International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 4 (2026)



ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
© 2026 IJERST. All Rights Reserved
Peer Reviewed, Referred & Indexed Journal

Research Paper

AN EXPLAINABLE NLP-BASED FRAMEWORK FOR DETECTING DEPRESSION IN SOCIAL MEDIA CONTENT

Madeeha Fatima[1], Dr. Muhammed Pasha[2]
[1]PG Scholar, Department of AI & DS, Shadan Women's College of Engineering and Technology, Hyderabad
madeehafatima0208@gmail.com
[2]Professor, Department of CSE, Shadan Women's College of Engineering and Technology, Hyderabad
muhammed.pasha@gmail.com

ABSTRACT

Social media's extensive usage offers useful information for tracking mental health in real time, especially when it comes to spotting depressive symptoms in user-generated content. This research uses the sequential modeling capabilities of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are used in this research to present a deep learning-based method for depression identification. The preprocessing pipeline incorporates emoji normalization, slang substitution using a custom vocabulary, and the extraction of emotion scores to improve semantic understanding in order to meet the difficulties presented by informal language. Annotated social media posts are used to train the hybrid LSTM-GRU model, which successfully identifies contextual and emotional patterns in the text. According to evaluation parameters including accuracy, precision, recall, and F1-score, experimental results demonstrate good performance. This architecture shows how LSTM and GRU may be combined to identify depression in noisy and emotionally complex social media contexts in a lightweight and efficient manner.

1. INTRODUCTION

In today's digitally linked society, mental health illnesses, especially depression, are becoming more and more of a concern. Because social media platforms are so widely used, people frequently utilize them to directly or indirectly share their ideas, feelings, and challenges. Researchers and developers now have the chance to use social media as a data source for identifying early indicators of depression. The lack of real-time monitoring, stigma, and accessibility are the main drawbacks of conventional diagnostic techniques. In this regard, a scalable, non-intrusive, and continuous method of supporting mental health evaluation is provided via automated depression identification using Natural Language Processing (NLP) and deep learning algorithms. But interpreting content from social media has special difficulties. Social media vocabulary, which is full of slang, acronyms, emojis, and context-dependent terms, is much less formal than formal writing. It is frequently challenging for conventional machine learning models to correctly comprehend these components. Rich semantic context can be captured by current systems that use transformer-based models, such as BERT combined with BiLSTM, but they have limitations, including high computational cost, long inference time, and decreased interpretability. This study suggests a lightweight yet effective deep learning system that combines Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) to overcome these issues. A unique text pretreatment pipeline that incorporates emoji normalization, slang translation, and emotion score extraction to improve the machine's comprehension of informal language supports this hybrid model. The system successfully analyzes temporal patterns and emotional tone in social media messages by utilizing the sequential learning capabilities of LSTM and GRU. The outcome is a depression detection model that is suitable for use in practical mental health monitoring applications that is accurate, quick, and resource-efficient.

2. EXISTING SYSTEM OF RESEARCH

- Conventional machine learning methods like Support Vector Machines (SVM), Naive Bayes, and Logistic Regression are the mainstays of current social media depression detection systems. To represent text data, these models usually require human feature engineering, such as bag-of-words, TF-IDF scores, or simple sentiment analysis. The deeper emotional and contextual connotations behind informal or ambiguous statements, which are common in social media content, are frequently missed by these methods, even though they can detect some depressive signs.
- Deep learning techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks

(RNNs), particularly BiLSTM (Bidirectional Long Short-Term Memory) architectures, have been adopted by more sophisticated systems. Additionally, some incorporate pretrained language models that provide context-aware word embeddings for enhanced semantic understanding, such as BERT (Bidirectional Encoder Representations from Transformers). These models are less appropriate for real-time or resource-constrained applications due to their higher processing requirements, despite their superior accuracy and resilience.

- Furthermore, preparation measures specifically designed for social media language are often overlooked by existing systems. They have trouble grasping components that contain important emotional indicators, such as slang, emoticons, and acronyms.
- In the absence of emoji normalization or language replacement, these models can misunderstand or disregard important indicators of depression. Because of this, current approaches are still unable to handle the informal, loud, and emotionally complex nature of real-world social media data, even with advances in technology.

Existing System Disadvantages

- High Computational Cost
- Slow Training and Inference Time
- Overfitting Risk on Small Datasets
- Dependency on Pretrained Language Context

3. RELATED WORK

The application of deep learning techniques to identify depression from textual data, especially user-generated content from social media platforms, is thoroughly examined in this work. The authors assess and contrast several neural architectures, such as CNNs and LSTMs, emphasizing how well they can learn contextual and semantic information associated with depressed language. They use embedding techniques and pre-processing tactics to reduce noise in casual online chat and increase detection accuracy. The study contributes to the creation of scalable AI-driven mental health monitoring technologies and highlights the potential of deep learning in detecting minor linguistic patterns linked to mental health disorders. This study uses a hybrid deep learning strategy to predict the severity of depression by integrating prosodic (intonation, rhythm) and semantic (meaning-based) elements in text and audio. The authors create a system that captures both temporal dynamics and local patterns in speech and written data by fusing a Bidirectional LSTM with a Time-Distributed CNN. Their approach outperforms conventional machine learning techniques in terms of accuracy and robustness, exhibiting great dependability in classifying various degrees of depression severity. This dual-feature fusion lays the groundwork for real-time AI-based depression evaluation systems in both clinical and non-clinical settings and offers insightful information on multimodal data interpretation. In order to identify sadness in social media messages, this work presents a hybrid model that combines the contextual power of BERT with the sequential processing strength of BiLSTM and the spatial feature extraction skills of CNN. The main goal is to develop explainable AI (XAI) models with excellent prediction accuracy and interpretability via feature attribution and attention visualization techniques. Experiments on several datasets are shown in the article, showing that their BERT-CNN-BiLSTM framework performs better than current baselines. The influence of using such models in mental health screening applications on society and ethical issues are also covered by the writers. This study looks into the model calibration of transformer-based architectures such as BERT and RoBERTa to improve the accuracy of stress and depression recognition from social media content. Model calibration ensures that the predicted probabilities more closely reflect actual likelihoods in sensitive domains such as mental health. The authors use isotonic regression and temperature scaling to evaluate and adjust model confidence and reduce false positives and negatives. Their results demonstrate significant improvements in prediction reliability and accuracy, highlighting calibration as an important but often overlooked component in the safe use of transformer models in the healthcare AI field. In order to effectively detect depression based on linguistic cues, this study introduces a hybrid deep learning model that blends convolutional layers with bidirectional LSTMs. In order to enhance model performance, the authors stress the significance of feature fusion, which uses both syntactic and semantic information. Real-world social media posts classified with signs of depression are part of the dataset. The hybrid architecture gains from the strength of BiLSTM in representing sequential dependencies and CNN's capacity to extract local n-gram information. The study also covers ethical deployment, potential real-time applications, and future extensions of the technology to multilingual depression. In order to effectively detect depression based on linguistic cues, this study introduces a hybrid deep learning model that blends convolutional layers with bidirectional LSTMs. In order to enhance model performance, the authors stress the significance of feature fusion, which uses both syntactic and semantic information. Real-world social media posts classified with signs of depression are part of the dataset. The hybrid architecture gains from the strength of BiLSTM in representing sequential dependencies and CNN's capacity to extract local n-gram information. The

study also covers ethical deployment, potential real-time applications, and future extensions of the technology to multilingual depression detection.

4. PROPOSED SYSTEM

- By offering a lightweight, effective, and precise deep learning framework for depression identification in social media messages, the suggested method seeks to solve the drawbacks of conventional and transformer-heavy systems. To efficiently capture both long-term and short-term dependencies within textual input, it uses a hybrid deep learning model that blends Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. Because of its architecture, the model can comprehend the emotional shifts and sequential flow in user-generated posts, which are frequently signs of depression.
- The technology uses a powerful text preparation pipeline to improve comprehension of informal and emotionally charged information. This includes slang replacement, which uses a proprietary lexicon to translate frequently used internet acronyms and colloquial expressions into standard language, and emoji normalization, which transforms emojis into their textual meaning. Furthermore, each post's emotional tone is measured using emotion score extraction, giving the model additional variables that aid in spotting minor depressive symptoms that could otherwise go unnoticed.
- The LSTM-GRU model is trained using labeled social media datasets that include posts from both depressed and non-depressed individuals. The model analyzes the sequential data to determine whether or not the content is indicative of sadness after preprocessing and feature enrichment. The suggested approach maintains computational efficiency while achieving great performance in a number of evaluation measures, such as accuracy, precision, recall, and F1-score. Because of this, it is ideal for scalable deployment in mental health monitoring systems, particularly those aimed at mobile or real-time applications.

Proposed System Advantages:

- Lightweight and Computationally Efficient
- Effective Sequential Learning
- Improved Handling of Informal Text
- Reduced Overfitting

5. MODULES

1. Dataset

The dataset, which includes annotated social media posts about depression and control groups, is the basis for this research. This dataset will often be made up of textual data, like tweets or social media comments, that have been labeled to indicate whether or not they contain content connected to depression. To make sure the training and assessment are grounded in accurate and pertinent data, this research makes use of a publicly accessible mental health dataset, such as the Mental Health in Social Media dataset. Ensuring data quality, relevance, and completeness for later stages is the main goal of this module.

2. Analyzing

Exploratory data analysis (EDA) is used in this module to comprehend the features of the dataset. Patterns, distributions, and imbalances in the data, such as the frequency of postings about sadness compared to control posts, can be found using EDA. The structure of the data can be examined using visualization tools like word clouds, bar graphs, and histograms, which can assist in identifying any biases or trends that might affect model performance. Preprocessing procedures, such as how to manage class imbalances or missing data, are also guided by this analysis.

3. Cleaning the data

To make sure the input data is appropriate for the model, data cleansing is essential. In this stage, extraneous information is eliminated, including URLs, special characters, non-textual content, and user mentions (like @username). It also entails addressing problems like missing values and eliminating or fixing noisy data. To make the text data easier for the model to learn from, tokenization, lowercasing, and other fundamental text preprocessing techniques are used. Overfitting is avoided, and the model performs better when cleaned properly.

4. NLTK Processing

Advanced text preparation is done with the Natural Language Toolkit (NLTK). In order to extract important features, the text data is further processed in this stage. This comprises tasks like lemmatization (grouping diverse forms of a word), stemming (reducing words to their base form), and stop-word removal (removing common words that do not add to sentiment analysis). In order to improve the feature set used to train the model, NLTK is also utilized for named entity recognition, part-of-speech tagging, and other NLP-specific tasks. This stage guarantees that the data is prepared for machine learning algorithms and has rich semantic content.

5. Data Splitting

The dataset is divided into training, validation, and testing subsets in order to prevent overfitting and guarantee the generalizability of the model. Usually, 20% of the data is set aside for testing, and the remaining 80% is used for training and validation. While the testing dataset assesses the performance of the finished model,

the training and validation datasets are used to train and fine-tune the model. This stage is crucial for determining how well the model generalizes to new data and guarantees the accuracy of the outcomes.

6. Algorithm Application

In this module, the preprocessed data is subjected to the chosen algorithms, namely LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit). These two methods are examples of Recurrent Neural Networks (RNNs), which are particularly good at identifying long-term relationships in sequential data, such as text. The algorithm is trained to identify textual patterns that differentiate between posts connected to depression and those that are not. The model modifies its weights during training in order to reduce loss functions and enhance its forecasts**.**

7. Model Evaluation

Several performance measures are used to assess the model on the test data once it has been trained. Accuracy, precision, recall, F1-score, and confusion matrix are common evaluation measures that show how well the model can identify depression and control postings. These indicators aid in pinpointing areas that need development, such as if the model is biased in favor of one class or has trouble with particular kinds of text.

8. Result

This module presents the research's final outcomes, including an analysis of the model's predictive power and performance measures. In this stage, the model's outputs are interpreted, the results are displayed using tables and graphs, and the findings' implications are discussed. To demonstrate the efficacy of LSTM and GRU for depression identification, the findings can be contrasted with baseline models or alternative methods. Additionally, the outcomes will direct future research, possible enhancements, and useful applications of the model in actual mental health monitoring.

6. TECHNIQUES USED IN RESEARCH

6.1. EXISTING TECHNIQUE: -

- After the BERT embeddings are created, they are fed into a BiLSTM network, which learns both forward and backward temporal dependencies to further process the series of embeddings.
- This aids the model in comprehending the emotional tone and idea flow of a post. In order to determine whether the text has depressive tendencies, the BiLSTM output is subsequently fed into fully connected layers with a sigmoid or softmax activation.
- Although computationally costly, this hybrid technique enables the system to take advantage of the sequential learning capability of BiLSTM and the semantic capacity of BERT, making it extremely successful.

6.2. PROPOSED TECHNIQUE USED:

The suggested method detects depression from social media posts using a hybrid deep learning model that combines Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) networks. While GRU provides comparable performance with fewer parameters and a quicker training time, LSTM is good at maintaining long-term dependencies and emotional flow in sequences. By combining the two, the system is able to identify intricate linguistic and emotional patterns in the text, which makes it appropriate for noisy and informal user input. A unique preparation pipeline that includes emotion score extraction, slang substitution, and emoji normalization is used prior to feeding data to the model. These procedures guarantee that the input is contextually rich and that emotionally significant clues are not lost. The LSTM-GRU network, which learns the temporal and emotional patterns linked to sadness, is fed the cleaned and tokenized text after preprocessing. The post is categorized as depression or non-depressive by the final output layer, which achieves excellent accuracy with optimal computing efficiency.

6.2.1 SYSTEM ARCHITECTURE

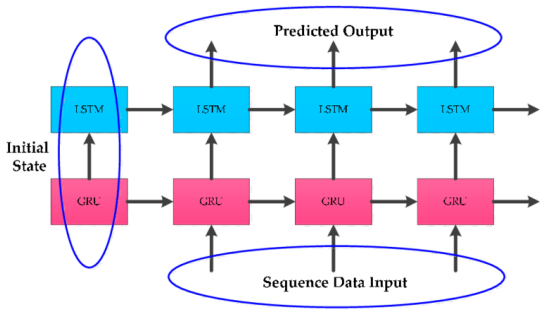


Fig. 1: System Architecture

7. RESULTS

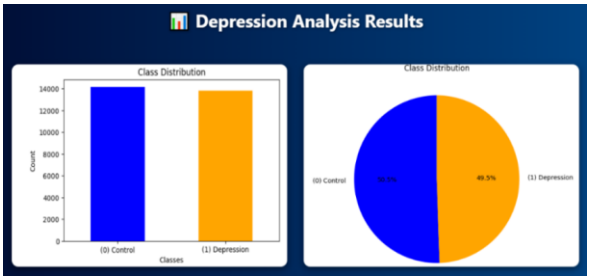


Fig. 2: Performance Analysis

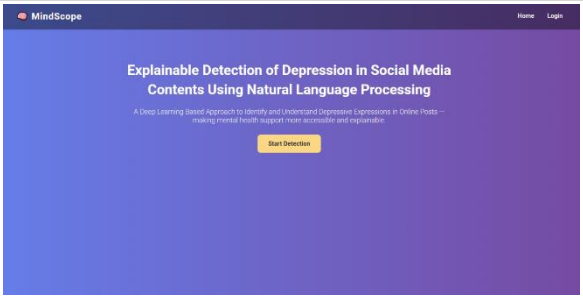


Fig. 3: Main Website

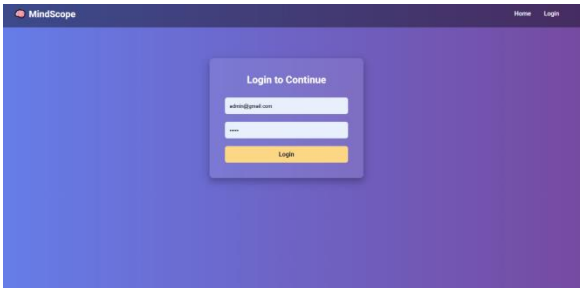


Fig. 4: Login Page



Fig. 5: Social Media Text Input – Sample 1

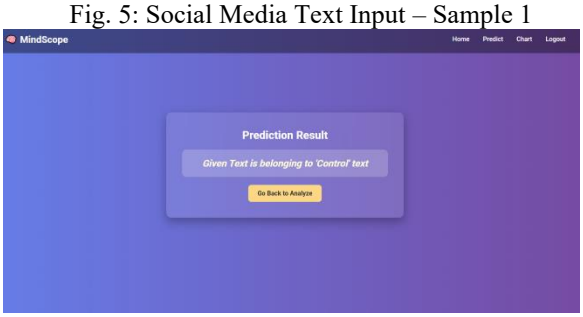


Fig. 6: Text Analysis and Depression Detection Results – Sample 1

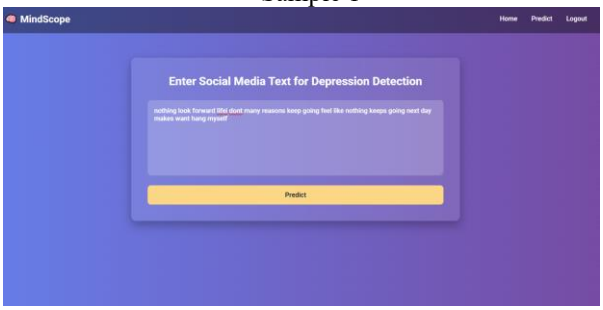


Fig. 7: Social Media Text Input – Sample 2

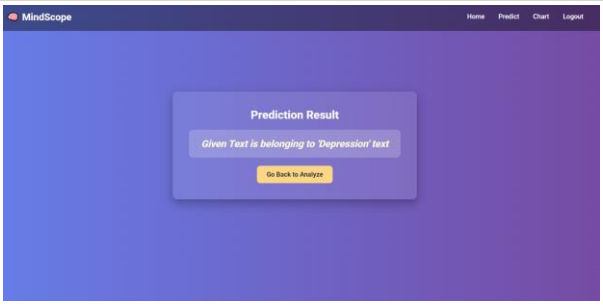


Fig. 8: Depression Detection Results – Sample 2

8. CONCLUSION

To identify sadness in textual data, this study effectively illustrates the use of cutting-edge deep learning techniques, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. The program successfully recognizes emotional indicators that are suggestive of depression tendencies by examining linguistic patterns in user-generated content. The LSTM-GRU architecture improves prediction accuracy over conventional machine learning techniques by capturing both short- and long-term dependencies in text. The method shows strong promise for early detection initiatives, allowing for prompt mental health care. Overall, this work advances the broader objective of utilizing AI to improve mental health treatment while also demonstrating the potency of neural networks in sentiment analysis.

9. FUTURE ENHANCEMENT

This research can be greatly improved by adding multilingual support, which will enable the system to identify depression-related patterns in text material that isn't in English and increase its worldwide applicability. The model's understanding of complex emotional expressions may also be enhanced by using context-aware transformers like BERT or RoBERTa. Prediction accuracy can be improved, and early intervention alerts made possible by adding real-time social media feeds to the dataset and implementing a sentiment intensity score. Additionally, the model can be implemented as a browser extension or mobile application to provide users with real-time mental health evaluations. Lastly, by combining this system with chatbots or mental health support platforms, users may receive tailored mental health resources, transforming it from a detection tool into a complete mental health solution.

REFERENCES

[1] P. Mehta, ‘‘Pioneering the future of mental health with AI: Exploring promising directions,’’ in Precision Health in the Digital Age: Harnessing AI for Personalized Care. Hershey, PA, USA: IGI Global, 2025, pp. 277–304.

[2] S. D'Alfonso, ''AI in mental health,'' Current opinion Psychol., vol. 36, pp. 112–117, Jun. 2020.
[3] D. F. Hunt, J. Bailey, B. R. Lennox, M. Crofts, and C. Vincent, ''Enhancing psychological safety in mental health services,'' Int. J. Mental Health Syst., vol. 15, no. 1, pp. 1–18, Dec. 2021. [4] M. Edgelow, A. Fecica, C. Kohlen, and K. Tandal, ''Mental health of public safety personnel: Developing a model of operational, organizational, and personal factors in public safety organizations,'' Frontiers in Public Health, vol. 11, Mar. 2023, Art. no. 1140983, doi: 10.3389/fpubh.2023.1140983.
[5] J. Liu, Y. Liu, W. Ma, Y. Tong, and J. Zheng, ''Temporal and spatial trend analysis of all-cause depression burden based on global burden of disease (GBD) 2019 study,'' Sci. Rep., vol. 14, no. 1, p. 12346, May 2024.
[6] S. Nochaiwong, C. Ruengorn, K. Thavorn, B. Hutton, R. Awiphan, C. Phosuya, Y. Ruanta, N. Wongpakaran, and T. Wongpakaran, ''Global prevalence of mental health issues among the general population during the coronavirus disease-2019 pandemic: A systematic review and meta-analysis,'' Sci. Rep., vol. 11, no. 1, p. 10173, May 2021, doi: 10.1038/s41598-021-89700-8.
[7] Á. Zsila and M. E. S. Reyes, ''Pros & cons: Impacts of social media on mental health,'' BMC Psychol., vol. 11, no. 1, p. 201, Jul. 2023.
[8] Y. Meng, H. Li, J. Wang, Y. Xu, and B. Wang, ''Cognitive behavioral therapy for patients with mild to moderate depression: Treatment effects and neural mechanisms,'' J. Psychiatric Res., vol. 136, pp. 288–295, Apr. 2021, doi: 10.1016/j.jpsychires.2021.02.001.
[9] M. J. Samidoss and V. A. Doss, ''Depression: An overview in the pathophysiology and treatment,'' Tech. Rep., 2021.
[10] L. Dobrek and K. Głowacka, ''Depression and its phytopharmacotherapy—A narrative review,'' Int. J. Mol. Sci., vol. 24, no. 5, p. 4772, Mar. 2023, doi: 10.3390/ijms24054772.
[11] J. P. Thekkekara, S. Yongchareon, and V. Liesaputra, ''An attention-based CNN-BiLSTM model for depression detection on social media text,'' Exp. Syst. Appl., vol. 249, Sep. 2024, Art. no. 123834.
[12] X. Wang, ''Emotional analysis of social media mental health based on deep learning,'' Proc. SPIE, vol. 12162, pp. 310–316, Feb. 2021.
[13] D. Dutta and A. D. Muni, ''Artificial intelligence for mental health: A review-based analysis of early detection and management of depression in elderly citizens,'' Library Progress-Library Sci., Inf. Technol. Comput., vol. 44, no. 3, 2024. /popets-2022-0039.php
[14] A. Amanat, M. Rizwan, A. R. Javed, M. Abdelhaq, R. Alsaqour, S. Pandya, and M. Uddin, ''Deep learning for depression detection from textual data,'' Electronics, vol. 11, no. 5, p. 676, Feb. 2022.
[15] K. Nanggala, G. N. Elwirehardja, and B. Pardamean, ''Systematic literature review of transformer model implementations in detecting depression,'' in Proc. 6th Int. Conf. Comput. Informat. Eng. (ICIE), Sep. 2023, pp. 203–208.
[16] A. Vaswani, ''Attention is all you need,'' in Proc. Adv. Neural Inf. Process. Syst., 2017.
[17] J. Devlin, M. Chang, K. Lee, and K. Toutanova, ''BERT: Pre-training of deep bidirectional transformers for language understanding,'' in Proc. NAACL-HLT, vol. 1, 2019, p. 2.
[18] C. Xin and L. Q. Zakaria, ''Integrating BERT with CNN and BiLSTM for explainable detection of depression in social media contents,'' IEEE Access, vol. 12, pp. 161203–161212, 2024.
[19] M. Choraś, M. Pawlicki, D. Puchalski, and R. Kozik, ''Machine learning— The results are not the only thing that matters! What about security, explainability and fairness?'' in Proc. 20th Int. Conf., Amsterdam, The Netherlands. Springer, Jun. 2020, pp. 615–628.
[20] Y. Hong, J. Lian, L. Xu, J. Min, Y. Wang, L. J. Freeman, and X. Deng, ''Statistical perspectives on reliability of artificial intelligence systems,'' Qual. Eng., vol. 35, no. 1, pp. 56–78, Jan. 2023.
[21] A. A. Khaparde, R. Das, and R. Bhargava, ''Transformer-based approach for depression detection,'' in Proc. 15th Int. Conf. Develop. eSystems Eng. (DeSE), Jan. 2023, pp. 369–374. [22] S. Boopathi, ''Deep learning techniques applied for automatic sentence generation,'' in Promoting Diversity, Equity, and Inclusion in Language Learning Environments. Hershey, PA, USA: IGI Global, 2023, pp. 255–273.
[23] M. R. Ilham and A. D. Laksito, ''Comparative analysis of using word embedding in deep learning for text classification,'' Jurnal Riset Informatika, vol. 5, no. 2, pp. 195–202, Mar. 2023. [24] M. Z. Uddin, ''Depression detection in text using long short-term memory-based neural structured learning,'' in Proc. Int. Conf. Innov. Sci., Eng. Technol. (ICISET), Feb. 2022, pp. 408–414.
[25] G. K. Kamalam, S. K. Mithila, and N. M. M. Shiry, ''A text-based approach for diagnosing depression using social media texts,'' in Proc. Int. Conf. Circuit Power Comput. Technol. (ICCPCT), Aug. 2023, pp. 181–185.
[26] S. Boopathi, ''Deep learning techniques applied for automatic sentence generation,'' Promoting Diversity, Equity, and Inclusion in Language Learning Environments (Advances in Educational Technologies and Instructional Design Book Series), 2023, pp. 73–255, doi: 10.4018/978- 1-6684-3632-5.ch016.
[27] K. Mao, W. Zhang, D. B. Wang, A. Li, R. Jiao, Y. Zhu, B. Wu, T. Zheng, L. Qian, W. Lyu, M. Ye, and J. Chen, ''Prediction of depression severity based on the prosodic and semantic features with bidirectional LSTM and time distributed CNN,'' IEEE Trans. Affect.

Comput., vol. 14, no. 3, pp. 2251–2265, Jul./Sep. 2023, doi: 10.1109/TAFFC.2022.3154332.
[28] Vandana, N. Marriwala, and D. Chaudhary, ‘‘A hybrid model for depression detection using deep learning,’’ Meas., Sensors, vol. 25, Feb. 2023, Art. no. 100587.
[29] M. Trotzek, S. Koitka, and C. M. Friedrich, ‘‘Utilizing neural networks and linguistic metadata for early detection of depression indications in text sequences,’’ IEEE Trans. Knowl. Data Eng., vol. 32, no. 3, pp. 588–601, Mar. 2020.
[30] C. Zhang, ‘‘Text classification using deep learning methods,’’ in Proc. IEEE Conf. Telecommun., Opt. Comput. Sci. (TOCS), Dec. 2022, pp. 1327–1332.
[31] J. Devlin, M. Chang, K. Lee, and K. Toutanova, ‘‘BERT: Pretraining of deep bidirectional transformers for language understanding,’’ arXiv:1810.04805, 2018.
[32] A. Raj, Z. Ali, S. Chaudhary, K. K. Bali, and A. Sharma, ‘‘Depression detection using BERT on social media platforms,’’ in Proc. IEEE Int. Conf. Artif. Intell. Eng. Technol. (IICAIET), Aug. 2024, pp. 228–233.
[33] M. Arbane, R. Benlamri, Y. Brik, and A. D. Alahmar, ‘‘Social media-based COVID-19 sentiment classification model using bi-LSTM,’’ Exp. Syst. Appl., vol. 212, Feb. 2023, Art. no. 118710.
[34] A. Vm, E. J. T. Fredrik, N. K. Kumar, F. Torres-Cruz, J. P. B. Colque, and G. Manoharan, ‘‘A deep learning approach for natural language processing and sentiment analysis in social media,’’ in Proc. 6th Int. Conf. Contemp. Comput. Informat. (ICI), vol. 6, Sep. 2023, pp. 1746–1750.
[35] M. Hasan and S. Ghane, ‘‘Data-driven depression detection system for textual data on Twitter using deep learning,’’ in Proc. 2nd Asian Conf. Innov. Technol. (ASIANCON), Aug. 2022, pp. 1–5.
[36] S. Verma, R. C. Joshi, M. K. Dutta, S. Jezek, and R. Burget, ‘‘AI-enhanced mental health diagnosis: Leveraging transformers for early detection of depression tendency in textual data,’’ in Proc. 15th Int. Congr. Ultra-Modern Telecommun. Control Syst. Workshops (ICUMT), Oct. 2023, pp. 56–61.
[37] M. Kumari, G. Singh, and S. D. Pande, ‘‘Depressonify: BERT, a deep learning approach to detection of depression,’’ EAI Endorsed Trans. Pervasive Health Technol., vol. 10, Mar. 2024. [38] C. Pananookooln, J. Akaranee, and C. Silpasuwanchai, ‘‘Comparing selective masking methods for depression detection in social media,’’ Comput. Linguistics, vol. 49, no. 3, pp. 525–553, Sep. 2023.
[39] L. Ilias, S. Mouzakitis, and D. Askounis, ‘‘Calibration of transformer-based models for identifying stress and depression in social media,’’ IEEE Trans. Computat. Social Syst., vol. 11, no. 2, pp. 1979–1990, Apr. 2024.
[40] C. Shen and Z. Zhao, ‘‘Detection of negative emotions and depression in social networks based on BERT-LSTM model,’’ in Proc. 2nd Int. Conf. Image, Algorithms Artificial Intell. (ICIAAI), Oct. 2024, pp. 911–920.
[41] N. Firoz, O. G. Beresteneva, and S. V. Aksyonov, ‘‘Enhancing depression detection: Employing autoencoders and linguistic feature analysis with BERT and LSTM model,’’ in Proc. Int. Russian Autom. Conf. (RusAutoCon), Sep. 2023, pp. 299–304.
[42] D. Liu, X. L. Feng, F. Ahmed, M. Shahid, and J. Guo, ‘‘Detecting and measuring depression on social media using a machine learning approach: Systematic review,’’ JMIR Mental Health, vol. 9, no. 3, Mar. 2022, Art. no. e27244.
[43] N. A. M. Ripah, A. A. Latif, Z. C. Cob, S. M. Drus, R. M. Anwar, and H. M. Radzi, ‘‘Depression detection based on features of depressive behaviour through social media analytics: A systematic literature review,’’ in Proc. Int. Conf. Comput. Sci. Technol. Singapore: Springer, Aug. 2022, pp. 193–203.
[44] E. Bisong, Building Machine Learning and Deep Learning Models on Google Cloud Platform, 2019, pp. 59–64.
[45] M. Vakili, M. Ghamsari, and M. Rezaei, ‘‘Performance analysis and comparison of machine and deep learning algorithms for IoT data classification,’’ 2020, arXiv:2001.09636.
[46] D. M. W. Powers, ‘‘Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation,’’ 2020, arXiv:2010.16061.
[47] Y. Sasaki, ‘‘The truth of the F-measure,’’ Teach Tutor Mater, vol. 1, no. 5, pp. 1–5, 2007. [48] A. C. J. W. Janssens and F. K. Martens, ‘‘Reflection on modern methods: Revisiting the area under the ROC curve,’’ Int. J. Epidemiol., vol. 49, no. 4, pp. 1397–1403, Aug. 2020.
[49] P. Giudici and E. Raffinetti, ‘‘RGA: A unified measure of predictive accuracy,’’ Adv. Data Anal. Classification, vol. 19, no. 1, pp. 67–93, Mar. 2025.
[50] S. Sathyanarayanan and B. R. Tantri, ‘‘Confusion matrix-based performance evaluation metrics,’’ Afr. J. Biomed. Res., vol. 27, no. 4, pp. 4023–4031, 2024.
[51] V. R. Joseph and A. Vakayil, ‘‘Split: An optimal method for data splitting,’’ Technometrics, vol. 64, no. 2, pp. 166–176, Apr. 2022.
[52] M. Nesca, A. Katz, C. Leung, and L. Lix, ‘‘A scoping review of preprocessing methods for unstructured text data to assess data quality,’’ Int. J. Population Data Sci., vol. 7, no. 1, Oct. 2022.
[53] B. Bala and S. Behal, ‘‘A brief survey of data preprocessing in machine learning and deep learning techniques,’’ in Proc. 8th Int. Conf. I-SMAC (IoT Social, Mobile, Analytics Cloud) (I-SMAC), Oct. 2024, pp. 1755–1762.
[54] L. Hickman, S. Thapa, L. Tay, M. Cao, and P. Srinivasan, ‘‘Text preprocessing for text mining in organizational research: Review and

recommendations,'' Organizational Res. Methods, vol. 25, no. 1, pp. 114–146, Jan. 2022.
[55] H.-T. Duong and T.-A. Nguyen-Thi, ''A review: Preprocessing techniques and data augmentation for sentiment analysis,'' Comput. Social Netw., vol. 8, no. 1, p. 1, Dec. 2021.
[56] J. Kamps, N. Kondylidis, and D. Rau, ''Impact of tokenization, pretraining task, and transformer depth on text ranking,'' in Proc. TREC, 2020.
[57] Y. Mo, H. Qin, Y. Dong, Z. Zhu, and Z. Li, ''Large language model (LLM) AI text generation detection based on transformer deep learning algorithm,'' 2024, arXiv:2405.06652. [58] S. Sarica and J. Luo, ''Stopwords in technical language processing,'' PLoS ONE, vol. 16, no. 8, Aug. 2021, Art. no. e0254937.
[59] A. Atta, D. Elsayad, D. Ezzat, S. Amin, and M. ElGamal, ''Automated depression screening of clinical transcript optimized by grey wolf optimizer,'' Int. J. Intell. Comput. Inf. Sci., vol. 24, no. 3, pp. 58–69, Sep. 2024.
[60] A. A. M. Shoeb and G. de Melo, ''Assessing emoji use in modern text processing tools,'' 2021, arXiv:2101.00430.
[61] C. Liu, F. Fang, X. Lin, T. Cai, X. Tan, J. Liu, and X. Lu, ''Improving sentiment analysis accuracy with emoji embedding,'' J. Saf. Sci. Resilience, vol. 2, no. 4, pp. 246–252, Dec. 2021. [62] R. Kanani, J. Fiaidhi, and V. Patel, ''Depression sentiment analysis based on social media content like Twitter,'' Authorea Preprints, Dec. 2022.
[63] Y. Kasanneni, A. Duggal, R. Sathyaraj, and S. P. Raja, ''Effective analysis of machine and deep learning methods for diagnosing mental health using social media conversations,'' IEEE Trans. Computat. Social Syst., vol. 12, no. 1, pp. 274–294, Feb. 2025.
[64] X. Ren, H. A. Burkhardt, P. A. Areán, T. D. Hull, and T. Cohen, ''Deep representations of first-person pronouns for prediction of depression symptom severity,'' in Proc. AMIA Annu. Symp., Jan. 2023, p. 1226.
[65] H. Ji, ''Depression detection on Twitter text based on negative emotion score and level of depression,'' Highlights Sci., Eng. Technol., vol. 81, pp. 368–373, Jan. 2024.
[66] K. Gasmi, ''Improving BERT-based model for medical text classification with an optimization algorithm,'' in Advances in Computational Collective Intelligence (Communications in Computer and Information Science), 2022, pp. 11–101, doi: 10.1007/978-3-031-16210-7_8.
[67] A. Raj Shekhar and T. Gupta, ''Sentiment analysis of social media data for mental health monitoring,'' in Proc. 2nd Int. Conf. Futuristic Technol. (INCOFT), Nov. 2023, pp. 1–6.
[68] Z. Li, J. Yang, J. Wang, L. Shi, J. Feng, and S. Stein, ''LBKT: A LSTM BERT-based knowledge tracing model for long-sequence data,'' in Generative Intelligence and Intelligent Tutoring Systems (Lecture Notes in Computer Science), 2024, pp. 84–174, doi: 10.1007/978-3-031-63031- 6_15.
[69] C. Xu, K. Shen, and H. Sun, ''Supplementary features of BiLSTM for enhanced sequence labeling,'' 2023, arXiv:2305.19928.
[70] H. Alamro, T. Gojobori, M. Essack, and X. Gao, ''BioBBC: A multifeature model that enhances the detection of biomedical entities,'' Sci. Rep., vol. 14, no. 1, Apr. 2024, doi: 10.1038/s41598-024-58334-x. [71] B. Ogunleye, H. Sharma, and O. Shobayo, ''Sentiment-informed sentence BERT-ensemble algorithm for depression detection,'' Big Data Cognit. Comput., vol. 8, no. 9, p. 112, Sep. 2024.
[72] Y. Zhang, X. Long, X. Shu, and J. Shu, ''Depression tendency detection of Weibo users based on knowledge graph,'' in Proc. 6th Int. Conf. Artif. Intell. Big Data (ICAIBD), May 2023, pp. 542–547.