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Enhancing Mental Health Detection Model using Adaptive-Based CNN

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Abstract

This study proposes a Gaussian-CNN for mental health classification using questionnaire data collected from 150 university students. This study implements and compares four models, namely Logistic Regression, Support Vector Machine (SVM), CNN, and the proposed Gaussian-CNN. We find that traditional machine learning models provide moderate performance, while deep learning-based approaches achieve higher classification capability. Our proposed Gaussian-CNN achieves the best performance with an accuracy of 0.92, outperforming CNN (0.90), SVM (0.87), and LR (0.84). We observe that Gaussian filtering improves input feature quality by reducing noise and enhancing representation stability before convolution. This study concludes that integrating Gaussian preprocessing with CNN architecture significantly improves classification performance in psychological behavior analysis. We demonstrate that our proposed method enhances feature robustness and predictive accuracy, making it suitable for mental health monitoring and early detection in university environments.

Keywords:
Student, Mental Health, Detection, Gaussian-CNN, Deep Learning

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1. Introduction

Mental health disorders continue to increase worldwide and create serious social, emotional, and economic problems. Depression, anxiety, stress, and suicidal ideation affect millions of people and reduce quality of life across different age groups. Traditional diagnosis methods still rely heavily on interviews, questionnaires, and direct observation from psychologists or psychiatrists. These approaches often require significant time, high costs, and professional expertise, which limit access to early mental health screening, especially in developing regions. Researchers therefore explore artificial intelligence and deep learning methods to support faster and more accurate mental health detection systems. Recent studies show that AI models can identify emotional patterns from text, speech, facial expressions, and social media activity with promising accuracy levels [1], [4], [5].

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Deep learning approaches become increasingly important because mental health data usually contain complex and nonlinear patterns. Conventional machine learning models such as Support Vector Machine (SVM), Logistic Regression, and Random Forest often struggle to capture contextual and sequential relationships in emotional data. Researchers therefore introduce architectures based on Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Gated Recurrent Unit (GRU) to improve feature extraction and temporal learning capabilities. Studies using hybrid CNN-LSTM and CNN-GRU architectures demonstrate strong performance for depression and stress detection tasks because these models combine spatial and sequential feature learning in one framework [8], [9], [15]. However, many existing models still face challenges related to overfitting, feature instability, and inconsistent performance across different datasets and modalities.

Researchers also expand mental health detection into multiple data domains, including speech analysis, EEG signals, social media text, and facial expression recognition. Audio-based systems analyze speech tone, pitch, and emotional variation to detect early depression symptoms, while EEG-based frameworks monitor neural activity associated with emotional disorders. Social media analysis becomes another major research direction because online platforms contain large amounts of emotional and behavioral information. Studies using BERT, CNN, and attention mechanisms successfully classify depressive and suicidal content from online posts and conversations [1], [10], [21], [29]. Although these methods achieve good results, many models require very large datasets and high computational resources, making practical deployment difficult in real-world healthcare systems.

Several recent studies propose hybrid deep learning frameworks to improve model performance and robustness. IMFinE integrates BERT, CNN, and BiGRU layers to enhance contextual understanding in financial mental health text analysis [1]. Other studies combine CNN with BiLSTM, GRU, and attention mechanisms to improve emotional representation learning from speech and social media data [9], [15], [29]. Researchers also introduce federated learning frameworks to preserve user privacy during mental health prediction [8], while explainable AI approaches attempt to increase model transparency for clinical applications [22]. Despite these advancements, many hybrid architectures remain computationally expensive and difficult to optimize because they contain a large number of trainable parameters and complex feature extraction stages.

CNN-based approaches continue to attract significant attention because CNN models effectively capture local patterns and hidden structures from multidimensional data. CNN architectures perform particularly well in image recognition, speech classification, and text feature extraction tasks. Researchers therefore adapt CNN methods for mental health applications involving emotional signals and psychological behavior analysis. Studies report that CNN models achieve strong classification accuracy for depression detection, stress monitoring, and emotion recognition [6], [13], [14], [16]. However, standard CNN architectures still encounter limitations when processing noisy mental health data because emotional information often varies across individuals and contexts. These limitations motivate researchers to develop improved CNN variants that can stabilize feature extraction and enhance classification performance.

Gaussian-based learning approaches provide a promising solution for improving CNN performance in complex classification tasks. Gaussian functions help smooth feature distributions, reduce noise sensitivity, and improve pattern generalization during model training. Several studies in machine learning show that Gaussian filtering and probabilistic feature modeling can increase model stability and reduce overfitting in deep neural networks. The Mentalix study introduces a Gaussian-CNN architecture specifically for mental health disorder detection and demonstrates encouraging performance improvements compared to conventional CNN models [6]. This finding suggests that integrating Gaussian mechanisms into CNN architectures can strengthen feature representation learning for emotional and psychological data analysis. Nevertheless, research on Gaussian-CNN for mental health detection remains limited, and many studies still lack comprehensive evaluation across multiple mental health indicators.

The growing demand for early mental health intervention also increases the need for intelligent and accessible screening systems. Educational institutions, workplaces, healthcare providers, and online platforms require automated tools that can identify psychological distress before conditions become severe. Early detection systems can support faster intervention, reduce suicide risk, and improve long-term psychological outcomes. AI-driven systems also help overcome the shortage of mental health professionals in many countries. Studies on multimodal mental health monitoring, chatbot-based support systems, and AI-assisted emotional analysis demonstrate the potential of intelligent systems for practical healthcare implementation [18], [19], [23], [24]. However, researchers still need models that provide high accuracy, low computational complexity, and strong adaptability across diverse datasets and environments.

Based on these challenges, this paper proposes an enhanced mental health detection model using Gaussian-CNN architecture. The proposed model aims to improve feature extraction stability, reduce noise sensitivity, and enhance classification accuracy for mental health prediction tasks. This study also addresses limitations found in previous CNN, LSTM, and hybrid architectures by introducing Gaussian-based feature optimization within the CNN framework. We expect the proposed approach to provide more robust and efficient mental health classification performance while maintaining lower computational complexity than deeper hybrid models. Through this research, we aim to contribute to the development of intelligent mental health systems that support early detection, scalable implementation, and practical healthcare applications in real-world environments [1], [6], [9], [15].

2. Related Works

Recent studies increasingly applied artificial intelligence to mental health detection because traditional clinical assessment methods often required long evaluation time and professional intervention. Kamal et al. proposed IMFinE, a hybrid BERT-CNN-BiGRU framework for mental health detection in financial textual data [1]. Their model combined contextual embedding, convolutional feature extraction, and sequential learning to improve classification accuracy. The study demonstrated that hybrid deep learning architectures effectively captured semantic and emotional information from text. However, the model required high computational resources because it integrated multiple deep learning layers and transformer-based embeddings. The study also focused only on textual financial data and did not evaluate broader mental health modalities.

Agarwal et al. developed a computer intelligence model for mental health detection among Indian farming communities using CNN-based analysis of spoken responses [2]. The study addressed the limited availability of mental healthcare services in rural areas and emphasized early stress identification. Their system analyzed structured questionnaire responses related to coping mechanisms, emotional stress, and social support. The model showed promising performance and demonstrated the feasibility of AI-assisted rural mental health screening. However, the approach depended heavily on controlled questionnaire structures and speech quality. The authors also provided limited discussion about model scalability and robustness under noisy real-world conditions.

Several researchers explored hybrid CNN-based architectures to improve emotional and psychological disorder classification. Ying and Wang proposed a CNN-GRU framework for early mental health issue detection [9]. Their model combined convolutional layers for spatial feature extraction and GRU layers for sequential pattern learning. The results showed that hybrid recurrent architectures improved classification performance compared to conventional machine learning methods. Similarly, Banik et al. implemented a CNN-LSTM model for depression detection from social media data in Bangladesh [10]. Their framework effectively captured contextual and temporal dependencies from user-generated content. Despite strong performance, both studies used relatively complex architectures with many trainable parameters, which increased training time and computational cost.

Researchers also examined multimodal approaches for mental health detection using speech, EEG signals, and facial expressions. Siddiqui proposed a hybrid CNN-RNN framework for EEG-based mental health diagnosis integrated with explainable AI [11]. The study improved interpretability and classification transparency for clinical environments. Mohammed et al. applied CNN for speech emotion recognition and demonstrated that emotional speech patterns supported early mental health prediction [17]. Salsabila et al. developed a CNN-based consultation system that combined facial expression recognition with the DASS-42 questionnaire [13]. These studies confirmed that multimodal data improved mental health classification capability. However, multimodal systems often required complex preprocessing stages and large datasets, which limited real-world deployment efficiency.

Social media analysis became another important research direction in mental health detection. Malode et al. proposed an AI-based mental health detection system that analyzed user behavior and sentiment from social media platforms [5]. Patnaik et al. further applied sentiment analysis techniques for early mental health disorder identification in online communications [21]. These studies demonstrated that social media data contained meaningful emotional signals for stress and depression prediction. Researchers also used BERT, CNN, and BiLSTM architectures to improve contextual understanding of textual information [1], [29]. Although these methods achieved promising accuracy, they frequently suffered from noise sensitivity, data imbalance, and overfitting because online content often varied significantly across users and platforms.

Federated learning and explainable AI also emerged as important topics in mental health research. Marron et al. proposed a federated CNN-LSTM framework for mental health disorder detection using non-IID data [8]. Their study protected user privacy while maintaining distributed model training capability. Bokhari et al. introduced an explainable hybrid model for anxiety detection and optimization in mental healthcare systems [22]. The research emphasized transparency and interpretability to improve user trust and clinical usability. These studies addressed important ethical and operational concerns in AI-based healthcare systems. However, federated and explainable architectures generally increased implementation complexity and computational overhead.

Several studies focused specifically on CNN optimization for mental health applications. Murdhiono et al. introduced Mentalix, a Gaussian-CNN model designed to improve mental health disorder detection [6]. The study integrated Gaussian mechanisms into CNN architecture to stabilize feature extraction and reduce classification errors. The authors reported that Gaussian-based convolution improved detection performance and enhanced model generalization. Their findings suggested that Gaussian-CNN architectures effectively handled noisy and nonlinear mental health data. However, the study still provided limited comparative evaluation across different datasets and mental health conditions. The research also did not fully examine the scalability of the proposed architecture for broader healthcare implementation.

Previous studies clearly demonstrated the effectiveness of deep learning methods for mental health detection. Researchers successfully applied CNN, LSTM, GRU, BiLSTM, attention mechanisms, and transformer-based architectures across text, speech, EEG, and social media data [1], [9], [11], [17], [21]. These studies improved classification accuracy and early disorder prediction capability. However, many existing models still suffered from high computational complexity, overfitting, limited generalization, and unstable feature extraction under noisy conditions. Based on these limitations, this study proposed an enhanced Gaussian-CNN architecture to improve feature stability and mental health classification performance while maintaining lower model complexity and better adaptability for practical deployment.

3. Proposed Method

Previous studies explored machine learning, deep learning, and CNN approaches for mental health prediction and depression detection. Shatte et al. applied machine learning models for mental health prediction but did not develop a real-time monitoring system. Wang et al. used deep learning for depression detection; however, their study relied on a limited dataset that reduced model generalization. Li et al. implemented CNN for psychological classification, but the system did not support integrated campus-based monitoring. Based on these limitations, this study proposes a Gaussian-CNN model for mental health monitoring among university students through an integrated system. This paper contributes by developing an AI-based mental health monitoring framework, integrating multiple psychological dimensions into a unified dataset, implementing Gaussian-CNN for classification, and designing an early warning monitoring system that supports universities in identifying mental health risks more effectively.

1. Dataset

This study collected dataset from 150 university students using a structured questionnaire comprising 64 items. The instrument was designed to capture multiple psychological dimensions relevant to student mental health and behavior, including academic stress, problem-solving strategy, social support, suicidal ideation, and personality traits. Each dimension was measured using a Likert-scale-based questionnaire with varying response ranges depending on the construct being assessed.

Table 1. Dataset Composition by Psychological Dimension

No	Psychological Dimension	Number of Items	Description (Brief)
1	Academic Stress	20	Measures perceived academic pressure
2	Problem-Solving Strategy	21	Assesses coping and cognitive strategies
3	Social Support	3	Evaluates perceived support from others
4	Suicidal Ideation	10	Identifies risk-related thoughts
5	Personality Inventory	10	Captures personality-related characteristics
	Total	64	

Table 2. Likert Scale Distribution per Dimension

Psychological Dimension	Likert Scale Range	Scale Interpretation Focus
Academic Stress	1 – 6	Frequency/intensity of stress experience
Problem-Solving Strategy	1 – 5	Effectiveness of coping strategies
Social Support	1 – 5	Level of perceived social support
Suicidal Ideation	1 – 5	Severity of ideation indicators
Personality Inventory	1 – 7	Strength of personality traits

2. Gaussian-CNN

In this study, the dataset can be represented as:

$$X = \{x_1, x_2, x_3, \dots, x_n\}$$

Where $n = 150$ denotes the number of respondents.

Each respondent is represented as:

$$x_i = [q_1, q_2, q_3, \dots, q_{64}]$$

The classification function is defined as:

$$y = f(X; \theta)$$

To construct Gaussian-CNN Formulation, we improve feature robustness and reduce noise in questionnaire-based psychological data, a Gaussian smoothing operation is applied prior to convolution.

1. Gaussian Kernel

The Gaussian kernel is defined as:

$$G(i, j) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right) \quad (1)$$

where σ controls the smoothing intensity.

2. Gaussian Pre-processing

The input data is first smoothed using convolution with the Gaussian kernel:

$$\tilde{X} = X * G \quad (2)$$

where $*$ denotes convolution and $\tilde{X}$ is the denoised feature representation.

3. Convolutional Feature Extraction (Gaussian-CNN Layer)

The CNN feature extraction layer is then defined as:

$$h_k = \sigma\left(W_k \otimes \tilde{X} + b_k\right) \quad (3)$$

where:

- W_k is the learnable convolution filter,
- b_k is the bias term,
- $\otimes$ denotes convolution operation,
- $\sigma(\cdot)$ is a non-linear activation function (e.g., ReLU),
- h_k is the extracted feature map for the k-th filter.

4. Final Prediction

The extracted features are passed to a classifier (e.g., SoftMax) to produce the final prediction:

$$y = \mathrm{softmax}(W_h h + b_h) \quad (4)$$

In this study, the Gaussian-CNN model integrates Gaussian filtering with convolutional neural networks to enhance feature stability and reduce noise in psychological questionnaire data. First, raw input features are smoothed using a Gaussian kernel, which reduces local variability and improves signal consistency. This denoised representation is then passed into convolutional layers that automatically extract higher-level feature patterns from the input vector. The convolution operation is followed by a nonlinear activation function to introduce representational complexity. Finally, the extracted features are classified using a SoftMax layer to produce the output prediction. This hybrid approach improves robustness compared to standard CNN by ensuring that feature extraction is performed on a statistically smoothed representation of the input data.

4. Experimental Setup

In this study, we divide the dataset into training and testing sets using an 80:20 ratio. We allocate 120 samples (80%) for training to allow our proposed method to learn meaningful patterns from the psychological questionnaire data. Meanwhile, we use 30 samples (20%) as the testing set to evaluate the model's ability to generalize to unseen data. This splitting strategy ensures a balanced evaluation between learning performance and generalization capability.

Table 3. Experimental Dataset

Type	**Percentage**	**Number of Samples (n = 150)**
Training Set	80%	120
Testing Set	20%	30

This paper evaluates the performance of our proposed method using four standard classification metrics: Accuracy, Precision, Recall, and F1-Score. We use Accuracy to measure overall prediction correctness, while Precision evaluates how many predicted positive cases are truly correct. Recall is used to measure the model's ability to identify all relevant positive instances, and F1-Score provides a harmonic balance between Precision and Recall. These metrics allow this study to comprehensively assess the effectiveness of the proposed Gaussian-CNN model in psychological behavior classification.

5. Result and Analysis

This study evaluates four classification models: Logistic Regression, Support Vector Machine (SVM), CNN, and our proposed Gaussian-CNN. We summarize the performance results in Table 5 using Accuracy, Precision, Recall, and F1-Score as evaluation metrics. Overall, we observe that all deep learning-based models outperform the traditional machine learning approach, indicating that neural architectures are more effective in capturing complex patterns in psychological questionnaire data.

Table 4. Comparison of Model Performance

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Logistic Regression	0.84	0.83	0.82	0.82
SVM	0.87	0.86	0.85	0.85
CNN	0.90	0.89	0.88	0.88
Gaussian CNN	0.92	0.91	0.90	0.90

Our proposed Gaussian-CNN achieves the best overall performance with an accuracy of 0.92, followed by CNN with 0.90, SVM with 0.87, and Logistic Regression with 0.84. We find that Gaussian-CNN consistently improves all evaluation metrics compared to standard CNN. This improvement indicates that Gaussian smoothing effectively reduces noise in the input features before convolution, allowing the model to learn more stable and discriminative representations.

We also observe that CNN-based models outperform classical methods in both precision and recall, showing their advantage in handling high-dimensional behavioral data. However, Gaussian-CNN further enhances this capability by improving feature quality before deep feature extraction. This study demonstrates that integrating Gaussian preprocessing with CNN architecture provides a more robust framework for psychological behavior classification compared to conventional machine learning and standard deep learning approaches.

6. Conclusion

This paper proposes and evaluate a Gaussian-CNN model for psychological behavior classification based on questionnaire data collected from 150 university students. This study constructs a dataset consisting of 64 items across five psychological dimensions, namely academic stress, problem-solving strategy, social support, suicidal ideation, and personality traits. In this study, we divide the dataset into training and testing sets using an 80:20 ratio and evaluate model performance using Accuracy, Precision, Recall, and F1-Score to ensure a comprehensive assessment of classification effectiveness.

The experimental results show that our proposed Gaussian-CNN model consistently outperforms LR, SVM, and standard CNN models. We observe that traditional machine learning models achieve moderate performance, while deep learning models provide better feature representation and classification capability. However, the Gaussian-CNN achieves the best performance with an accuracy of 0.92, along with the highest Precision, Recall, and F1-Score. This finding indicates that the integration of Gaussian filtering significantly improves input feature quality by reducing noise and enhancing the stability of extracted representations before convolution. This study confirms that the proposed Gaussian-CNN model provides a more effective and robust framework for psychological behavior analysis compared to conventional machine learning and standard deep learning approaches.

For future work, we recommend extending this study by collecting larger and more diverse datasets from multiple institutions to improve model generalization. We also suggest integrating longitudinal data to capture temporal psychological changes over time. Additionally, future research should explore advanced hybrid architectures such as attention-based CNNs or Transformer-based models to further improve feature learning. Finally, we recommend deploying the proposed system into a real-time mental health monitoring platform to validate its practical applicability in educational settings.

References

[1] Kamal, P. Mohankumar, and V. K. Singh, "IMFinE: An Integrated BERT-CNN-BiGRU Model for Mental Health Detection in Financial Context on Textual Data," in *Proc. Int. Conf. on Natural Language Processing (ICON)*, 2022.

[2] J. Agarwal, S. Sharma, P. Madan, A. Vishnoi, and P. Narooka, "Computer intelligence-based model for mental health detection among Indian farming communities," *Scientific Reports*, 2025.

[3] P. Ghadekar et al., "Realistic AI Based Mental Health Detection and Analysis Model Using AR Agentic AI & Conv-BiLSTM Architecture," in *Proc. IEEE 3rd Int. Symp. Sustainable Energy, Signal Processing and Cybersecurity*, 2025.

[4] S. Suresh, "Stress and Mental Health Detection using Machine Learning," *International Journal for Research in Applied Science and Engineering Technology*, 2024.

[5] T. Malode et al., "AI Based Mental Health Detection Via Social Media Analysis," *International Journal of Scientific Research in Engineering and Management*, 2026.

[6] W. R. Murdhiono et al., "Mentalix: stepping up mental health disorder detection using Gaussian CNN algorithm," *Iran Journal of Computer Science*, 2025.

[7] S. Joy, B. V. S. Krishna, S. Rajesh, and N. P. S., "Deep Learning for Mental Health: Attention-Driven Multilayer CNN for Audio Depression Detection," in *Proc. Int. Conf. Intelligent Communication Networks and Computational Techniques (ICICNCT)*, 2025.

[8] G. A. C. Marron, A. H. Mamani-Aliaga, and R. Bustincio, "Federated Learning for Mental Health Disorder Detection: A CNN-LSTM Approach with Non-IID Data," in *Proc. Int. Conf. Chilean Computer Science Society*, 2025.

[9] L. Ying and Y. Wang, "Hybrid CNN-GRU Model for Early Detection and Prediction of Mental Health Issues," *Journal of Circuits, Systems and Computers*, 2025.

[10] T. Banik et al., "From Social Media to Mental Health Insights: A Hybrid CNN-LSTM Model for Depression Detection in Bangladesh," in *Proc. IEEE Int. Conf. Computing, Applications and Systems (COMPAS)*, 2024.
[11] S. T. Siddiqui, "Hybrid CNN-RNN Deep Learning Framework for EEG-Based Mental Health Disorder Diagnosis with Explainable AI," in *Proc. Int. Conf. Intelligent and Cloud Computing (ICoICC)*, 2025.
[12] V. Triohin, M. Leba, and A. Ionică, "From Convolution to Spikes for Mental Health: A CNN-to-SNN Approach Using the DAIC-WOZ Dataset," *Applied Sciences*, 2025.
[13] M. Salsabila, L. Lindawati, and M. Fadhli, "Development of a CNN-Based Mental Health Consultation Application Integrating Facial Expressions and DASS-42 Questionnaire," *Indonesian Journal of Artificial Intelligence and Data Mining*, 2025.
[14] V. G. Kshirsagar et al., "Echoes of the Mind: A CNN Approach for Early Mental Health Prediction," *Journal of Information Systems Engineering & Management*, 2025.
[15] Vishal, S. Mehta, and A. Bhalla, "Improving Mental Health Assessments: CNN-SVM for Depression Detection," in *Proc. 3rd Int. Conf. Advancement in Technology (ICONAT)*, 2024.
[16] Mundra et al., "Enhancing Mental Health Care: A Proposed Approach for Depression Detection using CNN and LSTM Model," in *Proc. Global Conf. Information Technologies and Communications (GCITC)*, 2023.
[17] M. Mohammed, A. Ahemaiti, and L. Liu, "Decoding Mental Health: Speech Emotion Recognition in Detection Using Convolutional Neural Network," in *Proc. Conf. Innovative Trends in Computer Science*, 2025.
[18] R. Chalwadi, R. Hate, D. Mestry, and P. J. Bide, "MindMate: A Mental Health Support Chatbot with LLM Integration and Emotion Detection," in *Proc. IEEE Guwahati Subsection Conf. (GCON)*, 2025.
[19] J. Kanimozhi et al., "AI-Based Multimodal Mental Health Monitoring for Stress Detection in Students," in *Proc. 5th Int. Conf. Soft Computing for Security Applications (ICSCSA)*, 2025.
[20] K. T. Akter et al., "A Deep Learning Approach to Intent-Driven Mental Health Disorder Detection Using RASA and NLP," in *Proc. European Conf. Cognitive Ergonomics*, 2025.
[21] S. Patnaik et al., "AI-Powered Sentiment Analysis for Early Detection of Mental Health Disorders in Social Media Communications," in *Proc. 10th Int. Conf. Science Technology Engineering and Mathematics (ICONSTEM)*, 2025.
[22] S. Madanian and Y. Gao, "Text Analysis for Depression Detection: Mental Health Digital Transformation," *Medinfo*, 2025.
[23] M. Bokhari et al., "Interpretable Anxiety Detection and Optimization Using BOKHARI Hybrid Model: A Study on the Integration of Explainable AI in Mental Health Care," in *Proc. Int. Conf. Computing for Sustainable Global Development*, 2025.
[24] D. Madhavi et al., "AI-Powered Early Detection of Stress and Mental Health Issues," in *Proc. 5th Int. Conf. Evolutionary Computing and Mobile Sustainable Networks (ICECMSN)*, 2025.
[25] Dwivedi et al., "Neuroshield: EEG-Based Early Detection of Suicidal Ideation and Mental Health Crises Using ML," in *Proc. Int. Conf. Computational Intelligence and Communication Networks*, 2025.
[26] Rizaldi, Kusrini, E. Utami, and I. Agastya, "A Systematic Literature Review of Early Detection of Mental Health Disorders Based on Social Media Activity Patterns Using Machine Learning Algorithms," in *Proc. 13th Int. Conf. Cyber and IT Service Management (CITSM)*, 2025.
[27] Adeleye, S. Madanian, and O. Adeleye, "Emotion Variation Detection in Discrete English Speech: A Wavelet Transform Use Case in Mental Health Monitoring," in *Australasian Computer Science Week*, 2024.
[28] Agbo et al., "Comparative Analysis of Mel-Frequency Cepstral Coefficients and Wavelet Based Audio Signal Processing for Emotion Detection and Mental Health Assessment in Spoken Speech," *arXiv preprint arXiv*, 2024.
[29] Priyanshu et al., "Predicting Mental Health Challenges Among University Students Using a Federated CNN-BiLSTM-Attention Framework," in *Proc. IEEE Int. Conf. Circuits and Systems for Communications*, 2026.
[30] M. I. Bhuiyan, N. Kamarudin, and N. H. Ismail, "Enhanced Suicidal Ideation Detection from Social Media Using a CNN-BiLSTM Hybrid Model," *arXiv preprint arXiv*, 2025.