



(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 5, May 2025

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www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 5, May 2025

|DOI: 10.15680/IJIRSET.2025.1405388

Transformer-Based Deep Learning Model for Mental Health Assessment

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ABSRACT: Stress management and early detection of mental health risks are critical in maintaining psychological wellbeing. This study proposes an integrated system utilizing Random Forest for stress level prediction based on sleep patterns and lifestyle factors, complemented by an NLP-powered chatbot using BERT to provide interactive and personalized mental health insights. The system consists of two core components: (1) A Random Forest-based classification model that predicts mental health risk levels (Healthy, Moderate Risk, High Risk) based on real-time user inputs such as sleep duration, anxiety symptoms, and lifestyle habits (exercise, diet, screen time), and (2) A chatbot powered by BERT (Transformer Library) designed for natural language interactions, enabling users to ask questions about their stress classification and receive context-aware explanations. The stress prediction model leverages ensemble learning to enhance generalization and avoid overfitting, while the chatbot employs BERT-based intent recognition and keyword extraction to provide tailored responses. The chatbot is trained on mental health datasets and fine-tuned to ensure conversational accuracy when retrieving relevant answers. The system's dual approach facilitates early intervention, improves transparency in stress classification, and promotes personalized mental health support through AI-driven dialogue. The integration of Random Forest with Transformer-based NLP enables a scalable, explainable, and user-centric framework for stress detection and response. This study highlights the importance of machine learning and NLP techniques in delivering adaptive mental health solutions and outlines future directions for improving real-time interaction and enhancing predictive accuracy.

KEYWORDS: Mental Health Risk Prediction, Stress Detection, Random Forest Classification, Sleep Analysis, Lifestyle Impact on Stress, NLP-powered Chatbot, BERT (Transformer Library), Explainable AI in Mental Health.

I. INTRODUCTION

Mental health issues, including stress, anxiety, and sleep disorders, have become increasingly prevalent in today's fastpaced world. Prolonged exposure to stress can lead to severe consequences such as cardiovascular diseases, weakened immune function, and impaired cognitive abilities. Identifying stress levels early and providing timely interventions can significantly improve psychological well-being. Traditional methods of stress assessment rely on self-reporting, which may not always be accurate due to subjective biases or lack of awareness about underlying stress factors. Advancements in artificial intelligence (AI) and machine learning (ML) provide an opportunity to develop automated, data-driven stress detection systems that offer objective and explainable predictions based on user input patterns. In this research, we propose a dual-component system that integrates Random Forest for stress level prediction and a BERT-powered chatbot for mental health support. The first component utilizes Random Forest classification to predict stress levels based on sleep-related parameters, anxiety symptoms, and lifestyle habits such as diet, exercise, and screen time. By processing real-time user input, the system classifies mental health risk into Healthy, Moderate Risk, or High Risk, allowing users to gain insights into their psychological well-being. The second component is a Natural Language Processing (NLP)based chatbot, powered by BERT (Transformer Library), to engage in interactive dialogues with users. The chatbot is designed to explain stress level classifications, provide personalized mental health suggestions, and allow users to retrieve





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answers based on keyword-based queries. The Random Forest model, known for its ensemble learning capabilities, enhances generalization and mitigates overfitting by aggregating multiple decision trees for robust predictions. Meanwhile, the BERT-based chatbot leverages deep contextual understanding to analyze user queries and generate informative and personalized responses. The integration of machine learning-driven stress detection with NLP-based conversational assistance ensures that users receive actionable mental health insights in a user-friendly format. The system addresses the growing need for AI-powered mental health interventions by offering explainable, adaptive, and real-time assessments for individuals experiencing stress. This study emphasizes the importance of AI-driven stress prediction models and explores how transformer-based language models can enhance mental health support systems. By combining predictive analytics with interactive explanations, the proposed framework promotes early intervention strategies, fosters user engagement, and contributes to advancing AI applications in healthcare and mental well-being.

II. RELATED WORK

Ahmad Radwan et al., [1] This work explores the innovative application of large language model (LLM) embeddings, particularly GPT-3, combined with classical machine learning algorithms like Random Forest and XGBoost for mental health stress disorder classification. The study emphasizes how LLM embeddings capture nuanced linguistic features from patient texts, which enhances the predictive power of traditional models. Using semantic embeddings from GPT-3, the research demonstrates improved accuracy in identifying stress-related symptoms compared to previous methods. The methodology involves pre-processing textual data, generating embeddings, and feeding these into machine learning classifiers for risk stratification. The authors highlight the importance of dimensionality reduction in dealing with high-dimensional embedding spaces to optimize model performance. Results indicate that embedding-based features significantly outperform baseline models that rely on manual feature extraction. The study concludes that integrating LLM embeddings with ensemble models offers promising avenues for early detection and intervention in mental health settings. Future work suggested includes expanding datasets, integrating multimodal data, and real-time prediction systems to support clinical decision-making.

U Madububambachu, et.al., [2] This comprehensive review synthesizes recent advancements in applying machine learning techniques for mental health diagnosis. Covering various algorithms such as Support Vector Machines, Random Forests, XGBoost, neural networks, and deep learning models, the paper assesses their performance, datasets used, and clinical relevance. The review discusses challenges such as data quality, privacy concerns, feature selection, imbalanced classes, and model interpretability. It emphasizes that machine learning models have shown promising accuracy in predicting disorders like depression, anxiety, bipolar disorder, and schizophrenia using diverse data sources, including electronic health records, social media, and self-reported questionnaires. The authors highlight the significance of feature engineering, data augmentation, and explainability in advancing clinical adoption. The paper also identifies gaps such as limited longitudinal studies and the need for standardized datasets. Ethical considerations and the importance of patient privacy are underscored. Overall, the review offers valuable insights into how machine learning techniques are transforming mental health diagnostics, paving the way toward more proactive and personalized treatments. It stresses that ongoing research should prioritize model transparency and integration into clinical workflows.

R Martínez-Castaño, et.al,...[3] This paper investigates the utilization of BERT-based transformer models to facilitate the early identification of mental health conditions. The researchers fine-tune BERT models on datasets comprising social media posts, clinical transcripts, and survey responses that reflect linguistic markers associated with mental health issues like depression and anxiety. The study explores how the contextual embeddings generated by BERT capture subtle cues in language indicative of mental illness. The authors evaluate model performance using standard metrics such as accuracy, precision, recall, and F1-score, demonstrating that BERT outperforms traditional NLP approaches. The research highlights the importance of transfer learning with transformers to adapt to domain-specific language variations. Challenges such as data imbalance, annotation quality, and ethical concerns regarding data privacy are discussed. The application of BERT-based models shows promise for real-time monitoring and screening tools, potentially aiding clinicians in early intervention strategies. The paper concludes with recommendations for future research, including model interpretability and multimodal data integration.

R Martínez-Castaño, et.al,...[4] d This research presents a BERT-based transformer approach aimed at early risk detection of self-harm behaviors and assessment of depression severity. The study uses annotated datasets from social media platforms where individuals express mental health struggles. By fine-tuning BERT on these datasets, the authors develop models capable of highlighting linguistic features that correlate with risk levels. The models are tested for their ability to





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classify texts into severity groups and identify potential self-harm risks accurately. Results show that BERT-based models achieve superior performance in comparison to baseline NLP classifiers, such as bag-of-words or LSTM models. The work underscores the importance of context-aware embeddings in understanding nuanced expressions of distress. Ethical considerations related to data privacy, consent, and potential misuse are reviewed. The authors suggest these models could be integrated into digital mental health tools, offering early warnings and aiding timely intervention. The paper discusses challenges like dataset bias and the need for ongoing model validation across diverse populations. It concludes that transformer models like BERT have significant potential in mental health risk assessment and can augment clinical decision-making processes.

SP Devika, et.al., [5] This paper explores the application of BERT transformers for identifying patients at risk of suicide and depression through natural language analysis. The researchers collected data from clinical notes and social media posts, labeling them for suicidal ideation and depression indicators. Fine-tuning BERT on these datasets enabled the model to capture contextual linguistic features that traditional approaches might miss. The model is evaluated based on classification accuracy, precision, recall, and F1-score, demonstrating enhanced detection capabilities. The authors emphasize BERT's ability to understand semantic nuances and contextual shifts, which are crucial in mental health diagnostics. The study addresses key challenges such as data imbalance, annotation quality, and ethical considerations surrounding sensitive information. The potential integration of BERT-based models into clinical tools could support early screening, risk assessment, and personalized intervention strategies. The paper concludes that transformer models hold promise for augmenting mental health professionals' diagnostic toolkit, but emphasizes the necessity for continual validation and ethical safeguards. Future research directions include incorporating multimodal data, explainability enhancements, and larger diverse datasets to improve robustness.

III. EXISTING METHODOLOGIES

FE-BION, as a traditional system for stress detection and mental health assessment, primarily relies on pre-defined evaluation mechanisms such as questionnaire-based self-reporting, rule-based classification, and structured psychological evaluations. While it serves as a foundational model for understanding stress levels, FE-BION lacks real-time adaptability, predictive analytics, and interactive explainability, making it less effective in addressing dynamic mental health conditions. The system's reliance on static methods leads to potential limitations in classification accuracy, as it does not leverage machine learning-based pattern recognition.

Additionally, since FE-BION does not incorporate ensemble learning techniques like Random Forest, it may suffer from bias in stress classification, often depending on limited user responses rather than a broader spectrum of lifestyle and sleep-related indicators. A significant drawback of FE-BION is its lack of personalized interaction. Users typically receive generic assessments without tailored feedback based on real-time data inputs.

Unlike the proposed AI-powered system, which employs BERT-based NLP for adaptive conversations, FE-BION does not engage users through contextual dialogues or refine responses based on historical interactions. This leads to lower user engagement and satisfaction, as individuals seeking mental health support may not receive meaningful explanations or coping strategies based on their unique stress conditions.

Besides, FE-BION does not integrate multi-source data processing, meaning it does not effectively analyze factors such as sleep latency, screen time, diet, exercise, and anxiety symptoms in conjunction. The absence of ensemble learning in its classification process limits its ability to capture complex relationships between lifestyle patterns and stress levels, potentially leading to misclassifications. Additionally, its static implementation makes it less scalable, restricting deployment in large healthcare applications or digital wellness platforms.

IV. PROPOSED SYSTEM

The proposed system seamlessly integrates machine learning-driven stress detection using Random Forest with an NLPpowered mental health chatbot, leveraging BERT (Transformer Library) to provide personalized and explainable AIbased mental health support. This system is designed to predict and classify users' stress levels based on real-time user input, including sleep habits, anxiety symptoms, and lifestyle choices, while simultaneously offering interactive explanations and personalized mental health guidance.





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The stress detection module employs Random Forest as an ensemble classification model, ensuring a robust and reliable method for identifying stress levels based on multiple predictive features. These include sleep duration, efficiency, latency, screen time, diet, exercise habits, anxiety symptoms, and environmental conditions. The model classifies users into three distinct mental health risk categories:

- Healthy (low stress levels with stable sleep and lifestyle habits),
- Moderate Risk (early signs of stress requiring caution),
- High Risk (severe stress levels that may demand intervention and lifestyle modifications).

Through bootstrapped sampling and randomized feature selection, Random Forest enhances classification accuracy while reducing overfitting, making it highly reliable for real-time predictions. As users continue interacting with the system, ongoing data updates allow for iterative model refinements, ensuring adaptive learning for stress detection.

The mental health chatbot, powered by BERT-based NLP, serves as an interactive explanation and support module, capable of processing natural language queries and delivering context-aware mental health insights. The chatbot intelligently tokenizes user input, extracts key phrases, and retrieves personalized responses based on its fine-tuned mental health dialogue model. The chatbot supports multi-turn conversations, adjusting its responses dynamically based on the user's assigned stress classification. Its intent recognition mechanism effectively maps queries into categories such as stress management advice, symptom explanations, and coping techniques, ensuring that users receive relevant and actionable guidance.

By combining AI-driven classification with conversational NLP, this system enhances accessibility, engagement, and transparency in mental health assessments. It provides automated, personalized, and explainable responses, ensuring that users not only receive a stress classification but also understand their mental health risks and possible coping strategies.



Fig 1 shows the proposed architecture

Fig 1: Proposed architecture

4.1 DATASETS ACQUISITION

The effectiveness of both the stress prediction model (Random Forest) and the mental health chatbot (BERT) relies on high-quality, well-structured datasets. The stress detection dataset should include features such as sleep patterns (duration, efficiency, latency), lifestyle factors (exercise, diet, screen time), anxiety symptoms, age, gender, and stress levels,





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collected from clinical trials, wearable devices, and mental health surveys. Open-source datasets like PhysioNet's Sleep-EDF, Stress Recognition in Daily Life, or Kaggle's Mental Health Prediction datasets can provide valuable insights for training. For the chatbot, dataset acquisition should focus on mental health conversations, symptom discussions, coping strategies, and therapy-based dialogues. Sources such as mental health forums, therapy transcripts, Reddit discussions, and pre-existing NLP mental health datasets (e.g., Sentiment140 for emotion detection, the Empathetic Dialogues dataset) can enhance chatbot responsiveness. Data cleaning and ethical considerations like anonymizing user responses must be adhered to for privacy compliance.

4.2 PREPROCESSING

- Handling missing values using mean imputation or regression-based estimation.
- Feature scaling and normalization for consistency in measurements.
- Encoding categorical variables (age groups, gender) for ML model compatibility.
- Feature engineering to derive meaningful insights, such as sleep efficiency calculations. For chatbot training, preprocessing includes:
- Tokenization and text segmentation for structured input processing.
- Removing noise (irrelevant stop words, non-contextual symbols) to enhance learning.
- Sentence embedding and vectorization using BERT-tokenized word representations.
- Intent classification labeling to map user queries to chatbot responses.

4.3 MODEL BUILDING

The stress prediction model is built using Random Forest, leveraging multiple decision trees to reduce overfitting and enhance classification accuracy. The architecture consists of:

- Bootstrapped training samples to diversify learning.
- Tree-based ensemble predictions to handle complex correlations.
- Hyper parameter tuning (tree depth, number of estimators) for model optimization. For the chatbot, BERT-based NLP architecture is constructed:
- Fine-tuning a pre-trained BERT model on conversational mental health datasets.
- Transformer-based attention mechanisms ensuring contextual understanding.
- Multi-turn dialogue processing to maintain coherent responses.

4.4 ACTIVITY CLASSIFICATION

- Deep neural networks possess key advantages in their capability to model complex systems and utilize automatically learning skin tone through several network layers.
- As such, deep neural networks are used to carry out precision-driven tasks such as classification and classification
- Design a CNN architecture that takes in a facial image as input and predict whether the person in the image is stressed or not.
- The architecture typically consists of multiple convolutional layers followed by max-pooling layers to take out features from the images. The final layers of the network are fully connected layers that categorize the image as positive or negative

4.5 STRESS PREDICTION

The stress level prediction module processes real-time user inputs, including sleep duration, anxiety symptoms, and lifestyle factors, using Random Forest ensemble learning. The system first collects and preprocesses data, where features are scaled, missing values are handled, and categorical variables are encoded. Once preprocessed, the feature selection process ranks important variables, such as screen time, sleep efficiency, and anxiety indicators, optimizing model accuracy. The Random Forest model, trained on historical data, undergoes a classification phase where each decision tree independently predicts stress levels, and the aggregated voting process determines the final classification. The system then categorizes users as Healthy (low stress), Moderate Risk (early signs of stress), or High Risk (severe stress). Robust validation ensures performance metrics such as accuracy, sensitivity, and specificity remain optimal. One of the significant advantages of using Random Forest for stress detection is its ability to handle large-scale feature interactions while mitigating overfitting. The ensemble structure enables the system to recognize complex relationships between sleep





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habits and stress levels, ensuring real-time adaptability. The final output provides an interpretable, explainable classification, assisting users in early stress interventions and personalized recommendations.

4.6 CHATBOT INTERFACE

The BERT-powered chatbot interface enables users to ask questions regarding their stress classifications and receive interactive, context-aware responses. When a user enters a query, the chatbot tokenizes input text using BERT's sentence embeddings, allowing it to retrieve relevant answers based on semantic similarity. Unlike rule-based bots, this chatbot dynamically adapts by analyzing the relationships between stress indicators and mental health advice, improving response coherence. The chatbot operates using Transformer-based multi-attention layers, ensuring deep contextual understanding. The model is fine-tuned using mental health conversation datasets, allowing it to retain conversational memory and refine responses. Additionally, it supports multi-turn dialogue, enabling the chatbot to retain conversational memory and refine responses over multiple exchanges. Users can ask about their stress category, request mental health coping strategies, or seek explanations for their classification. A key advantage of BERT-based NLP is its ability to offer personalized recommendations, enhancing user trust and engagement. By leveraging deep bidirectional learning, it improves query interpretation, making conversations fluid and intuitive. This chatbot goes beyond basic answer retrieval, functioning as a mental health assistant, guiding users toward stress management strategies, interactive learning, and improved well-being.

4.7. EXPERIMENTAL RESULTS

For stress detection using Random Forest, the system is tested on classification metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Robustness is assessed across real-time user data variations, including sleep patterns, lifestyle habits, and anxiety symptoms. Cross-validation techniques prevent overfitting and enhance generalization, while hyperparameters tuning optimizes the model's tree depth, feature selection, and estimator count, improving sensitivity for high-risk stress level detection.

Comparisons with traditional models like FE-BION highlight the advantages of ensemble learning in managing nonlinear stress indicator relationships.For chatbot evaluation using BERT, the assessment focuses on response relevance, contextual accuracy, and user satisfaction. Fine-tuned on mental health dialogues, the chatbot undergoes multi-turn conversation testing, ensuring it retains context across queries. BLEU scores, perplexity, and coherence ratings validate fluency and correctness in responses, while precision-recall metrics ensure intent recognition accuracy. Sentiment analysis integration enhances chatbot interactions, verifying that users find responses engaging and supportive.

The false rejection rate is the measure of the likelihood that the biometric security system will incorrectly reject an access attempt by an authorized user. A system's FRR typically is stated as the ratio of the number of false rejections divided by the number of identification attempts

FALSE REJECT RATE = FN / (TP+FN) FN =Genuine Scores Exceeding Threshold TP+FN = All Genuine Scores

	FRR
Random Forest	0.22
Bert Model	0.20
CNN classifier	0.38
FE-BION	0.35

Table 1: False rejection rate





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Volume 14, Issue 5, May 2025





Fig 2: False rejection rate

VI. CONCLUSION

The proposed AI-driven system integrates Random Forest-based stress prediction and a BERT-powered chatbot, providing a comprehensive approach to mental health assessment and interactive support. By leveraging ensemble learning for classification accuracy and transformer-based NLP for personalized engagement, the system bridges the gap between predictive analytics and conversational AI. Unlike traditional methods, which rely on static surveys and rule-based chatbots, this system ensures real-time adaptability, explainability, and user-centric mental health guidance. The stress detection module effectively classifies users into Healthy, Moderate Risk, or High Risk, enabling early intervention strategies. Meanwhile, the chatbot interface improves transparency in stress classifications, offering interactive explanations, coping mechanisms, and symptom discussions. Performance evaluations demonstrate high accuracy, reliability, and scalability, validating the system's applicability for digital healthcare platforms. By focusing on machine learning-driven classification and personalized user interactions, this framework advances AI-powered mental health support, ensuring users receive not only predictive insights but also actionable recommendations to improve well-being.

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