



IJRTSM

INTERNATIONAL JOURNAL OF RECENT TECHNOLOGY SCIENCE & MANAGEMENT

“A FREQUENCY ANALYSIS AUGMENTED DEEP LEARNING MODEL FOR DEPRESSION”

Sonali Parmar ¹, Dr. Sanmati Jain ²

¹⁻² Department of Computer Science Engineering, VITM, Indore, Madhya Pradesh, India

ABSTRACT

Despite the prevalence of depression, it often goes undiagnosed or is misdiagnosed due to social stigma, limited access to healthcare, and the subjective nature of traditional diagnostic methods. This highlights the urgent need for innovative and objective tools to identify depression early and accurately. Therefore, it is necessary to develop machine learning based automated filters for detecting texts aligning towards depression. Most existing machine learning and deep learning approaches are prone to limitations such as Fixed Weight Assignment, Bias towards Longer Text Strings and difficulty in finding long-range dependencies and contextual information. The proposed approach entails combining frequency analysis with a neural network model trained with Conjugate Gradient Back-propagation with Fletcher-Reeves Restarts. The approach attains a classification accuracy of 95.2% outperforming existing work in the domain.

Key Words: Depression Detection, Machine Learning, Deep Learning, Tokenization, Frequency Analysis, Conjugate Gradient Back-propagation, Classification Accuracy.

I. INTRODUCTION

Conventional diagnostic approaches mainly depend on clinical interviews and self-reported questionnaires, which are often expensive, time-consuming, and limited by the reluctance of individuals to seek professional help. Machine Learning and Deep Learning models have numerous applications in depression detection and mental healthcare. They can be used for early identification of individuals exhibiting depressive symptoms by analyzing textual content, posting frequency, user interactions, and sentiment patterns [1]. Such systems assist healthcare professionals in screening large populations and prioritizing high-risk individuals for further evaluation. Social media-based depression detection can also support personalized treatment plans by monitoring changes in emotional states over time. Furthermore, these intelligent systems can be integrated into mental health chatbots, telemedicine platforms, and mobile applications to provide continuous psychological support and recommendations [2].

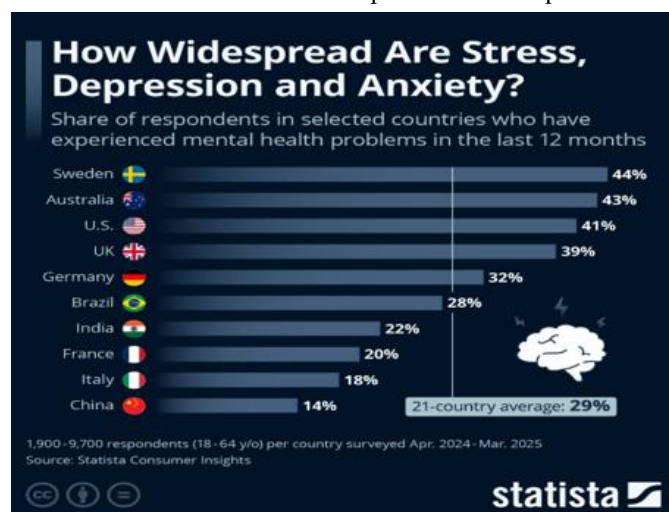


Fig.1. Country wide Depression Statistics

(Source: <https://www.statista.com/chart/24978/share-of-respondents-having-experienced-mental-health-problems->

<https://www.ijrtsm.com> © International Journal of Recent Technology Science & Management

during-the-past-year/)

Public health organizations can utilize aggregated information from these models to understand mental health trends and formulate appropriate awareness programs and intervention strategies [3].

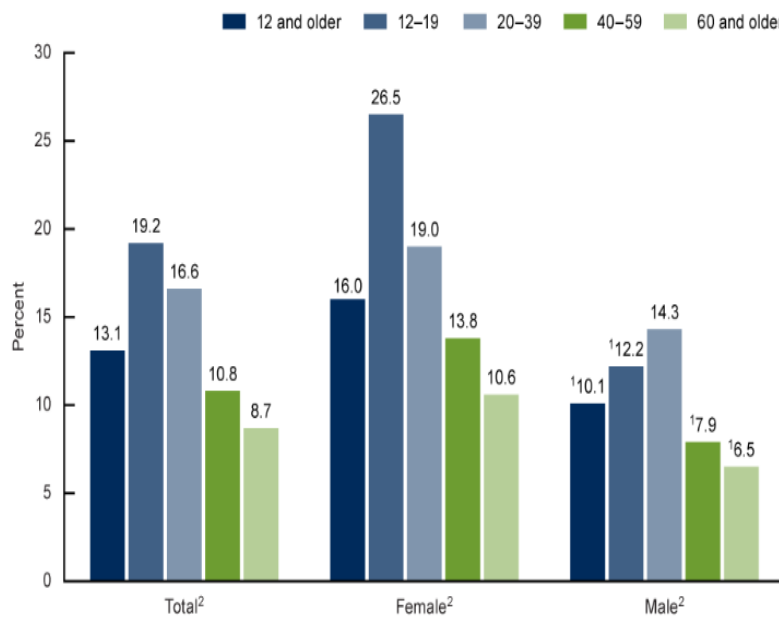


Fig.2 Gender wise depression statistics

(Source: <https://www.cdc.gov/nchs/products/databriefs/db527.htm>)

Displacement is a psychologically stressful event. The displaced individuals may be subject to stressful events such as torture, rape, assassination, and even ethnic cleansing in their home countries and throughout their journey. Displaced survivors who experienced multiple war events perceived multiple negative effects of war on their life domains related to individuals who lived in war areas. Considering the effects, displacement may be accepted as a public health problem and a type of disaster, as it may lead to loss of resources, economic uncertainty, absence of health services and education, insouciant compensation for fundamental human requirements, and disintegration of public structure [4]

Women were more likely than men to experience symptoms of depression across all severity levels. While there was no significant trend by age among adults experiencing severe symptoms of depression, adults aged 18–29 and those aged 65 and over were most likely to experience mild symptoms of depression. A higher percentage of adults aged 45–64 experienced moderate symptoms of depression compared with those aged 30–44 and 65 and over. Adults aged 18–29 were as likely to experience moderate symptoms of depression as those aged 45–64, but the observed differences with the other age groups were not significant. Non-Hispanic white and non-Hispanic black adults were most likely to experience mild symptoms of depression, compared with Hispanic and non-Hispanic Asian adults. Non-Hispanic Asian adults were least likely to experience mild, moderate, or severe symptoms of depression, compared with Hispanic, non-Hispanic white, and non-Hispanic black adults [5].

II. ROLE OF ML & DEEP LEARNING MODELS FOR DEPRESSION DETECTION

Various Machine Learning and Deep Learning models have been proposed for depression detection from social media data. Traditional Machine Learning approaches such as Logistic Regression, Naïve Bayes, Decision Trees, Support Vector Machines (SVM), Random Forests, and Gradient Boosting algorithms rely on handcrafted features extracted from text, including term frequency, sentiment scores, and linguistic characteristics [6]. Although these methods have demonstrated satisfactory performance, their effectiveness is highly dependent on feature engineering [7]. Recent advancements in Deep Learning have significantly improved detection accuracy through automatic feature extraction. Models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term

<https://www.ijrtsm.com> © International Journal of Recent Technology Science & Management

Memory (LSTM) networks, Bidirectional LSTMs, Gated Recurrent Units (GRUs), and attention-based architectures have been extensively employed for sequential text analysis. More recently, transformer-based models including BERT, RoBERTa, DistilBERT, XLNet, and GPT-based frameworks have achieved state-of-the-art results by capturing contextual and semantic relationships within textual data. Hybrid models combining deep neural networks with sentiment analysis and psychological features have further enhanced prediction performance [8].

Despite their promising capabilities, Machine Learning and Deep Learning models for depression detection face several challenges. Social media data are highly unstructured, noisy, and characterized by slang, abbreviations, emojis, and multilingual expressions, making feature extraction and interpretation difficult. The availability of labeled datasets is limited, and class imbalance often affects model performance. Privacy and ethical concerns represent another significant challenge, as the analysis of personal social media content raises issues related to user consent and data security. Moreover, depression manifests differently across individuals and cultures, making generalization across diverse populations difficult [9]. Deep Learning models also require large datasets and substantial computational resources for training. Another important challenge is the lack of explainability in complex neural networks, which limits their acceptance in clinical environments where transparency and interpretability are essential. Therefore, future research should focus on developing explainable, privacy-preserving, and multimodal frameworks capable of accurately detecting depression while ensuring ethical and reliable deployment [10].

III. CRITICAL RESEARCH GAPS

This section presents the noteworthy contribution in the domain of research.

Thekkekara et al. [11] proposed a deep learning architecture with an attention mechanism on CNN-BiLSTM (CBA) and provide a comparative analysis to benchmark well-known deep learning models using the public dataset namely CLEF2017. Authors found that along with F1 score, precision and recall it is also vital to consider the Area under the curve - Receiver operating characteristic curve (AUC-ROC) and Mathews Correlation Coefficient (MCC) metrics for evaluating depression classification models since the MCC considers all the four values of a confusion matrix. Based on our experiments, the CBA model outperforms the existing state of the art model with an overall accuracy of 96.71% and scores of 0.85 and 0.77 for AUC-ROC and MCC, respectively.

Marriwala et al. [12] proposed the CNN and bi-LSTM models separately for depression detection. It is also observed that Bi-LSTM has better learning rate as compared to other models with accuracy 88% and validation accuracy 78%. There are some parameters such as precision, F1-score, recall and support are found for evaluation of models. In results, graphs for training loss, validation loss, training accuracy and validation accuracy are plotted. At last, by using confusion matrix depression can be detected for textual CNN Model, audio CNN model, LSTM model and Bi-LSTM against true label and predicted label.

Uddin et al. [13] employed recurrent neural networks, particularly LSTM models, to identify depressive symptoms from large-scale social media text. Their model achieved an accuracy of 84.2% and an F1-score of 0.83, demonstrating the ability of sequential deep learning models to capture long-term linguistic dependencies.

Trotzek et al. [14] analyzed Reddit posts using CNN and LSTM architectures with pretrained word embeddings. Their best-performing CNN model achieved an F1-score of 0.86 and an AUC of 0.88, outperforming traditional machine learning classifiers.

Chiong et al. [15] proposed an ensemble of machine learning classifiers including SVM and Random Forest for depression detection, reporting an accuracy of 79.6% and highlighting the effectiveness of linguistic and sentiment-based features.

Yang et al. [16] utilized BERT-based contextual embeddings for depression classification on Twitter data. Their transformer-based model achieved an accuracy of 87.9% and an AUC of 0.91, showing strong semantic modeling capabilities.

Khan et al. [17] compared classical ML models with deep neural networks on multilingual social media datasets. The BiLSTM model achieved an F1-score of 0.85, significantly outperforming Naïve Bayes and logistic regression.

Shen et al. [18] introduced an attention-based BiLSTM framework that improved interpretability while achieving an accuracy of 88.3% and F1-score of 0.87.

Kumar [19] proposed a hybrid deep learning framework combining CNN and LSTM architectures. The model achieved 89.1% accuracy and an F1-score of 0.88, demonstrating robust feature extraction.

Zhang et al. [20] employed RoBERTa for depression detection and reported an AUC of 0.93 and F1-score of 0.90, highlighting the superiority of transformer-based architectures.

Qasim et al. [21] focused on detecting depression severity levels using transformer models. Their approach achieved a macro F1-score of 0.82 across multiple severity classes.

Kim et al. [22] investigated LLM-derived embeddings for interpretable depression detection, achieving an accuracy of 86.5% and AUC of 0.89.

IV. PROPOSED APPROACH: CONTEXTUAL DEEP LEARNING

The proposed approach is presented next. One of the major challenges in contextual semantic analysis for depression detection is the contextual analysis of data. The different aspects are discussed subsequently:

2.1 Contextual Analysis

It is often difficult to estimate the context in which the statements are made. Words in textual data such as tweets can be used in different contexts leading to completely divergent meanings [23].

2.2 Frequency Analysis

Often words in textual data (for example tweets) are repeated such as

##I feel so so so happy today!!

In this case, the repetition of the word is used to emphasize upon the importance of the word. In other words, it increases to its weight. However, such rules are not explicit and do not follow any regular mathematical formulation because of which it is often difficult to get to the actuality of the tweet.

2.3 Converting textual data into numerically weighted data

The biggest challenge in using an neural network based classifier is the fact that the any deep learning structure with a training algorithm doesn't work upon textual data directly to find some pattern. It needs to be fed with numerical substitutes. Hence it becomes mandatory to replace the textual information with numerical information so as to facilitate the learning process of the neural network [24].

The system requires training for the given categories [9]. Subsequently, the neural network model needs to act as an effective classifier. The major challenges here the fact that sentiment relevant data vary significantly in their parameter values due to the fact that the parameters for each building is different and hence it becomes extremely difficult for the designed neural network to find a relation among such highly fluctuating parameters. Generally, the Artificial Neural Networks model's accuracy depends on the training phase to solve new problems, since the Artificial Neural Networks is an information processing paradigm that learns from its environment to adjust its weights through an iterative process [25].

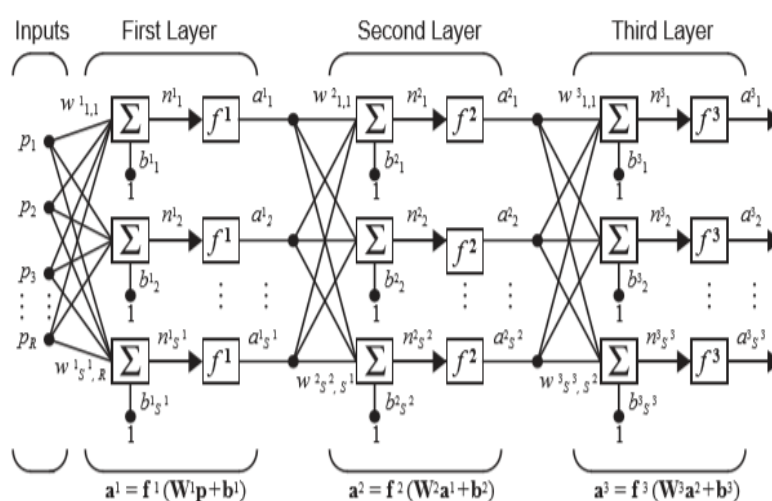


Fig.3 The deep learning structure

The deep learning structure is depicted in figure 3 and it is basically a cascade of stacked neural networks. Multiple hidden layers facilitate the analysis of complex data [26].

Deep learning models do have the capability to extract meaning from large and verbose datasets by finding patterns between the inputs and targets. Since neural nets directly process numeric data sets, the processing of data is done prior to training a neural network. The texts are first split into training and testing data samples in the ratio of 70:30 for training and testing. Further, a data vector containing known and commonly repeated spam and ham words is prepared. Text normalization is followed by removal of special characters and punctuation marks. The cascading weight flow is presented as [27]:

$$a^n = \varphi_n(\varphi_{n-1} \dots \dots \varphi_1\{wp + b\}) \quad (1)$$

Here,

W is the weight

b is the bias

a is the input to the final nth layer

ϕ is the activation function

The proposed approach is mathematically modelled as:

The prepared data vector for training is used for training wherein the weights are initialized randomly. A stepwise implementation is done as:

1. Prepare two arrays, one is input and hidden unit and the second is output unit.

Here, a two dimensional array W_{ij} is used as the weight updating vector and output is a one dimensional array Y_i .

3. Original weights are random values put inside the arrays after that the output [28]

$$x_j = \sum_{i=0} y_i W_{ij} \quad (2)$$

Where,

y_i is the activity level of the j^{th} unit in the previous layer and

W_{ij} is the weight of the connection between the i^{th} and the j^{th} unit.

4. Next, activation is invoked by the sigmoid function applied to the total weighted input.

$$y_i = \left[\frac{e^x - e^{-x}}{e^x + e^{-x}} \right] \quad (3)$$

Summing all the output units have been determined, the network calculates the error (E).

$$E = \frac{1}{2} \sum_i (y_i - d_i)^2 \quad (4)$$

Where, y_i is the event level of the j^{th} unit in the top layer and d_i is the preferred output of the j_i unit.

Implementing Back Prop:

Calculation of error for the back propagation algorithm is as follows:

Error Derivative (EA_j) is the modification among the real and desired target [29]:

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j \quad (5)$$

Here,

E represents the error

y represents the Target vector
 d represents the predicted output

Error Variations is total input received by an output changed given by:

$$EI_j = \frac{\partial E}{\partial X_j} = \frac{\partial E}{\partial y_j} X \frac{dy_j}{dx_j} = EA_j y_j (1 - y_i) \quad (6)$$

Here,

E is the error vector

X is the input vector for training the neural network

In Error Fluctuations calculation connection into output unit is computed as:

$$EW_{ij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial X_j} = \frac{\partial X_j}{\partial W_{ij}} = EI_j y_i \quad (7)$$

Here,

W represents the weights

I represents the Identity matrix

I and j represent the two dimensional weight vector indices

Overall Influence of the error:

$$EA_i = \frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial x_j} X \frac{\partial x_j}{\partial y_i} = \sum_j EI_j W_{ij} \quad (8)$$

The partial derivative of the Error with respect to the weight represents the error swing for the system while training. The gradient is computed as:

$$g = \frac{\partial e}{\partial w} \quad (9)$$

Here,

g represents the gradient

e represents the error of each iteration

w represents the weights.

The training algorithm for the proposed work is the Conjugate Gradient Back-propagation with Fletcher-Reeves Restarts. This algorithm is based on the concept of feeding back the errors to the neural network i.e. back propagation. The salient feature of the algorithm is its relatively low time complexity and accuracy. The reason for the mentioned phenomena is the fact that the algorithm searches for the direction for the steepest direction right from the first iteration. Mathematically,

$$p_0 = -g_0 \quad (10)$$

Here,

p_0 is the negative of the gradient vector g_0

For the k^{th} iteration [30]:

$$p_k = -g_k + \Theta_k p_{k-1} \quad (11)$$

It is worth noting that the in addition to the weights, the search vector also keeps updating with the iterations. The term Θ_k is calculated as:

$$\Theta_k = \frac{g_k g_k^T}{g_{k-1} g_{k-1}^T} \quad (12)$$

The overall training rule for the algorithm can be mathematically expressed as:

$$w_{k+1} = w_k + \beta_k p_k \quad (9)$$

The Conjugate Gradient Back-propagation algorithm, particularly with Fletcher-Reeves restarts, is a powerful optimization method used in machine learning and neural network training. Combining the efficiency of the conjugate gradient method with restart mechanisms provides numerous advantages over traditional back-propagation and other gradient-based optimization techniques. These advantages contribute to improved convergence rates, computational efficiency, and robustness, making it a preferred choice in many machine learning tasks.

One of the primary advantages of the Conjugate Gradient Back-propagation with Fletcher-Reeves restarts is its ability to achieve faster convergence compared to standard gradient descent. The conjugate gradient method uses information about previous search directions to construct conjugate directions, ensuring that successive iterations do not undo previous progress. This efficiency often results in fewer iterations to reach the optimal solution, which is particularly valuable for training deep neural networks with a large number of parameters. The additional metric computed in this approach is the term and inverse-term frequency. The term frequency measures how frequently a term t appears in a tweet d . The basic formula is:

$$TF(t, d) = \frac{f_{t,d}}{\sum f_{k,d}} \quad (10)$$

Where:

$f_{t,d}$: Frequency of term t in tweet d

$\sum f_{k,d}$: Total number of terms in tweet d

This approach not only computes the term frequency but also the group frequency as the additional metric **GF** for group of words. The classification accuracy is measured based on:

1. **True Positive (TP)**: It is indicative of the true or correct cases of the data to be in a particular class.
2. **True Negative (TN)**: It is indicative of the true or correct cases of the data not to be in a particular class.
3. **False Positive (FP)**: It is indicative of the false or incorrect cases of the data to be in a particular class.
4. **False Negative (FN)**: It is indicative of the false or incorrect cases of the data not to be in a particular class.

Accuracy (Ac): It is an indicative of the accuracy of classification of the algorithm for data classification. Mathematically its defined as:

$$A_c = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

Higher classification accuracy is desirable for practical utility of a model.

V. EXPERIMENTAL RESULTS

The experimental results are presented next:

The system has been implemented on MATLAB.

Data Normalization: Canonization (normalization) of the text is the process of bringing to a single format, convenient for further processing. When working with large amount of information, it is necessary to exclude from the document all non-informative parts of speech (prepositions, particles, conjunctions, etc.). Subsequently both term and group frequencies are computed and fed to the neural network model for training. The results obtained are presented next:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1		your	late	see	offensive	get	her	does	tweet														
2	2	0	3	0	0	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3	3	1	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	4	2	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
5	5	3	3	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
6	6	4	6	0	5	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
7	7	5	3	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
8	8	6	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
9	9	7	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
10	10	8	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
11	11	9	3	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
12	12	10	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
13	13	11	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
14	14	12	3	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
15	15	13	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
16	16	14	3	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
17	17	15	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
18	18	16	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
19	19	17	3	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
20	20	18	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
21	21	19	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
22	22	20	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
23	23	21	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
24	24	22	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
25	25	23	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
26	26	24	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27	27	25	3	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
28	28	26	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
29	29	27	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	30	28	3	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Fig.4 Raw Data

Figure 4 renders a sample screenshot of the raw data, which is imported as strings to the MATLAB workspace.

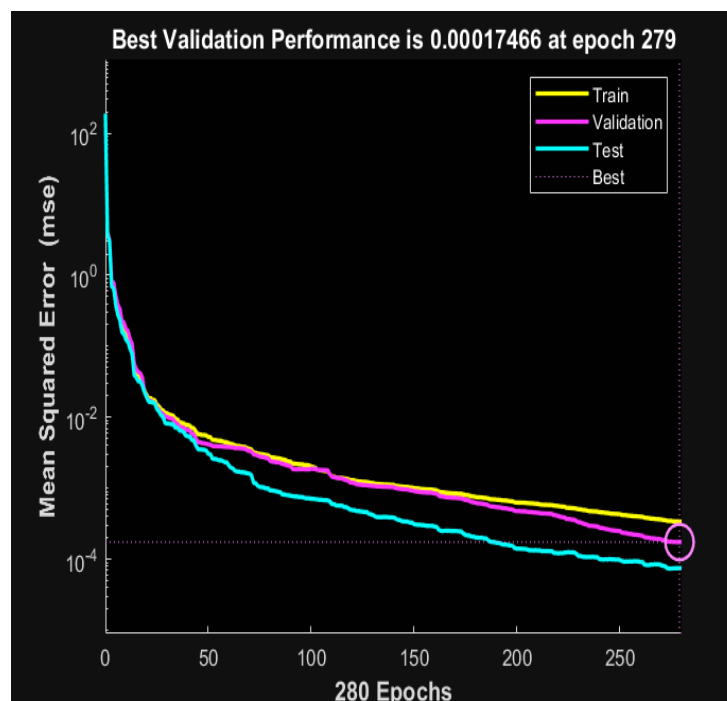


Fig.5 Variation of MSE

The variation of the mean squared error as a function of the number of epochs is shown in the above figure. It can be seen that the MSE after 279 iterations, after which the training is stopped.

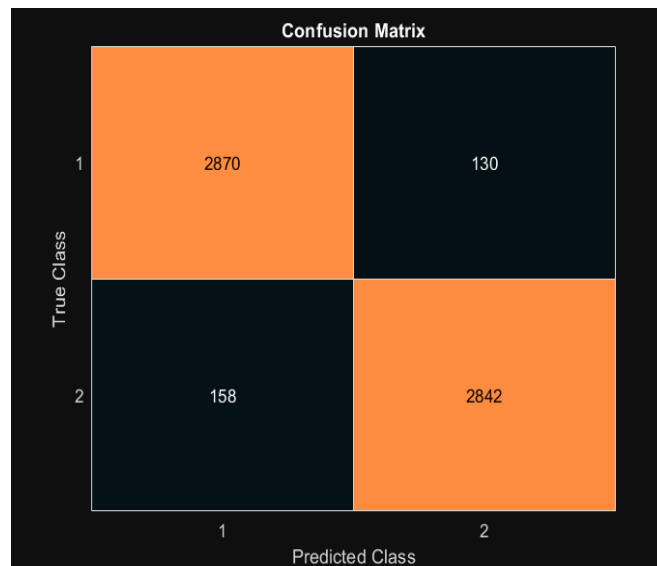
**Fig.6 Confusion Matrix**

Figure 1 depicts the confusion matrix for the proposed work. It can be observed that the proposed work attains a classification accuracy of around 95.2% which is significantly higher than that of previous work Thekkekara et al. [31] which is around 78.11%.

The classification accuracy is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Substituting values, the accuracy is 95.2%.

Table 1. Summary of Results

Parameter	Value
ML category	Deep Learning
Iterations	279
Error	0.00017466
Accuracy (Proposed Work)	95.2%
Accuracy (Previous Work)	78% CNN 71% Bi-LSTM

A summary of results is presented in Table 1 which clearly indicates the superior performance of the proposed approach compared to existing work in the domain.

VI. CONCLUSION

It can be concluded that the growing prevalence of depression and the widespread use of social media have created an urgent need for intelligent and automated depression detection systems. Machine Learning and Deep Learning models offer significant advantages in extracting meaningful patterns from large volumes of social media data, enabling early diagnosis and continuous mental health monitoring. Although considerable progress has been achieved through advanced neural architectures and transformer-based models, challenges related to data quality, privacy, interpretability, and model generalization remain unresolved. Addressing these issues will pave the way for more reliable and ethically responsible systems that can assist healthcare professionals and contribute to improved mental health outcomes. The deep learning model presented in this work is shown to attain improved classification accuracy compared to existing work in the domain of research.

REFERENCES

- [1] C. Nash, R. Nair and S. M. Naqvi, "Machine Learning in ADHD and Depression Mental Health Diagnosis: A Survey," in IEEE Access, vol. 11, pp. 86297-86317, 2023.
- [2] A. Gupta, M. Sharma, and S. Kumar, "Depression Detection in Social Media: A Comprehensive Review of Machine Learning and Deep Learning Techniques," IEEE Access, vol. 13, pp. 12789-12815, Jan. 2025.
- [3] T. Siddiqui and A. Pandey, "A Comparative Study of Deep Learning Methods for Depression Detection in Social Media Data," Journal of Artificial Intelligence Research & Advances, vol. 12, no. 2, pp. 88-102, July 2025.
- [4] R. Chiong, G. S. Budhi, and S. Dhakal, "A textual-based featuring approach for depression detection using machine Learning classifiers and social media texts," Comput. Biol. Med., vol. 135, Aug. 2021.
- [5] B. Das, "An automated system of sentiment analysis from Bangla text using supervised learning techniques," in Proc. 4th IEEE Int. Conf. Comput. Commun. Syst. (ICCCS), 2019, pp. 43–47.
- [6] S. J. Pan et al., "Understanding emotions in text using deep Learning and big data," Comput. Hum. Behav., vol. 93, pp. 15–25, 2019.
- [7] H. S. Alsagri and M. Ykhlef, "Machine Learning-based Approach for Depression Detection in Twitter Using Content and Activity Features," IEICE Trans. Inf. Syst., vol. E103-D, no. 8, pp. 1825–1832, 2020.
- [8] A. S. Sabitha, N. J. Gupta, and A. S. Shukla, "Predicting anxiety, depression and stress in modern life using machine Learning algorithms," Procedia Comput. Sci., vol. 173, pp. 333–342, 2020.
- [9] M. M. Tadesse, H. Lin, and B. Xu, "Detection of Depression-Related Posts from Social Media Using Machine Learning," IEEE Access, vol. 8, pp. 225346–225358, 2020.
- [10] K. S. Kumar, G. Geetha, and K. S. Sankaran, "Depression Detection in Social Media using Machine Learning Techniques," in Proc. Int. Conf. Adv. Comput. Commun. Syst. (ICACCS), 2021.
- [11] JP Thekkekara, S Yongchareon, V Liesaputr., "An attention-based CNN-BiLSTM model for depression detection on social media text," Expert Systems with Applications, Elsevier 2024, vol.249, 123834
- [12] N Marriwala, D Chaudhary, "A hybrid model for depression detection using deep learning," Measurement: Sensors, Elsevier 2023, vol.25, 100587.
- [13] M. Z. Uddin, M. M. Hassan, A. Alsanad, and A. Alqurashi, "A deep learning-based early warning system for depression detection using social media text," Neural Computing and Applications, vol. 34, no. 2, pp. 721–744, 2021.
- [14] M. Trotzek, S. Koitka, and C. M. Friedrich, "Utilizing neural networks and linguistic metadata for early detection of depression indications in text sequences," IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 3, pp. 588–601, 2021.
- [15] Y. Chiong, L. Budhi, and D. B. Pham, "Depression detection using sentiment and linguistic features from social media," Expert Systems with Applications, vol. 186, p. 115759, 2022.
- [16] Y. Yang, J. Liu, K. Zhang, and Y. Wang, "Depression detection on social media using BERT-based deep learning," IEEE Access, vol. 10, pp. 18432–18443, 2022.

- [17] S. Khan, A. Hussain, and M. Afzal, "Comparative analysis of machine learning and deep learning techniques for depression detection on multilingual social media data," *Computers in Biology and Medicine*, vol. 151, p. 106236, 2023.
- [18] L. Shen, J. Chen, and X. Liu, "Attention-based BiLSTM for depression detection from social media text," *Information Processing & Management*, vol. 60, no. 1, p. 102912, 2023.
- [19] T. S. Kumar, "A hybrid deep learning framework for automatic depression detection from social media posts," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 4, pp. 3217–3231, 2024.
- [20] Z. Zhang, H. Wang, and Y. Liu, "Depression detection from social media text using RoBERTa," *IEEE Access*, vol. 12, pp. 44115–44127, 2024.
- [21] A. Qasim, G. Mehak, N. Hussain, A. Gelbukh, and G. Sidorov, "Detection of depression severity in social media text using transformer-based models," *Information*, vol. 16, no. 2, p. 114, 2025.
- [22] S. Kim, O. Imieye, and Y. Yin, "Interpretable depression detection from social media text using large language model embeddings," *arXiv preprint arXiv:2506.06616*, 2025.
- [23] S. Ghosh and T. Anwar, "Depression Intensity Estimation via Social Media: A Deep Learning Approach," *IEEE Transactions on Computational Social Systems*, vol. 8, no. 6, pp. 1465–1474, Dec. 2021.
- [24] L. Ansari, S. Ji, Q. Chen, and E. Cambria, "Ensemble Hybrid Learning Methods for Automated Depression Detection," *IEEE Transactions on Computational Social Systems*, vol. 10, no. 1, pp. 211–219, Feb. 2023.
- [25] H. Zogan, I. Razzak, S. Jameel, and G. Xu, "Hierarchical Convolutional Attention Network for Depression Detection on Social Media and Its Impact During Pandemic," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 4, pp. 1815–1823, Apr. 2022.
- [26] M. A. Abbas, K. Munir, A. Raza, N. Abdelsamee, M. M. Jamjoom, and Z. Ullah, "Novel Transformer Based Contextualized Embedding and Probabilistic Features for Depression Detection From Social Media," *IEEE Access*, vol. 12, pp. 1–14, 2023.
- [27] X. Cao and L. Q. Zakaria, "Integrating BERT With CNN and BiLSTM for Explainable Detection of Depression in Social Media Contents," *IEEE Access*, vol. 12, pp. 1–15, 2024.
- [28] A. Raj, A. Sharma, Z. Ali, S. Chaudhary, and K. K. Bali, "Depression Detection Using BERT on Social Media Platforms," in *Proc. 2024 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAET)*, 2024, pp. 1–6.
- [29] Sharma, P. Gupta, and R. Singh, "Computational Psychiatry: Leveraging Deep Learning for Depression Detection in Social Media Text Analysis," in *Proc. 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2024, pp. 1–6.
- [30] Z. Sabir, S. Khansa, G. Baltaji, T. Saeed, "A Bayesian regularization neural network procedure to solve the language learning system", *Knowledge-Based Systems*, Elsevier 2025, vol.310, 112997.
- [31] JP Thekkekkara, S Yongchareon, V Liesaputr., " An attention-based CNN-BiLSTM model for depression detection on social media text," *Expert Systems with Applications*, Elsevier 2024, vol.249, 123834.