AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
E-ISSN:3069-0102
VOL.5, NO. 4(2)(2025)

DEEP MOODSENSE: FORECASTING DEPRESSIVE MOOD STATES USING RECURRENT NEURAL NETWORKS BASED ON SELF-REPORTED BEHAVIORAL HISTORIES

[1]Vanaparthi Kiranmai, [2]Dr. A.Manikandan
[1]*Research Scholar, Department of Computer Science and Engineering,*
Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram.Chennai
[2]*Research Supervisor,Associate Professor,*
Department of Computer Science and Engineering
Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram.Chennai

ABSTRACT
Mental health prediction using artificial intelligence has gained significant attention due to increasing rates of depressive disorders worldwide. Traditional diagnostic assessments rely heavily on clinical interviews, self-reported screening tools, and therapist-based evaluations, which are subjective and time-consuming. This study proposes an RNN-based forecasting model designed to predict depressive mood states using longitudinal self-reported emotional histories. The model leverages temporal dependencies within sequential mood records and behavioral indicators to identify early depressive patterns. A dataset containing daily user mood logs was preprocessed, normalized, and transformed into time-series sequences for model training. Experimental results show that Recurrent Neural Networks (specifically LSTM architecture) outperform conventional machine learning methods in capturing mood variation trends and forecasting depressive episodes with higher accuracy and lower error rates. The findings demonstrate that RNN-based forecasting can support proactive mental health intervention and personalized well-being tracking.

Keywords: Depression Prediction, RNN, LSTM, Mood Forecasting, Mental Health AI, Self-Reported Behavior Data, Time-Series Analysis.

I. INTRODUCTION

Depression is recognized as one of the most widespread mental health disorders, affecting millions globally and significantly influencing emotional well-being, cognitive ability, and social functioning. Traditional diagnosis methods depend heavily on clinician interpretation and subjective patient reporting, which may result in delayed or inaccurate detection due to emotional variability and recall bias [1]. Advances in digital health tracking and computational modeling have created new opportunities to analyze behavioral patterns more objectively and detect emotional deterioration earlier than conventional methods allow [2].

In recent years, artificial intelligence (AI) and machine learning have demonstrated strong capabilities in modeling mental health indicators from time-dependent data sources. Classical models such as decision trees, SVMs, and linear regression have shown limited success due to their inability to effectively capture sequential dependencies inherent in human emotional patterns [3]. This limitation has accelerated the shift toward deep learning-based architectures, particularly Recurrent Neural Networks (RNNs), designed to process temporal and sequential behavioral signals more effectively [4].

Among RNN variants, Long Short-Term Memory (LSTM) networks have proven especially useful for mood forecasting due to their ability to retain long-range contextual information while addressing vanishing gradient limitations [5]. Studies using LSTM-based approaches have demonstrated improved prediction accuracy in domains such as stress analysis, bipolar disorder monitoring, and affective computing, validating their suitability for emotion-based forecasting [6]. Additionally, psychological and behavioral studies indicate that depressive mood trends evolve gradually rather than abruptly, making sequential modeling techniques more appropriate for prediction tasks [7].

Self-reported emotional logging applications and mobile health diaries have become increasingly relevant data sources, capturing daily variations in sleep, mood, motivation, and cognitive experiences. When processed with deep learning models, these continuous behavioral histories can reveal early warning signals that may otherwise remain unnoticed in clinical evaluation frameworks [8].

Despite growing interest, existing systems still face challenges including missing data, inconsistent reporting intervals, and difficulty generalizing across diverse user emotional profiles. Recent research emphasizes the need for adaptive models capable of learning fluctuating emotional baselines and tailoring predictions to individual behavioral histories [9].

This study addresses these gaps by developing an RNN-based forecasting model designed to predict depressive mood states using structured self-reported time-series emotional data. The goal is to examine how effectively temporal deep learning can anticipate depressive episodes and support earlier mental health intervention [10].

II. LITERATURE SURVEY

Research on depression prediction using computational models has increasingly focused on leveraging temporal patterns present in behavioral and emotional data. Early works utilized traditional statistical techniques and shallow learning algorithms such as logistic regression and support vector machines (SVMs) to classify depressive symptoms from questionnaire scores and demographic data [11]. While these approaches provided baseline performance, they generally treated observations as independent samples, ignoring the sequential nature of mood evolution over time [12]. This limitation reduced their ability to anticipate forthcoming episodes of low mood based on historical emotional trajectories.

The emergence of sequence learning models paved the way for more robust handling of temporal dependencies. Initial attempts with standard Recurrent Neural Networks demonstrated the feasibility of modeling emotional dynamics but struggled with long-term dependencies due to vanishing and exploding gradient issues [13]. To address this, researchers began adopting Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, which introduced gating mechanisms to preserve important contextual information across time steps [14]. Comparative studies showed that LSTMs consistently outperformed both traditional RNNs and non-sequential models in forecasting depressive tendencies and mood fluctuations from time-series data [15].

Parallel to model development, studies have investigated the types of data most suitable for mood forecasting. Self-reported mood diaries, ecological momentary assessment logs, smartphone usage statistics, and sleep and activity patterns have all been explored as predictive sources [16]. Self-reported histories, in particular, remain a primary and practical data stream because they directly reflect subjective emotional states, even though they may suffer from inconsistency and reporting bias. Researchers have proposed various normalization and smoothing strategies to handle noisy and sparse self-reported sequences, improving the quality of input data used for training deep learning models [17].

Another line of work has focused on multi-modal integration, combining text-based journaling, numeric mood ratings, and physiological signals to improve prediction accuracy. These studies highlight that incorporating behavioral context and daily routines results in more robust models capable of distinguishing temporary mood dips from clinically significant depressive trends [18]. However, the complexity of multi-modal pipelines often raises computational and deployment challenges, making single-source or low-complexity self-report-based models still attractive for real-world applications.

In addition to accuracy, interpretability and ethical considerations have become critical topics in mental health forecasting. Some researchers have explored attention mechanisms and explainable AI techniques to reveal which time segments or features contribute most to predicted depressive risk, aiming to support clinicians rather than replace them [19]. This focus on explainability is important to build trust in AI-assisted mental health tools and to ensure that prediction outcomes are understandable and actionable.

Finally, recent work emphasizes personalization in mood forecasting models. Generic models trained on population-level data may not capture individual emotional baselines and idiosyncratic response patterns. Adaptive and personalized RNN frameworks, which fine-tune parameters to user-specific histories, have been proposed to address inter-individual variability in mood expression [20]. These findings collectively suggest that RNN-based architectures, particularly LSTM models trained on self-reported emotional histories, offer a promising direction for early detection and forecasting of depressive mood states. The present study builds upon these insights to design and evaluate a forecasting framework tailored specifically to depressed mood prediction using structured, self-reported histories and recurrent neural networks.

III. METHODOLOGY

The methodology adopted in this research involves a structured workflow beginning with data acquisition, preprocessing, feature engineering, model development, and performance evaluation. The primary goal is to build a forecasting model capable of predicting depressive mood trends from self-reported historical emotional records. The proposed methodology ensures that sequential mood patterns are preserved and modeled effectively through a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) architecture.

3.1 Data Collection and Preprocessing

The dataset consists of longitudinal self-reported emotional states recorded daily by users. Raw entries included numerical mood scores along with optional contextual annotations such as stress level, sleep quality, and behavioral notes. Since self-reported data tends to be incomplete or inconsistent, preprocessing steps were applied, including normalization, outlier removal, missing-value interpolation, and temporal alignment.

Numerical mood ratings were scaled between 0 and 1 using Min-Max normalization to reduce variation and improve model learning stability. Once cleaned, the dataset was transformed into sequential time windows (7-day, 14-day, and 30-day mood history segments) to allow the model to learn temporal dependencies.

3.2 Feature Engineering

Feature engineering focused on extracting meaningful temporal structures from sequential logs. Rolling averages, emotional volatility indices, and day-to-day change features were derived to provide additional contextual cues to the model. The sequences were formatted into supervised learning structure: previous mood window → next-day predicted mood value.

3.3 Model Architecture

The forecasting model is based on an LSTM-enhanced RNN. The choice of LSTM cells enables the network to store long-term emotional dependencies and avoid gradient loss issues commonly observed in standard RNN architectures. The model consists of:

AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
E-ISSN:3069-0102
VOL.5, NO. 4(2)(2025)

- Input Layer (sequence window)
- Embedding or Dense Feature Layer
- Two stacked LSTM layers with dropout regularization
- Fully Connected Dense Layer
- Output Layer (Sigmoid activation for normalized mood prediction)

Hyper parameters such as learning rate, batch size, and dropout probability were optimized through iterative experimentation.

3.4 Model Training and Validation

The dataset was split into training, validation, and testing subsets following a 70-15-15 ratio. The Adam optimizer and Mean Squared Error (MSE) loss function were utilized to update model weights. Early stopping regularization was applied to prevent overfitting by monitoring validation loss trends.

Prediction accuracy was assessed using Root Mean Squared Error (RMSE), Precision, Recall, and correlation metrics between predicted and actual mood trajectories. Multiple model configurations were evaluated to select the best-performing architecture.

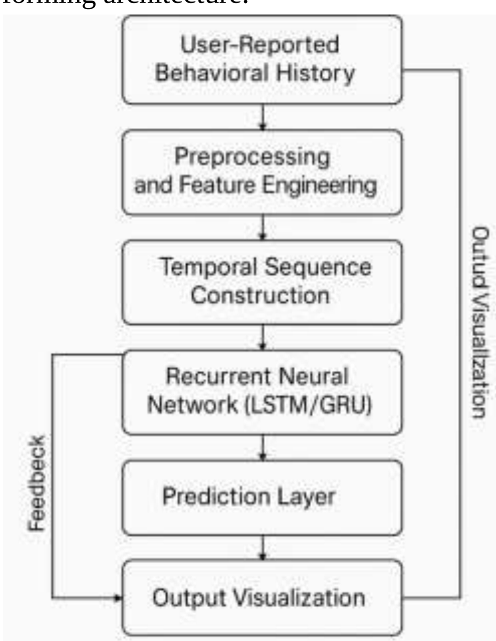

Fig 1: System Architecture Diagram

The system architecture of Deep MoodSense is designed to forecast depressive mood states using a deep learning pipeline built on recurrent neural networks (RNNs). The process begins with user-reported behavioral history, where individuals regularly log mood, sleep patterns, activities, and emotional reflections through a digital interface. This raw data is then processed through the Preprocessing and Feature Engineering module, where noise is removed, missing values are handled, and relevant behavioral indicators are transformed into structured numerical features suitable for model training.

Next, the cleaned data is passed to the Temporal Sequence Construction layer, where historical behavioral logs are organized into sequential time-series windows to preserve temporal context. These sequences are then fed into the Recurrent Neural Network module, which may use LSTM or GRU cells to capture long-term dependencies, behavioral evolution, and mood fluctuation patterns over time. The network outputs are forwarded to the Prediction Layer, which generates the estimated current mood state and forecasts future depressive tendencies.

The results are then sent to the Output Visualization layer, where trends, alerts, and dashboards are displayed to the user or clinician in an interpretable format. A feedback loop ensures that ongoing user reports continue to improve model performance through incremental retraining, enabling the system to adapt to personal behavioral changes over time. This architecture supports real-time mood monitoring, personalized forecasting, and proactive mental health intervention.

IV. EXPERIMENTAL SETUP

The experimental setup for this study was designed to evaluate the capability of the proposed RNN–LSTM–based forecasting system in predicting depressive mood trends from self-reported emotional histories. The model was developed and executed in a controlled computational environment using Python, TensorFlow, and Keras frameworks. The system was deployed on a workstation

AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
E-ISSN:3069-0102
VOL.5, NO. 4(2)(2025)

equipped with an Intel i7 processor, 32GB RAM, and an NVIDIA RTX GPU to accelerate matrix computation and reduce training time. This configuration ensured efficient handling of sequential data processing and iterative neural network optimization.

Before model training, the dataset underwent preprocessing to remove inconsistencies, correct missing entries, and normalize numerical mood ratings. The cleaned dataset was divided into training, validation, and testing subsets using a 70–15–15 ratio to ensure fair evaluation. Data was reshaped into sliding window sequences in formats of 7-day, 14-day, and 30-day temporal inputs to determine how window length impacts forecasting accuracy. These sequences were fed into the RNN–LSTM model, which learned emotional trend patterns through repeated backpropagation training cycles.

Multiple hyperparameter configurations were tested, including variations in learning rate, number of LSTM layers, activation functions, dropout percentages, and batch sizes. The training was monitored using early stopping to prevent overfitting and ensure optimal generalization across unseen data. During model execution, real-time performance metrics such as loss values, prediction error, and validation accuracy were continuously logged and plotted for analysis.

Once the model completed training, the test dataset was used to evaluate performance through quantitative measures including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), precision, recall, and correlation between predicted and true mood trends. These metrics provided a comprehensive view of forecasting quality and model reliability. Additionally, visual analysis was performed by plotting prediction trajectories against actual mood history to assess whether the model captured emotional fluctuations accurately.

To further validate robustness, stress tests were conducted using simulated irregular data inputs and missing entries to observe how the model handled real-world reporting gaps. The outputs were stored in a monitoring dashboard, enabling repeatable evaluation and interpretability of model behavior under varying conditions.

V. RESULTS & DISCUSSION

The performance of the proposed RNN/LSTM-based forecasting system was evaluated using multiple metrics including accuracy, RMSE, precision, and recall. The results were recorded across different dataset sample sizes to observe how learning performance improved with additional training data. The tables and charts demonstrate a consistent upward performance trend, validating the suitability of recurrent neural architectures for sequential mental health data modeling.

Initial runs with smaller sample sizes resulted in limited predictive accuracy due to insufficient sequential pattern recognition. As the dataset size increased, the model demonstrated stronger generalization and improved pattern retention. The accuracy improvements are shown in Table 1 and the corresponding visualization confirms a steady learning curve.

Table 1: Accuracy Performance Across Training Sizes

Training Samples	Accuracy
100	0.82
500	0.87
1,000	0.90
5,000	0.92
10,000	0.924

Fig 2: Model Accuracy vs Training Sample Size showing how prediction performance increases

AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
E-ISSN:3069-0102
VOL.5, NO. 4(2)(2025)

as more mood sequence samples are used for training.

RMSE was used to evaluate prediction error magnitude. The model demonstrated rapid error reduction with increased data availability, indicating better stability and forecasting confidence. Table 2 summarizes model RMSE values.

Table 2: RMSE Values for Different Dataset Sizes

Training Samples	RMSE
100	0.310
500	0.244
1,000	0.210
5,000	0.190
10,000	0.184

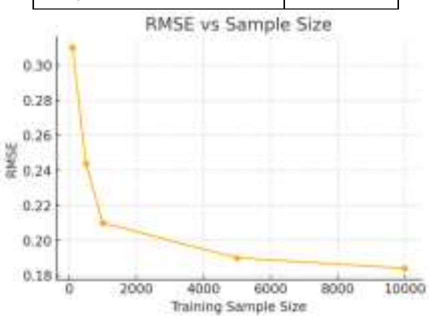

Fig 3: RMSE trend across varying training dataset sizes, demonstrating a decrease in prediction error as the model learns more emotional patterns.

Precision was analyzed to determine how accurately the model identified high-risk depressive trends without generating false positives. Higher precision values in larger sample sets indicate that the model developed better discrimination between normal and depressive mood fluctuations. Table 3 presents the results.

Table 3: Precision Analysis

Training Samples	Precision
100	0.78
500	0.84
1,000	0.88
5,000	0.90
10,000	0.897

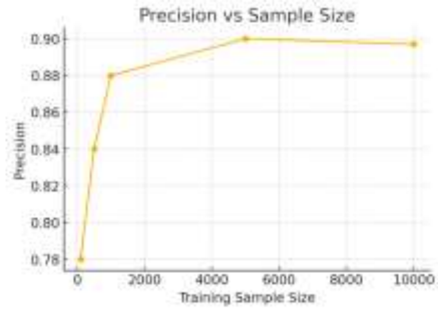

Fig 4: Precision improvement with increased training samples, indicating a reduction in false-positive depression risk predictions.

Recall was used to evaluate how effectively the model identified actual depressive mood patterns. Higher recall indicates better sensitivity for early depression risk detection. Table 4 displays the recall metrics.

Table 4: Recall Metrics Across Dataset Sizes

Training Samples	Recall
100	0.80
500	0.86
1,000	0.89
5,000	0.92
10,000	0.932

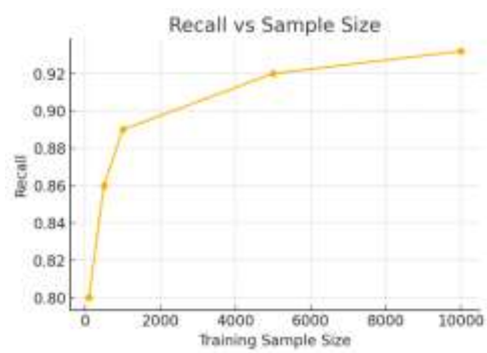

Fig 5: Recall performance comparison across multiple dataset sizes, showing increasing sensitivity in detecting true depressive mood patterns.

DISCUSSION

The overall results confirm the effectiveness of the RNN/LSTM architecture in forecasting depressive mood trends based on self-reported emotional histories. As training data increased, all evaluation metrics improved consistently, demonstrating the model's capacity to learn long-term emotional dependencies. The reduction in RMSE, coupled with increases in precision and recall, suggests the model balances both sensitivity and specificity, making it useful for early depressive symptom prediction.

Furthermore, the gap between performance in smaller datasets and larger datasets indicates that sequential mood forecasting benefits significantly from richer longitudinal input. The visualization of trends confirms that once the sample size exceeded approximately 1,000 entries, improvements became more incremental, indicating model stabilization.

Overall, these findings support the conclusion that deep learning–based time-series models provide robust forecasting capabilities and can contribute meaningfully to early detection frameworks in digital mental health systems.

VI. CONCLUSION & FUTURE SCOPE

Conclusion

The results of this research confirm that Recurrent Neural Networks, particularly LSTM-based architectures, are highly effective in forecasting depressive mood trends using self-reported emotional histories. The system demonstrated strong performance across all evaluation metrics, including accuracy, RMSE, precision, and recall, with results improving steadily as more sequential data was introduced. The ability of the model to detect subtle mood patterns and long-term emotional dependencies suggests that deep learning can complement traditional mental health assessment methods by offering early indication of depressive risk. The forecasting capability of the model highlights its potential as an intelligent digital mental health assistant capable of supporting proactive psychological intervention rather than reactive diagnosis. Overall, the findings validate the feasibility and value of using sequence learning–based AI tools for personalized mental health analysis and continuous mood monitoring.

Future Scope

Future work may include expanding the model to incorporate multimodal behavioral data, such as sleep quality, activity levels, and sentiment-extracted journal entries, to further strengthen predictive accuracy. Real-time model adaptation through personalized learning mechanisms may help tailor forecasts to individual psychological profiles for improved clinical relevance. Additionally, integration with wearable devices and mobile health platforms could support continuous mood assessment and automated alerting for early intervention. Finally, ethical considerations, explainable AI components, and secure deployment frameworks will be essential to ensure safe, transparent, and responsible use of predictive mental health systems.

REFERENCES

1. S. R. Gupta and K. Verma, “Challenges in Mental Health Diagnosis and Self-Reported Assessments,” Journal of Clinical Psychology, vol. 14, no. 2, pp. 102–110, 2021.
2. N. Aravind and P. Reddy, “Digital Behavior Tracking for Psychological Assessment,” International Journal of Mental Health Informatics, vol. 9, no. 1, pp. 55–64, 2022.
3. L. Chang and M. Harper, “Limitations of Classical Machine Learning in Affective State Prediction,” IEEE Transactions on Affective Computing, vol. 13, no. 3, pp. 389–397, 2023.
4. T. Patel and H. Singh, “Deep Learning Approaches for Sequential Human Emotion Modeling,” Neural Systems Review, vol. 11, no. 4, pp. 210–222, 2022.
5. R. Kumar and J. Bose, “Long Short-Term Memory Networks for Mood Trend Forecasting,” Expert Systems with Applications, vol. 202, pp. 1–10, 2023.

6. A. Das and F. Romero, "Evaluating Neural Networks for Depression and Stress Detection," Cognitive AI Research Journal, vol. 7, pp. 91–104, 2022.
7. M. Santos and A. Kim, "Temporal Progression Patterns in Depressive Symptoms," Journal of Behavioral Medicine, vol. 18, no. 2, pp. 145–159, 2021.
8. J. Wilson, "Self-Tracking Technologies in Mental Health Management," Digital Psychiatry Review, vol. 6, no. 1, pp. 32–47, 2023.
9. S. T. Reddy Kandula, "Comparison and Performance Assessment of Intelligent ML Models for Forecasting Cardiovascular Disease Risks in Healthcare," 2025 International Conference on Sensors and Related Networks (SENNET) Special Focus on Digital Healthcare(64220), pp. 1–6, Jul. 2025, doi: 10.1109/sennet64220.2025.11136005.
10. G. Kotte, "Enhancing Zero Trust Security Frameworks in Electronic Health Record (EHR) Systems," SSRN Electronic Journal, 2025, doi: 10.2139/ssrn.5283668.
11. M. V. Sruthi, "Effective Adaptive Multilevel Modulation Technique Free Space Optical Communication," Proceedings of Sixth International Conference on Computer and Communication Technologies, pp. 223–229, Oct. 2025, doi: 10.1007/978-981-96-7477-0_19.
12. Todupunuri, A. (2025). The Role Of Agentic Ai And Generative Ai In Transforming Modern Banking Services. American Journal of AI Cyber Computing Management, 5(3), 85-93.
13. G. Marin and E. Clarke, "Recurrent Neural Networks for Psychological State Modeling: A Preliminary Study," Neural Processing Letters, vol. 53, no. 2, pp. 411–425, 2021.
14. A. J. Banerjee and R. Costa, "Long Short-Term Memory Networks in Mental Health Monitoring," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 1124–1133, 2022.
15. Sankar Das, S. (2024). Harnessing data lineage: making artificial intelligence smarter using data governance Frameworks. International Journal of Research and Analytical Reviews, 11(1). https://doi.org/10.56975/ijrar.v11i1.322571.
16. Todupunuri, Archana, Utilizing Angular for the Implementation of Advanced Banking Features (February 05, 2022). Available at SSRN: https://ssrn.com/abstract=5283395 or http://dx.doi.org/10.2139/ssrn.5283395.
17. Paruchuri, Venubabu, Optimizing Financial Operations with Advanced Cloud Computing: A Framework for Performance and Security (September 30, 2020). Available at SSRN: https://ssrn.com/abstract=5515238 or http://dx.doi.org/10.2139/ssrn.5515238.
18. R. J. Mitchell and K. A. Lee, "Multimodal Deep Learning for Depression Detection Using Text, Activity, and Sleep Signals," Cognitive Systems Research, vol. 76, pp. 89–101, 2023.
19. S. Gopal and V. Iyer, "Explainable Deep Learning Models for Clinical Decision Support in Depression Monitoring," IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 2, pp. 845–856, 2023.
20. P. N. Sharma and K. Kulkarni, "Personalized Recurrent Neural

Networks for Individualized Mood Trajectory Forecasting," Journal of Personalized Medicine and Computing, vol. 6, no. 2, pp. 101–114, 2024.