressed in future research.

DATASETS AND PREPROCESSING

The success of any detection approach in terms of its ability to diagnose depression highly relies on the quality and diversity of datasets utilized in the process of training and testing. In recent years, a lot of efforts have been put by scholars in the use of various kinds of data in order to cover the aspects of human psychology and behavior from different angles. Social media data, clinical and survey data, speech data, and physiological data (Electroencephalogram (EEG)) are among the types of datasets that have been intensively studied.Social media has become the best source to discover any depression cases due to the ease and accessibility of the available information. This information extracted from platforms such as Twitter, Reddit, and Facebook gives chances for people to express themselves freely. Such textual information is useful for analyzing the state of a person by considering certain linguistic and behavioral aspects using the technique of natural language processing (NLP). There have been many studies done on depression detection and other mental states through NLP analysis based on sentiment polarity, vocabularies, frequencies, and behaviors in social media posts [13], [14]. Nevertheless, these pieces of information are not always clean and organized. Not only that, but the speech and audio information can also be analyzed based on voice features like intonation, pitch, and speech rhythm since it has been proven reliable in determining emotions of a person [22]. On the other hand, EEG information can help observe the brain activities indicating depressive states [9], [10].
On the contrary, the data collected via clinical studies and surveys is much more reliable. Generally, the database includes medical records, psychological assessment results, and questionnaires, for instance, PHQ-9 and BDI questionnaires. The value of such data lies in the fact that it consists of high-quality data labels collected in the laboratory environment [3],[4]. Nevertheless, one should take into account the fact that the size of such datasets is rather small due to multiple factors, including high expenses associated with the data collection process.
Physiological data, especially EEG data, represent another important aspect of detecting depression since EEG monitors brain activity. Thus, it is possible to find patterns in the activity that could indicate the occurrence of a depressive disorder. In recent years there has been an increase in the number of applications of deep learning models for EEG data analysis as they allow recognizing complex patterns difficult to discover otherwise [9], [10]. The mentioned approaches are considered more objective since they operate biological signs rather than textual expressions. Nevertheless, they require special equipment and conditions for collecting.However, there are many challenges in the use of diverse datasets despite their existence. The first major challenge is class imbalance, resulting from the fact that there are fewer samples of depressive states than non-depressive samples. This leads to biases in favor of the dominant class, leading to inaccurate classifications [11]. Another problem is the lack of data, including labeled samples, which is particularly common in domains such as clinical trials and physiology, which requires humans to annotate data [5]. Finally, linguistic, cultural, and behavioral differences among users from different datasets may affect model accuracy.
In addressing these issues, some steps have to be taken. One of the most crucial steps is data preprocessing. For textual data sets, some preprocessing techniques include data cleaning, tokenizing, stop-word removal, stemming, and lemmatization [15], [16]. These steps are crucial in the process of feature extraction because they will help remove any unnecessary noise, ensuring consistency in the data. Typical methods of feature extraction include TF-IDF vectors and word embeddings such as Word2Vec and GloVe [15]. There are also advanced techniques for feature extraction, such as contextual embedding from transformer models.On the other hand, concerning pre-processing steps for EEG signals, it is necessary to perform filtering of unwanted frequencies, remove eye-movement related artefacts or electromagnetic interference, and segment the input [10].
In addition, further data pre-processing steps, such as normalization, handling missing values, and balancing the dataset, may be considered. Normalization ensures that all the features are scaled to have comparable magnitudes, which improves the performance of models. The problem of missing values can be addressed using imputation techniques, while the imbalance problem may be handled using oversampling, under sampling, or synthetic data creation techniques like SMOTE [15], [20].Therefore, it is important to highlight that selecting appropriate datasets and conducting proper preprocessing is essential for creating successful models for detecting depression. Firstly, using social media datasets ensures scalability and availability of up-to-date information. Secondly, using clinical and physiological datasets guarantees high accuracy and reliability. Thus, combining multiple types of datasets and adopting innovative preprocessing techniques will definitely bring positive results. However, there might be problems associated with data quality, accessibility, and confidentiality, which need to be considered carefully.

MACHINE LEARNING MODELS

Machine The machine learning algorithm is very essential in automatic depression detection since it plays an important role in ensuring that a system learns from data that is of different types and gives a prediction in a very reliable manner. Various approaches have been experimented with before ranging from the basic machine learning algorithm to the deep learning algorithm. The selection of a suitable algorithm will be dependent on the type of data.

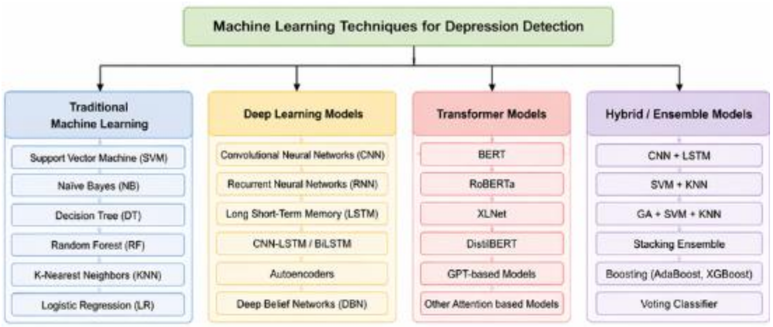

Figure 3: Classification of machine learning techniques used for depression detection.
Pinto, A., & Parente, R. (2020); Aleem, A., et al. (2022); Thekkekara, A. J., et al. (2022); Tejaswini, G., et al. (2021).

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4.1 Traditional Machine Learning Models

Traditional ML approaches have been widely used in the initial depression identification studies because of their simplicity, efficiency, and readability. SVM, NB, DT, and RF are popular algorithms among traditional ML methods. These approaches are particularly beneficial for processing structured data sets like the data collected from medical databases or surveys due to the interpretability and clear interpretation of features [3], [15].

Thus, SVM is distinguished by its stability against high dimensionality and accurate performance despite the lack of sufficient data for classification. The benefit of Naïve Bayes consists of efficient calculations and the possibility to be applied in text classification problems. At the same time, both DT and RF allow interpreting the obtained results and identifying non-linear dependencies between features [15].

However, despite the benefits outlined above, such ML approaches are based on a manual extraction of features and thus require much time. Furthermore, they are unable to process complex dependencies that exist within unstructured information, resulting in poor performance in relation to social media posts and multimedia [13], [16].

4.2 Deep Learning Models

The limitations associated with conventional ML algorithms led to the choice of deep learning algorithms, as they proved more effective. Deep learning algorithms have the ability to learn the features themselves and hence prove extremely useful in handling big data.

The Convolutional Neural Network (CNN) models find wide application in extracting spatial features. As far as classification of depression is concerned, CNN models could be employed for textual and audio data. CNN models have proved effective in the detection of depression in cases where they have been applied for the analysis of speech signals employing the Mel-frequency cepstral coefficients feature [22].

As far as sequential data such as textual data is concerned, the Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) prove highly effective. LSTM model has proved superior in handling time-series and textual data for detecting depression [8].

Moreover, CNN-LSTM hybrids have been explored for exploiting both spatial and temporal feature extraction techniques. In this regard, Thekkekara et al. [8] have proposed a CNN-BiLSTM model with attention mechanism, where both the CNN and bidirectional LSTM networks are used in combination with the attention mechanism.

4.3 Transformer-Based Models

The development of new techniques in NLP through the transformer architecture is another major breakthrough, making depression detection even more accurate. As opposed to earlier versions and classical machine learning techniques, transformers use an attention mechanism to recognize the connection between all elements in a sequence at once.

Bokolo and Liu [7] proved that transformer-based architectures are superior to classical machine learning and deep learning models when it comes to analyzing social media posts. The transformer model has proven efficient at recognizing and analyzing semantic connections in social media texts.

Another promising technique for processing large volumes of data is represented by the large language models and attention-based methods. These techniques have been successful in dealing with massive amounts of data and classification of data [14]. They are highly useful for social media platforms.

4.4 Hybrid and Ensemble Models

To address the weaknesses associated with individual models, hybrid and ensemble methods are the focus of attention.

Hybrid models are those that combine classical models and deep learning models or optimization models. An example is the hybridization of the genetic algorithm with other classifiers such as SVM (Support Vector Machine) and KNN (K-Nearest Neighbors). They were successful in selecting the best features and classifying them [5],[19].

On the other hand, ensemble models consist of combining the predictions of multiple models to create an output that is more reliable. There are many ensemble models, namely bagging, boosting, stacking, etc. Based on [5] and [19], the ensemble method performed better than single-model approaches in terms of accuracy..

4.5 Multimodal Learning Models

Depression is a complex illness that presents itself in several ways, among them through language, behavior, and physiology. Multimodal learning systems have therefore been created that utilize input from multiple sources to better recognize these various aspects.

Multimodal learning algorithms use text data from social networking platforms, speech data, and physiological data like electroencephalogram (EEG). It has been demonstrated that the use of multimodal data greatly increases the accuracy and reliability of the predictions [9], [10].

EEG data is used in deep learning models to recognize neurological trends, whereas text data is used to evaluate emotions. On the other hand, speech data is used to understand the voice.

4.6 Explainable Machine Learning Models

In regard to increased complexity in the machine learning models, the need for interpretation and transparency arises. Explainable Artificial Intelligence (XAI) may be viewed as a technological tool that serves for explanation of the decision-making process in the machine learning models in order to justify the results obtained and ensure the validity of the data obtained by the doctors.

Among the examples of traditional models that could be understood easily due to their simplicity, there are decision trees and logistic regression. However, their prediction rate does not match the prediction of deep learning models [11], [20]. On the contrary, such advanced algorithms as neural networks and transformers are viewed as "black box" models as they remain unpredictable and unexplainable [11], [20].

As far as XAI is concerned, its main development trend is based on the creation of explainable deep learning models and using interpretation techniques.

4.7 Comparative Insights and Challenges

From the analysis of different machine learning models, it can be concluded that there is no single best model which works effectively for different types of data. Traditional machine learning models perform well on structured data, but they do not work effectively for unstructured data. Deep learning models perform well with complex datasets but are resource-consuming and require large data sets [13]. The models based on transformers show advanced results due to their unique architecture but are complicated to understand and interpret [7].

However, hybrid and multimodal models offer the greatest potential for further research compared to other methods; however, they pose additional problems in comparison to the traditional machine learning models, namely, higher computational costs, complexities in managing data and interpreting models [5], [20].

In general, one can state that depression detection machine learning models have evolved since their emergence. Models have become more accurate, effective and diverse. At the same time, future research should focus on development of more accurate, interpretable and ethical models.

COMPARATIVE ANALYSIS

Evaluating the comparative advantages of both machine learning and deep learning techniques in diagnosis of depression can conclude that the accuracy of algorithms is highly contingent upon aspects such as: dataset type, feature presentation method, and complexity of the learning algorithm. During recent years, several scientific works have studied the comparative characteristics of the mentioned methods and pointed out their benefits and limitations in regard to social media analysis, diagnosis of depression in clinics, and recognition of physiometric signals.

Most common machine learning methods used include Support Vector Machine (SVM), Naïve Bayes, Decision Trees, and Random Forests. The above-listed methods proved to be highly efficient in the processing of structured data, for example, in relation to working with clinical reports, patient answers to surveys [3], [15]. These methods are cheap to compute, easy to understand, and easy to implement. Nevertheless, comparing the performance of the methods mentioned above shows that they cannot identify non-linear interdependencies between variables when processing unstructured data [13], [16]. Hence, machine learning methods prove inefficient in detecting depression from the information found in social media posts and other multimedia sources.

Deep learning models have shown their effectiveness and superiority in terms of performance while working with complicated and high-dimensional data. Deep learning approaches such as CNN, RNN, and LSTM can automatically detect vital features from the data provided. Therefore, there is no need for feature engineering, making the model capable of understanding complicated features related to depression [8,17]. Studies reveal that models based on CNN approach outperform in the analysis of spatial and signal data, which consists of speech and EEG data, while RNNs and LSTM are more efficient when working with sequential and temporal data such as text and time series signals. In general, all models of deep learning surpass conventional machine learning algorithms.

Transformers are a new approach that has shown its efficiency when working with linguistic information compared to other machine learning techniques. Contrary

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to sequential models, transformers apply the attention mechanism to learn the correlation among the elements of a sequence. The benefit of the transformer algorithm is that it can work with large data sets and create context-based representations of textual information. It leads to better detection of emotional signs in social media data, thus, outperforming traditional machine learning and deep learning approaches.

Among other solutions, hybrid and ensemble modeling techniques have proven themselves one of the most promising in terms of increasing the efficiency of depression diagnosis systems. The essence of hybrid and ensemble modeling consists in the usage of several algorithms simultaneously with the purpose of utilizing the advantages of each algorithm and overcoming the disadvantages of others. This way, combining traditional machine learning algorithms with deep learning architectures and optimization techniques can lead to a better outcome in terms of choosing relevant features and classification [5], [19]. It is also possible to mention ensemble methods like bagging and boosting, which provide higher stability and generalization capabilities to models.

Another crucial aspect of comparative analysis is the kind of data utilized to train the models. Data obtained from social media can be easily accessed and helps obtain information about the users in real-time. Models trained on social media data are very efficient in detecting linguistic and emotional cues related to depression [14], [21]. These types of data are often characterized by noise, unstructured data, and language/user variability. Clinical data, on the other hand, offer reliable information in a well-defined format but can only be obtained in small amounts due to privacy issues [3], [4].

Physiological data are an objective source for depression detection as they are based on EEG signals. Deep learning models trained using physiological data can detect neurological patterns related to depressive states with high efficiency [9], [10]. Comparative research indicates that EEG-based models are excellent in terms of diagnosis of depression, but their practical application is difficult because of the necessity to conduct the experiments in a laboratory equipped with special apparatus. Models based on speech data, which capture characteristics such as tone and pitch of the voice, have proven to be useful in detecting depression, but they are prone to noise [22].

Models employing multimodal methods, using various data sources including text, speech, and physiological data, have achieved the best outcomes in modern research. This type of approach allows for a more thorough analysis of the user's mental state since multiple data sources are employed. The comparative analysis has shown that models using multimodal methods demonstrate better performance and reliability compared to models relying on one type of data source because of the greater variety of factors affecting individuals with depression [9], [20], [10]. Such an approach presents difficulties associated with data processing and synchronization.

Nevertheless, while the models' performance has been significantly improved, certain challenges still persist for each of them. First, there is a significant problem of class imbalance caused by the large number of non-depressed individuals among the total samples used to train models. Also, due to the limited amount of training data available, especially concerning the clinical and physiological aspects of depression [5], the generalization capability of the models is considerably lower. Differences in language, culture, and user behavior represent another challenge.

The second key issue in comparative analysis is model interpretability. Deep learning and transformer models show higher performance compared to other models, but they work like black boxes, meaning that it is hard to grasp the inner workings of the algorithm. It becomes especially problematic when applied in healthcare, where the interpretability of the algorithm is crucial for its acceptance by medical practitioners [11], [20]. However, traditional ML models provide greater interpretability but lower performance.

Finally, computational complexity should be taken into account. Models like deep learning and transformers are quite sophisticated and, therefore, consume many computational resources. Hence, they cannot always be deployed in resource-limited settings. However, simpler models do not consume as much computational power but might fail to reach the required performance levels [7].

Overall, a comparative study on machine learning models used for depression detection reveals that no model fits all situations, and none can be considered universal. Machine learning models are ideal for structured data and produce understandable results; meanwhile, deep learning and transformer models have proven their excellence in dealing with complex and unstructured data. Hybrid and multimodal models appear to be the most effective way forward, due to combining the benefits of different approaches and types of data. Nevertheless, issues such as low-quality data, privacy concerns, explain ability, and high cost of implementation should be resolved.

Table 1: Comparative Analysis of Selected Studies

Study	Technique Used	Data Type	Key Features	Accuracy (%)	Remarks
Smys& Raj [1]	Deep Learning Models	Social Media	Textual feature extraction, sentiment analysis	85–90	Better than traditional ML for text data
Sarkar et al. [2]	CNN	EEG Signals	Brain signal analysis	88–92	Effective for clinical diagnosis
Pinto & Parente [3]	ML + Hybrid	Mixed Data	Feature selection, ensemble learning	89–93	Hybrid improves performance
Tahir et al. [4]	ML & DL	Social Media	NLP-based analysis	87–91	Good for real-time monitoring
Aleem et al. [6]	SVM, RF, NB	Structured Data	Statistical features	80–88	Simple but less effective for complex data
Bokolo& Liu [7]	Transformer Models	Social Media	Context-aware embeddings	90–94	High accuracy and scalability
Hasib et al. [8]	ML & DL	Mixed Data	Multi-feature learning	86–92	Handles diverse datasets
Thekkekara et al. [13]	CNN-BiLSTM	Text Data	Attention mechanism	91–95	Captures sequential patterns well
Tejaswini et al. [22]	Hybrid DL Model	Social Media	NLP + Deep learning	92–96	Best overall performance
Das & Naskar [27]	CNN	Audio/Speech	MFCC features	87–91	Effective for speech-based detection

CHALLENGES

Nevertheless, despite the fast development of machine learning and deep learning methods applied to depression detection, there remain several significant problems that limit the efficacy of their use and prevent them from practical applications. To tackle these limitations, one must focus on various issues associated with data collection, ethics, performance of models, and other aspects.One of the key problems in the area concerns the problem of collecting datasets and the quality thereof. It is well known that machine learning algorithms require huge amounts of high-quality labeled data to yield satisfactory results. But in the case of depression detection, it is hard to collect a large number of samples because of the private nature of patients' mental health information [9], [4]. In clinical cases, the data collected by experts is not only costly but also limited in number, making its use rather problematic. The same issue emerges with physiological data such as EEG signals [3], [10].Another important challenge is that of class imbalance, which arises from the fact that there are far more non-depressive than depressive samples in many datasets. Such imbalance leads to the creation of biased models that will predict that the sample does not suffer from depression regardless of the actual case [11]. Despite some suggestions that aim at solving this challenge through methods such as undersampling, oversampling, or even data augmentation, balancing the data still proves challenging.Another very important aspect related to the detection of depression using machine learning algorithms concerns the diversity of datasets. Each individual, culture, or setting in which depression is experienced has its own set of symptoms, making generalizing between these groups challenging. For example, there is variation in languages and writing styles between datasets, thus leading to different outcomes [20]. The same challenge exists when considering the development of multilingual and cross-cultural depression detection systems.

The presence of noise and ambiguity in the data sets used in the detection process poses yet another obstacle to developing efficient depression detection models. Social media posts are often filled with slang words, acronyms, sarcastic comments, and incomplete information, making it difficult for machine learning models to understand the emotions experienced by users [14], [16]. In addition, all the negative emotions expressed through social media posts do not necessarily suggest that a person suffers from depression.Data security, privacy, and ethical concerns related to the use of such data for the development of models for detecting depression should be considered an important issue in this matter. Depression detection algorithms require personal data to make their predictions. This personal data can include the information gathered from a patient's social media accounts or other personal devices. Data confidentiality is a critical aspect of such research due to ethical considerations [11], [12].The non-interpretable nature of sophisticated artificial intelligence algorithms is another constraint. The high precision provided by deep learning and transformer algorithms is accompanied by the non-transparency of the decision-making process. The absence of transparency makes it challenging to use these tools within the healthcare sector since all decisions should be understandable [11], [20]. Although Explainable Artificial Intelligence (XAI) research helps resolve the issue, there is a need to find an optimal solution that combines accuracy and transparency.

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Another key drawback is related to the algorithm's complexity and resource costs. The training process of deep learning and transformer algorithms requires significant computation power, memory resources, and time. As a result, it becomes challenging to implement such models in practice, especially when using smartphones and other portable gadgets or in remote locations with limited access to infrastructure [7]. On the other hand, less complex models are less resource-intensive but less accurate.Feature extraction and selection pose difficulties as well, especially when one is working with high-dimensional and multimodal data. Finding appropriate features in textual, speech, and physiological data needs adequate pre-processing and specialized knowledge. Insufficient feature extraction may negatively impact modeling results and cause overfitting [15]. Besides, multimodal integration complicates the process of feature usage in modeling by introducing the task of synchronizing data from multiple sources [20].

The problem of weak generalization capabilities is also highly important. There have been many instances of successful models for specific datasets that failed when used for other datasets [5]. This phenomenon happens because the model overfits its training dataset, learning some characteristics that are unique to the dataset itself and not generally applicable.

Moreover, real-time deployment and scalability present further hurdles. Although many algorithms achieve impressive results in experimental environments, their application in practical contexts involves dealing with big data, low-latency requirements, and robustness. For instance, social media sites produce huge amounts of information on a continuous basis, making real-time processing very resource-intensive [21].

Lastly, benchmarking and evaluation concerns are also a factor that influences the credibility of depression detection tools. Various academic papers utilize distinct datasets, measures, and experimental conditions, complicating comparisons between different works. The absence of standard benchmarks poses significant difficulties in assessing the actual value of various algorithms and methods.

In conclusion, despite the promising results achieved by machine learning and deep learning methods in depression identification, there are still several problems that need to be overcome. Data availability, privacy, interpretability, and computational demands are some of the key issues that should be considered when designing and implementing such systems.

FUTURE SCOPE

Future directions of depression detection research are oriented towards increasing model accuracy, explain ability, and practicality. The implementation of Explainable Artificial Intelligence (XAI) can ensure the transparency and reliability of decision-making of the model, making it clinically useful. Maintaining the privacy of data is also very important considering its sensitive nature. Multimodality, which involves using data such as text, speech, and physiological data, will lead to better prediction performance. Improvements in the performance of models based on transformers as well as personalized systems will also improve predictions related to detecting depression.

CONCLUSION

Depression is a serious worldwide problem that affects people's mental well-being, thoughts, and social life; moreover, there is an increase in the number of patients, especially among students. Due to the limitations of traditional approaches to detecting depression because of the necessity to involve health practitioners and the time-consuming process, it is essential to develop more effective methods such as machine learning algorithms. This paper provides a review of different methods of identifying depression, including traditional machine learning, deep learning, transformer-based approaches, and hybrid models. For structured data, traditional models such as SVM and decision tree provide reliable results, while convolution neural network, recurrent neural network, and long short-term memory are used when it comes to unstructured data. Besides, transformer-based algorithms can achieve higher accuracy by analyzing the context of speech. In this case, it is also important to use different types of datasets such as social media data, clinical information, and electroencephalographic data, but some problems, including data privacy issues, the presence of class imbalance, small number of labeled samples, and insufficient interpretability remain relevant.

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