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# A CNN-LSTM-Attention Framework for Early Identification of Mental Health Intervention Needs Using Multidimensional Clinical and Behavioral Data

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**ABSTRACT**

Early identification of individuals who may require mental health intervention remains challenging because conventional assessment methods often rely on subjective reports and periodic clinical evaluation. This study proposes a hybrid deep learning framework based on Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), and temporal attention mechanisms for early prediction of mental health intervention needs. The proposed framework integrates multidimensional indicators, including clinical variables, psychological characteristics, behavioral patterns, and treatment-related information, to capture both feature interactions and temporal dependencies. The model was evaluated using a publicly available synthetic mental health dataset containing 500 records, with preprocessing, feature encoding, normalization, and stratified data partitioning applied before training. Experimental comparisons were conducted against traditional machine learning models and standalone deep learning approaches using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). The proposed CNN-LSTM-Attention model achieved an accuracy of 93.6%, precision of 92.8%, recall of 93.1%, F1-score of 92.9%, and AUC of 0.96, outperforming the compared baseline models. Repeated experiments further indicated stable performance with low variation across different runs. These results demonstrate the potential of hybrid deep learning for supporting early mental health risk screening. However, because the evaluation was conducted on a synthetic dataset, further validation using larger, clinically collected, and externally validated datasets is required before practical healthcare application.

## 1. INTRODUCTION

Mental disorders have become a major public health problem because of increasing prevalence and profound effects on individual well-being, social adaptation, productivity, and quality of life. Common conditions such as depression, anxiety, stress-related disorders, bipolar disorder, psychotic illnesses and mood disturbances typically develop insidiously and often remain undetected until a relatively advanced stage of illness. Consequently, most individuals seek professional care only after the severity of symptoms is sufficient to impair daily activities, occupational performance, relations with others or physical health [1]. Despite major advances in diagnostic and treatment methods, early identification of individuals who require intervention remains a formidable task [1]. Poor availability of trained mental health professionals, reluctance to seek care because of stigma, delays in referral and dependence on intermittent clinical evaluation further impair the ability to detect illness at an early stage and to initiate therapy promptly [2]. Authors [3] converted electroencephalography (EEG) signals into scalogram images and used a Convolutional Neural Network (CNN)-based deep learning model for automated schizophrenia detection. The study reported high classification performance, highlighting the potential of time–frequency image analysis for EEG-based diagnosis.

Conventional methods of mental health assessment generally depend on self-report questionnaires, clinical interviews, clinician observations and standardized measures of cognitive function. Although clinically useful, these methods are subject to limitations such as subjectivity, reporting bias, recall capacity, and the frequency of monitoring. Recent developments in artificial intelligence and methods of deep learning provide new opportunities for applications of mental health prediction and clinical decision support [4-6].

Traditional machine learning models such as Logistic Regression, Support Vector Machine (SVM), Random Forest, and boosting-based approaches have been used in automated screening and healthcare classification tasks because of their interpretability and comparatively lower computational complexity [7-9]. Recent developments in AI and DL methods provide new opportunities for applications of mental health prediction and clinical decision support [10, 11]. The use of standard instruments, such as the Mini-Mental State Examination, has been extensive in studies of neurological and cognitive function. Still, it may not fully capture subtle changes in behavior, sleep patterns, physiological activity, emotional expression, and capacity for daily functioning. As a consequence, there is increasing demand for data-integration approaches that will enable the identification of early indicators of potential need for treatment [12]. Deep learning methods provide stronger representation learning capability, particularly when applied to complex clinical, behavioural, and physiological datasets. For example, CNN-based and hybrid deep learning approaches have been applied in schizophrenia detection, EEG-based assessment, attention-deficit/hyperactivity disorder (ADHD) detection, Alzheimer's disease progression forecasting, and depression or anxiety prediction from clinical records and social media content [4, 5, 10, 11, 13, 14]. Large volumes of structured and unstructured data can be analyzed to detect nonlinear relationships and identify latent patterns that are not readily apparent with conventional statistical methods. The application of these models to data obtained from questionnaires, electronic health care records, social media, behavioral activity records, speech signals, physiological activity measures, electroencephalographic recordings, and sensor-based monitoring systems has been extensive. In addition, application of artificial intelligence (AI)-based systems of clinical decision support has reduced the workload of diagnostic evaluation, improved the efficiency of screening and facilitated clinical decision-making regarding treatment [15]. However, many of these models rely heavily on manually engineered features and may be insufficient for modeling complex temporal and multimodal patterns in mental health data. Standalone deep learning approaches also have limitations. Convolutional neural networks are effective at extracting local and spatial feature representations but are insufficient for modeling long-term temporal dependencies. Recurrent neural networks, including variants of long short-term memory or gated recurrent units, accommodate sequential representations of time-dependent processes but may be inadequate for heterogeneous feature patterns or for selected intervals of clinical importance. Use of attention mechanisms overcomes these limitations and increases the relative weighting of relevant features or time intervals during prediction. Consequently, integration of CNN-based methods for feature extraction, Recurrent Neural Network (RNN)-based methods for temporal modeling, and attention-based methods for weighting features provides a more comprehensive basis for prediction of the need for early mental health care.

However, major gaps in research remain. First, most studies emphasize classification of disease states, rather than prediction of the need for early clinical intervention. Second, many models achieve high levels of classification accuracy but fail to adequately address issues of interpretability, reproducibility, and clinical utility. Third, the results of most studies provide limited information on the model design, training parameters, validation strategies, and ethical requirements for research. Fourth, the application of multiple data modalities, including clinical variables, reports of psychological symptoms, patterns of behavior, and measures of physiologic function, remains limited in predicting the need for early treatment. In addition, experience with systems of digital health care, with chat-based services for mental health care and with models of AI-assisted clinical decision making further support the need for integration of methods of prediction with strategies for effective delivery of care, acceptance by users and attainment of readiness for implementation.

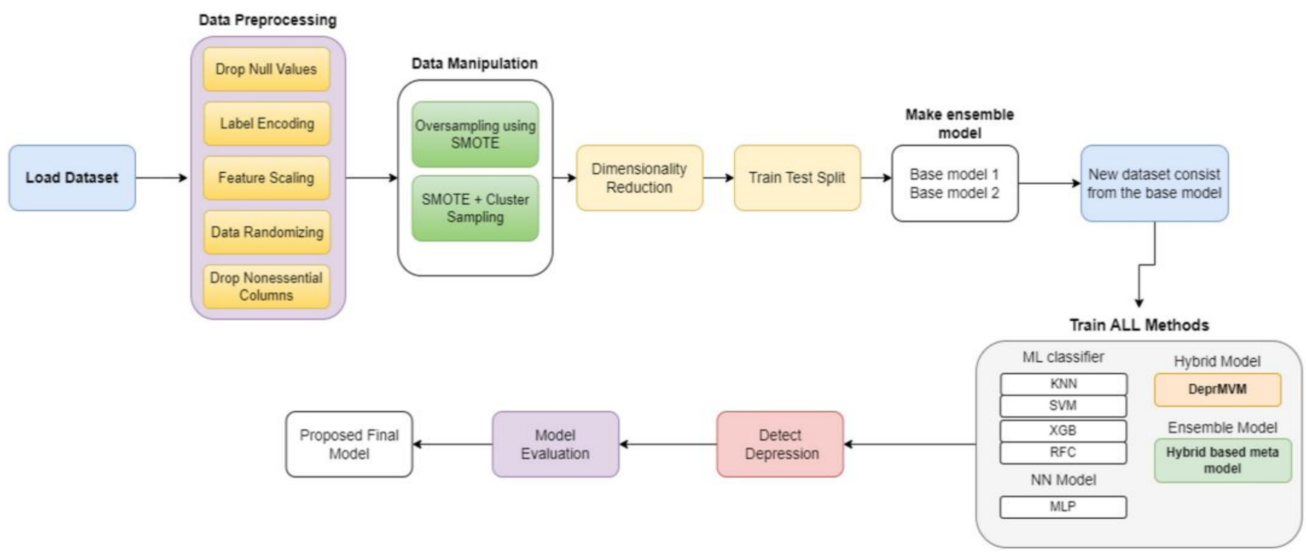


**Figure 1.** Conventional block diagram for mental health prediction using hybrid machine learning algorithms [3]

To overcome existing gaps, here we present an AI-enabled hybrid CNN-RNN-Attention architecture for early prediction of mental health care requirements. The CNN module identified relevant patterns within multi-dimensional input data, the RNN module captured temporal relationships across sequences of observations, and the attention mechanism weighted clinically relevant features and time points more highly. Our goal was not to replace clinical diagnosis, but to develop a decision-support system that may aid in identifying individuals who require additional evaluation or timely intervention. Evaluation with conventional performance measures and comparison with traditional machine learning and individual deep learning approaches confirmed the efficacy of our hybrid strategy. Finally, we illustrate the conventional approach to hybrid machine learning-based prediction of mental health care needs (Figure 1).

The major objectives of this study are as follows:

1. To develop a hybrid deep learning framework for early prediction of mental health treatment needs using multidimensional psychological, behavioural, clinical, and physiological indicators.
2. To reduce dependence on subjective assessment alone by incorporating data-driven feature learning and temporal pattern analysis.
3. To integrate CNN-based feature extraction, RNN-based temporal modelling, and an attention mechanism for improved representation of complex mental health patterns.
4. To evaluate the predictive performance of the proposed framework using standard classification metrics and compare it with conventional machine learning and standalone deep learning models.
5. To provide a clinically cautious decision-support approach that can assist early risk identification while acknowledging the need for further validation using larger and externally verified datasets.

The remaining sections of the paper are organized as follows. Section II presents a review of related work on AI-based mental health prediction, hybrid deep learning models, and attention-based healthcare prediction systems. Section III describes the proposed methodology, including data preprocessing, model architecture, attention formulation, training strategy, and evaluation protocol. Section IV presents the experimental results, comparative analysis, and discussion of model performance. Section V concludes the study by summarizing the major findings, limitations, and future research directions.

## 2. LITERATURE REVIEW

Early detection of mental disorders is an important area of research, because it improves clinical intervention, limits progression of symptoms, and facilitates better outcomes of treatment. The application of artificial intelligence, machine learning, and deep learning techniques has greatly expanded the ability to predict mental disorders by analysing responses to questionnaires, clinical records, behavioural observations, physiological signals, speech patterns, social media activity, and electronic health records. The clinical complexity of mental disorders reflects the interaction of psychological, neurobiological, biological, behavioural and contextual factors. As a result, studies of schizophrenia, bipolar disorder, impaired consciousness and neurocognitive status have demonstrated that mental disorders and neurological conditions are associated with complex patterns of signals and with multiple dimensions of clinical behaviour [4, 5, 8, 12].

Early studies largely employed conventional machine learning algorithms to detect patterns associated with depression, anxiety, stress and other common psychiatric disorders. These methods confirmed the feasibility of automated screening. Still, they were generally limited by manually derived features, small sample sizes, fixed representations of input data, and a reduced capacity to model complex non-linear relationships in heterogeneous psychiatric data [7, 9, 10, 16, 17]. The application of intelligent predictive methods has been highly successful across various engineering and clinical domains, including hybrid system prediction. However, direct application to mental health data required rigorous, domain-specific validation because of the highly sensitive, subjective, and time-dependent nature of psychiatric data [6].

With advances in deep learning, neural network-based methods have been extensively applied to mental health analysis. These methods provide fully automated learning of informative representations from both structured and unstructured data, and largely eliminate the need for manually defined features. Local feature patterns were extracted from text, physiological signals, EEG representations, and other structured data using convolutional neural networks. As a result, performance in classifying depression, schizophrenia, ADHD, and stress exceeded that achieved with conventional methods [4, 5, 10, 18] because of the ability to identify discriminative patterns in features derived from high-dimensional input representations. However, these methods were generally ineffective at capturing long-term patterns of temporal variation in mental health symptoms.

Social media and text-based behavioural data are also emerging as valuable resources for mental health prediction. Application of methods for representation learning enabled detection of signals associated with depression from social media content, in which linguistic, affective, and behavioural features served as surrogate indicators of psychological distress [13]. Likewise, use of electronic health records facilitated prediction of depression and anxiety in clinical samples in which detailed records of medical history, comorbidity and longitudinal clinical observations supported early identification of risk [14]. These results confirm that both unstructured behavioural data and well-structured clinical records can improve the accuracy of mental health predictions when analysed with appropriate methods of machine learning and deep learning.

To capture temporal dependencies, sequence-based models such as recurrent neural networks, long short-term memory and gated recurrent units have been applied to longitudinal prediction of mental health outcomes. These approaches provide effective methods for analysis of time-dependent data including variations in mood, behavioural records, sleep patterns, physiological signals and repeated clinical observations. Temporal processing with long short-term memory methods allows retention of prior contextual information and modelling of progression across multiple time intervals that are well suited for prediction of relapse, mood instability and risk progression [19]. Combined applications of convolutional and recurrent network methods also yielded improved predictions for progression of neurological diseases [11], and support the utility of integrated spatial and temporal learning for analysis of health-related sequential data. However, use of sequence models in isolation was limited when applied to data with multiple modes of representation or to situations in which strong contributions to final predictions were derived exclusively from specific intervals of time.

Hybrid deep learning architectures have therefore attracted interest for mental health prediction because they exploit the strengths of multiple architectural approaches. Integration of spatial feature extraction with temporal modelling enabled development of models capable of capturing both local interactions among features and sequential variations in indicators of mental health status. These models provided new approaches for detection of anxiety, assessment of stress, screening for depression, analysis of neurological disorders and prediction of clinical severity based on multimodal measures of behavioural, clinical and physiological function [11, 20]. Compared with individual model types, hybrid architectures generally yielded more stable estimates of predictive performance because they allowed the representation of multiple aspects of mental health data within a single learning system. However, most existing hybrid methods continue to emphasize the classification of disorders rather than the prediction of early clinical treatment requirements.

Attention-based models have further enabled deep learning systems to focus on important features or time points during prediction. In healthcare applications, attention mechanisms have facilitated identification of clinically relevant temporal events, increased sensitivity for high-risk cases and provided greater model interpretability. For prediction of mental health risk, attention-based RNN models increased the relative importance of clinically relevant symptoms, behavioural changes or physiologic variations to improve detection of patterns of early warning [21]. However, achieving greater model interpretability remains a major challenge. Most studies achieved high accuracy but offered limited insight into the basis for model predictions using methods of attention visualization, feature attribution, analysis of individual clinical cases or external validation.

Multisource and ensemble deep learning approaches also have been applied to mental health prediction tasks [22]. These methods integrate information from multiple data sources or from multiple models to increase robustness and reduce variability of predictions. While such ensemble methods improve stability of classification, they generally increase computational complexity and may be difficult to implement in real-time clinical or screening settings. In addition, integration of clinical, behavioural, psychological and physiological information required extensive efforts to achieve adequate data preprocessing, alignment, protection of privacy and validation to maintain reliability across different populations. AI-based systems also have been developed for broader applications in health care [15, 23]. These systems reduce the workload associated with clinical diagnosis, facilitate patient screening and improve the quality of clinical decision making. Additional applications of AI to improve access to mental health care were particularly striking in settings of limited availability of conventional clinical care [24]. However, effective implementation of AI in health care depended on the quality of service, organizational readiness, infrastructure availability, the development of appropriate governance systems, clinician acceptance, and the ability to overcome barriers to implementation [25, 26]. Finally, these limitations were particularly important for applications in mental health care, where data were highly sensitive and the adverse consequences of incorrect predictions were substantial.

A review of the literature highlights several important research gaps. First, most previous studies emphasize diagnosis or classification of mental illness, rather than prediction of risk for early treatment or clinical intervention. Second, use of single-modality data is insufficient to capture the multi-dimensional nature of mental illness. Third, limited details on model architecture, hyperparameters, training procedures, and validation strategies impair reproducibility. Fourth, although attention-based methods are generally considered interpretable, most studies fail to provide sufficient information on attention maps, measures of feature importance, or clinically meaningful representations of model output. Finally, concerns regarding data privacy, informed consent, methods of anonymization, sources of bias, and strategies for achieving clinical fairness and the responsible use of technology are generally inadequately addressed in studies of AI-based methods for predicting mental illness.

To overcome these limitations, we report here the development and testing of a hybrid convolutional neural network, recurrent neural network, and attention-based architecture for early prediction of treatment risk. Feature representations were obtained for multi-dimensional input data, and the recurrent neural network component captured temporal patterns of behaviour. Attention mechanisms identified and emphasized features and temporal intervals associated with early risk indicators. As a result, we developed a system for early screening, with appropriate caution and recognition of the need for additional clinical validation. Table 1 presents the survey of existing approaches for mental health prediction.

**Table 1.** Survey of AI-based approaches for mental health prediction

| Reference | Data Type Used | Methodology | Research Focus | Key Outcomes | Limitations Identified |
|---|---|---|---|---|---|
| [16] | Questionnaire and clinical data | Logistic Regression, SVM | Depression screening | Demonstrated the feasibility of automated mental health screening | Limited feature representation and reduced generalization |
| [17] | Social media text | Naïve Bayes, Random Forest | Mental health sentiment analysis | Identified linguistic markers associated with psychological distress | Did not model temporal behavioural patterns |
| [18] | Survey-based datasets | CNN | Depression detection | Improved classification through automated feature extraction | Lacked temporal modelling capability |
| [19] | Longitudinal patient records | LSTM | Mood disorder prediction | Captured symptom progression over time | Limited integration of contextual and spatial features |
| [20] | Multimodal behavioural data | CNN–LSTM hybrid | Anxiety and stress detection | Improved performance over standalone deep learning models | Focused mainly on diagnosis rather than treatment need prediction |
| [21] | Electronic Health Records | Attention-based RNN | Mental health risk prediction | Improved sensitivity for identifying high-risk individuals | Limited emphasis on early intervention and clinical explanation |
| [22] | Multisource mental health data | Ensemble deep learning | Severity-level prediction | Produced robust and stable predictions | Increased computational complexity and reduced deployment simplicity |

Note: AI = Artificial intelligence, SVM = Support Vector Machine, LSTM = Long Short-Term Memory, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

The literature supports a major role for AI-based models in mental health screening and risk prediction. However, current efforts remain limited by single-modality dependence, inadequate temporal modelling, poor interpretability, limited reproducibility and absence of strategies for early prediction of treatment needs. These limitations justify development of a hybrid CNN-RNN-Attention model incorporating methods for feature extraction, temporal learning and attention-modulated weighting to achieve early prediction of mental health treatment needs.

## 3. PROPOSED METHODOLOGY

The proposed study presents a reproducible CNN-Long Short-Term Memory (LSTM)-Attention framework for early screening of mental health treatment needs using multidimensional mental health-related indicators. The framework consists of dataset preparation, preprocessing, temporal feature representation, CNN-based local feature extraction, LSTM-based temporal modelling, temporal attention-based weighting, and final classification. The proposed model is designed only for early screening support and risk prioritization, not as a replacement for clinical diagnosis or professional mental health assessment.

### 3.1 Dataset description and experimental setup

The experimental evaluation was conducted using the publicly available Mental Health Diagnosis and Treatment Monitoring dataset obtained from Kaggle. The dataset contains 500 synthetic records representing mental health diagnosis, treatment monitoring, symptom-related indicators, treatment progress, and outcome-related information. Since the dataset is synthetic and publicly available, it does not contain real patient-identifiable information. Therefore, formal patient consent was not required for this experimental analysis. However, because the dataset is synthetic and limited in size, the findings should be interpreted as preliminary experimental validation. They should be verified externally using real-world clinical datasets before clinical use.

The dataset includes demographic variables such as age and gender; clinical and psychological indicators such as diagnosis, symptom severity, mood score, sleep quality, stress level, and AI-detected emotional state; treatment-related variables such as medication, therapy type, treatment duration, treatment progress, and treatment adherence; and the final treatment outcome. The target variable was derived from the treatment outcome field. Records indicating insufficient or negative treatment response were assigned to class 1, representing individuals requiring further treatment attention or early screening support. Records indicating improved treatment response were assigned to class 0, representing individuals with no immediate need for additional treatment based on the available indicators.

After removing non-predictive identifiers such as Patient ID, the remaining demographic, clinical, behavioral, physiological, and treatment-related variables were used as input features. The final dataset contained 500 samples. The dataset was divided into training, validation, and test subsets using a stratified split to preserve the class distribution across subsets. In this study, a 70:15:15 split was used, where 70% of the data were used for training, 15% for validation, and 15% for testing. A fixed random seed of 42 was used for reproducibility. The overall architecture of the proposed CNN-RNN-Attention framework is shown in Figure 2.

The proposed architecture is intended to support early risk identification rather than replace clinical diagnosis. The model output indicates whether an individual may require further mental health assessment or early intervention based on available psychological, behavioural, clinical, and physiological indicators.

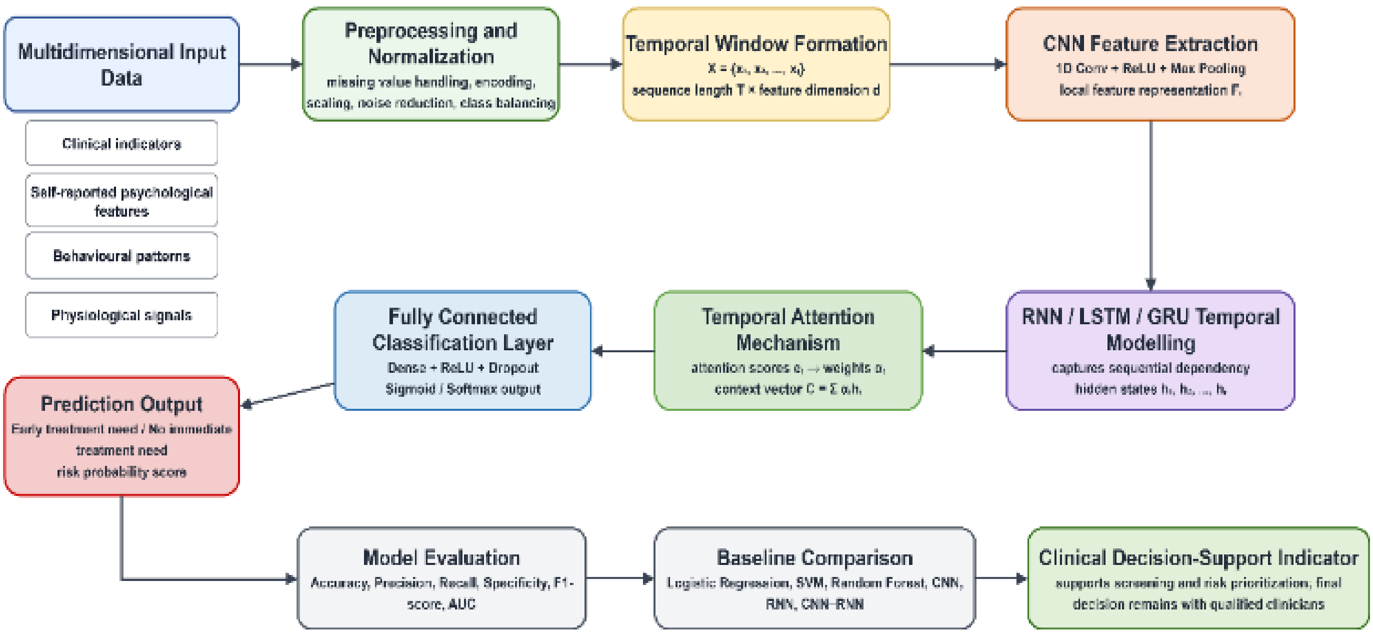


**Figure 2.** Proposed CNN-RNN-Attention framework for early prediction of mental health treatment needs
Note: LSTM = Long Short-Term Memory, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

### 3.2 Data preprocessing and temporal representation

The preprocessing stage included missing value handling, categorical encoding, feature scaling, class balancing, and temporal representation. Missing numerical values were replaced using median imputation, while missing categorical values were handled using mode-based imputation. Categorical variables such as gender, diagnosis, medication, therapy type, AI-detected emotional state, and treatment outcome were one-hot or label-encoded as appropriate. Continuous variables such as age, symptom severity, mood score, sleep quality, physical activity, treatment duration, stress level, treatment progress, and treatment adherence were normalized using min–max scaling:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where, $x$ is the original feature value, $x_{min}$ and $x_{max}$ are the minimum and maximum values of that feature, and $x'$ is the normalized value.

For sequence-based modelling, each sample was represented as a temporal feature matrix:

$$[X_i = \{x_1, x_2, \dots, x_T\}, x_t \in \backslash mathbbb\{R\}^{\{d\}}]$$

where, $x_t$ represents the feature vector at time step t, d denotes the number of input features, and $T$ denotes the temporal sequence length. In this study, the treatment duration and monitoring-related indicators were used to arrange the records into a structured temporal representation. Class imbalance, if present after label construction, was handled using class weighting during model training. The preprocessing and temporal alignment workflow is shown in Figure 3.

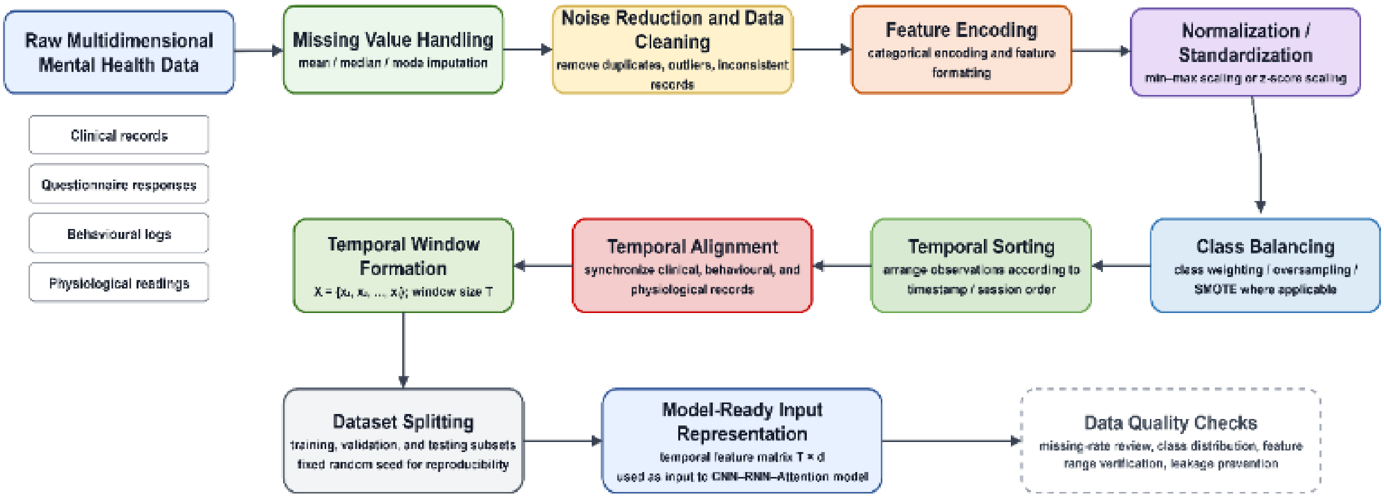


**Figure 3.** Data preprocessing and temporal alignment workflow

### 3.3 Proposed Convolutional Neural Network–Recurrent Neural Network–attention architecture

The proposed model consists of two one-dimensional convolutional layers, one LSTM layer, one temporal attention layer, one dense layer, and one output layer. The CNN module extracts local feature interactions from the pre-processed input sequence. The LSTM module captures temporal dependencies across sequential observations. The attention layer assigns higher importance to relevant time steps. The final dense layer and output layer generate the predicted probability of early treatment need.

The first convolutional layer uses 64 filters with kernel size 3 and ReLU activation. The second convolutional layer uses 128 filters with kernel size 3 and ReLU activation. Max pooling with pool size 2 is applied after convolution to reduce dimensionality. Batch normalization is used to stabilize training, and dropout with a rate of 0.30 is used to reduce overfitting. The recurrent component uses an LSTM layer with 128 hidden units. The attention layer computes temporal attention weights over the LSTM hidden states. The dense layer contains 64 neurons with ReLU activation, and the output layer uses sigmoid activation for binary classification.

The general model architecture is shown in Table 2.

**Table 2.** Proposed CNN-RNN-Attention model architecture

| Layer/Module | Configuration | Output Representation | Purpose |
|---|---|---|---|
| Input Layer | Temporal window of size T × d | X∈RT×d | Receives normalized sequential mental health features |
| CNN Layer 1 | 1D convolution, 64 filters, kernel size 3, ReLU | Feature maps | Extracts local feature patterns |
| Max Pooling | Pool size 2 | Reduced feature maps | Reduces dimensionality and noise |
| CNN Layer 2 | 1D convolution, 128 filters, kernel size 3, ReLU | Higher-level features | Learns deeper feature interactions |
| Batch Normalization | Standard batch normalization | Normalized features | Stabilizes training |
| Dropout | Dropout rate 0.30 | Regularized features | Reduces overfitting |
| RNN Layer | LSTM/GRU, 128 hidden units | Hidden sequence ht | Captures temporal dependency |
| Attention Layer | Temporal attention | Context vector C | Assigns weights to important time steps |
| Dense Layer | 64 neurons, ReLU | Dense representation | Learns final discriminative representation |
| Output Layer | Sigmoid/Softmax | Prediction probability | Predicts treatment need, class |

Note: LSTM = Long Short-Term Memory, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

### 3.4 Convolutional Neural Network-based feature extraction

For a given input vector $x_t$, the convolution operation is defined as:

$$F_t = f_{CNN}(x_t; W_c, b_c)$$
$$F_t = ReLU(W_c * x_t + b_c)$$

where, $F_t$ represents the CNN-extracted feature representation at time step $t$, $W_c$ represents the convolutional filter weights, $b_c$ is the bias term, and * denotes the convolution operation, and ReLU is the rectified linear unit activation function.

### 3.5 Long Short-Term Memory based temporal modelling

The CNN-extracted feature sequence is passed to an RNN module. The hidden state at each time step is computed as:

$$\left[h_t = f_{\{LSTM\}(F_t, h_{\{t-1\}}; W_r)}\right]$$

where, $h_t$ represents the hidden state at time step $t$, $F_t$ is the CNN feature representation, $h_{t-1}$ is the previous hidden state, and $W_r$ represents the recurrent weights.

The LSTM gate operations are defined as:

$$i_t = \sigma(W_i[F_t, h_{t-1}] + b_i)$$
$$f_t = \sigma\left(W_f[F_t, h_{t-1}] + b_f\right)$$
$$o_t = \sigma(W_o[F_t, h_{t-1}] + b_o)$$
$$\tilde{c}_t = tanh(W_c[F_t, h_{t-1}] + b_c)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$h_t = o_t \odot tanh(c_t)$$

where $i_t$, $f_t$, and $o_t$ denote the input, forget, and output gates, respectively; $c_t$ is the memory cell state; and $\odot$ denotes element-wise multiplication.

### 3.6 Temporal attention mechanism

The temporal attention layer is applied over the sequence of LSTM hidden states. The attention score for each hidden state is calculated as:

$$e_t = v_a^T tanh(W_a h_t + b_a)$$

The normalized attention weight is calculated using the Softmax function:

$$\alpha_t = \frac{exp(et)}{\sum_{k=1}^{T} e\,xp(ek)}$$

The attention-weighted context vector is then obtained as:

$$C = \sum_{t=1}^{T} \alpha_t\, h_t$$

where, $e_t$ is the attention score, $\alpha_t$ is the attention weight assigned to time step $t$, $W_a$, $v_a$, and $b_a$ are trainable attention parameters, and $C$ is the final attention-weighted context vector.

### 3.7 Classification layer and loss function

The context vector ($C$) is passed to a dense layer and then to the output layer. For binary early treatment-need prediction, sigmoid activation is used:

$$\hat{y} = \sigma(W_{out}C + b_{out})$$

where, $\hat{y}$ is the predicted probability, $W_{out}$ is the output weight matrix, $b_{out}$ is the output bias, and $\sigma$ denotes the sigmoid activation function.

The predicted class is assigned as:

$$y = \begin{cases} 1 & \text{if } \hat{y} \geq 0.5 \\ 0 & \text{if } \hat{y} < 0.5 \end{cases}$$

where, class 1 indicates that the individual may require early mental health intervention, and class 0 indicates no immediate treatment need based on the available input features.

For binary classification, binary cross-entropy loss is used:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i\, log(\hat{y}_i) + (1 - y_i)\, log(1 - \hat{y}_i)]$$

where, $N$ is the number of samples, $y_i$ is the actual label, and $\hat{y}_i$ is the predicted probability.

**Table 3.** Hyperparameter settings used for model training

| Parameter | Value/Setting |
|---|---|
| Dataset | Kaggle Mental Health Diagnosis and Treatment Monitoring |
| Dataset type | Public synthetic dataset |
| Total samples | 500 |
| Input format | Temporal feature matrix (T × d) |
| Train-validation-test split | 70:15:15 |
| CNN layers | 2 |
| CNN filters | 64 and 128 |
| Kernel size | 3 |
| Pooling method | Max pooling |
| Pool size | 2 |
| RNN type | LSTM |
| LSTM hidden units | 128 |
| Attention type | Temporal attention |
| Dense layer neurons | 64 |
| Activation function | ReLU for hidden layers, sigmoid for output |
| Optimizer | Adam |
| Learning rate | 0.001 |
| Batch size | 32 |
| Maximum epochs | 100 |
| Early stopping | Patience of 10 epochs |
| Dropout rate | 0.30 |
| Loss function | Binary cross-entropy |
| Random seed | 42 |

Note: LSTM = Long Short-Term Memory, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

### 3.8 Training configuration

The model was trained using the Adam optimizer with a learning rate of 0.001. The batch size was set to 32, and the model was trained for a maximum of 100 epochs. Early stopping with patience of 10 epochs was applied based on validation loss. Dropout with a rate of 0.30 and batch normalization were used to reduce overfitting. The same preprocessing procedure was applied to the baseline models wherever applicable. The hyperparameter settings used for training the proposed CNN-LSTM-Attention model are summarized in Table 3.

### 3.9 Validation strategy

To strengthen the reliability of the reported results, repeated experiments were conducted using different random seeds. The model was trained and evaluated across five independent runs using the same preprocessing steps, architecture, optimizer, learning rate, batch size, and early stopping configuration. The final performance was reported as mean ± standard deviation. This repeated-run strategy reduces the effect of random initialization and data splitting on the reported performance.

If sufficient computational resources are available, 5-fold cross-validation may also be used. In 5-fold cross-validation, the dataset is divided into five subsets; four subsets are used for training, and the remaining subset is used for testing in each iteration. The final result is calculated as the average performance across all folds. The complete training and evaluation procedure is summarized in Algorithm 1.

**Algorithm 1.** Training and Evaluation Procedure of the CNN-RNN-Attention Model

Input: Pre-processed mental health dataset X, labels Y
Output: Trained CNN-RNN-Attention model and prediction results
1. Load multidimensional mental health dataset.
2. Handle missing values and encode categorical variables.
3. Normalize numerical features using min–max scaling or standardization.
4. Arrange sequential observations into temporal windows of length T.
5. Split the dataset into training, validation, and testing subsets.
6. Initialize CNN, RNN, attention, and dense layer parameters.
7. For each epoch:
    a. Pass input data through CNN layers to extract local feature representations.
    b. Pass CNN features to the RNN layer for temporal modelling.
    c. Compute attention scores and attention weights.
    d. Generate attention-weighted context vector.
    e. Pass context vector to dense and output layers.
    f. Compute classification loss.
    g. Update model parameters using Adam optimizer.
    h. Monitor validation loss and apply early stopping if required.
8. Evaluate the trained model on the test dataset.
9. Compute accuracy, precision, recall, sensitivity, specificity, F1-score, and Area Under the Curve (AUC).
10. Compare the proposed model with baseline machine learning and deep learning models.

### 3.10 Ethical considerations and data privacy

The dataset used in this study is a publicly available synthetic dataset and does not contain real patient-identifiable information. Therefore, formal patient consent was not required. However, mental health data are highly sensitive in real-world applications. Any future use of real clinical data must include institutional ethics approval, informed consent, anonymization, secure storage, restricted access, and compliance with applicable privacy regulations. The proposed model should be used only as an early screening support tool and not as a standalone diagnostic or treatment-planning system.

## 4. RESULTS AND DISCUSSION

This section presents the performance analysis of the proposed CNN-RNN-Attention model for early prediction of mental health treatment needs. The model was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and AUC. The results were compared with conventional machine learning models, standalone deep learning models, and a CNN-RNN hybrid baseline. The purpose of this comparison was to examine whether integrating CNN-based feature extraction, RNN-based temporal modeling, and attention-based weighting improves prediction of early-stage mental health treatment needs.

The proposed model demonstrated improved performance over baseline models due to the complementary contributions of the components in the hybrid architecture. The CNN layers identified informative local patterns from multidimensional measures of mental health, and the RNN component integrated information across sequential observations. The application of an attention mechanism further optimized the representation by increasing the relative importance of informative time steps and local information patterns. Consequently, predictive performance was superior to that achieved with conventional machine learning methods or with separate applications of neural network techniques.

### 4.1 Comparative performance analysis

As shown in Table 4, the proposed CNN-RNN-Attention model achieved the highest performance across all evaluation metrics. The model obtained an accuracy of 93.6%, precision of 92.8%, recall of 93.1%, F1-score of 92.9%, and AUC of 0.96. Compared with the CNN-RNN hybrid model, the proposed model improved accuracy by 3.4 percentage points and AUC by 0.03. This indicates that the addition of an attention mechanism improved model performance by enhancing the selection of relevant temporal and feature-level information.

**Table 4.** Comparative performance analysis of machine learning, deep learning, and proposed hybrid models

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC |
|---|---|---|---|---|---|
| Logistic Regression [27] | 78.6 | 76.9 | 75.4 | 76.1 | 0.81 |
| SVM [28] | 81.3 | 80.1 | 79.2 | 79.6 | 0.84 |
| Random Forest [29] | 83.7 | 82.5 | 81.8 | 82.1 | 0.87 |
| CNN [30] | 86.4 | 85.9 | 84.6 | 85.2 | 0.89 |
| RNN (LSTM/GRU) [31] | 87.9 | 86.8 | 86.1 | 86.4 | 0.91 |
| CNN–RNN Hybrid [32] | 90.2 | 89.5 | 88.7 | 89.1 | 0.93 |
| CNN–RNN–Attention Proposed Model | 93.6 | 92.8 | 93.1 | 92.9 | 0.96 |

Note: SVM = Support Vector Machine, AUC = Area Under the Curve, LSTM = Long Short-Term Memory, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

Traditional machine learning methods (logistic regression, SVM, and random forests) yielded relatively low performance, likely due to their reliance on manually defined features and their inability to represent complex non-linear and temporal relationships. Performance was superior for CNN and RNN models, but limitations of each approach remained apparent. The CNN model provided good representation of local feature patterns, but failed to incorporate temporal information. In contrast, the RNN model provided good representation of temporal sequences, but did not explicitly identify the most important time points. Our hybrid approach eliminated these limitations and incorporated spatial, temporal, and attention-based components of learning.

### 4.2 Early-stage prediction performance

Table 5 shows the early-stage predictive performance for the baseline and proposed models. Our proposed CNN-RNN-Attention approach achieved an early-stage accuracy of 92.1% and reduced the false negative rate to 5.8%. This reduction in false-negative predictions is clinically important for mental health screening, because missed cases of high risk may impede subsequent evaluation and treatment. Compared with our CNN-RNN model, our proposed method further reduced the rate of false-negative predictions by 3.6%, reflecting improved sensitivity to detect patterns of early risk.

**Table 5.** Early-stage prediction performance of baseline and proposed models

| Model | Early-Stage Accuracy (%) | False Negatives (%) |
|---|---|---|
| CNN [30] | 82.5 | 14.6 |
| CNN-RNN [32] | 88.7 | 9.4 |
| RNN [33] | 84.3 | 13.1 |
| CNN-RNN-Attention Proposed Model | 92.1 | 5.8 |

Note: CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

However, these results should be interpreted cautiously. The findings suggest that the proposed model may be useful as a decision-support tool for early screening, but additional validation using larger datasets, external testing, and clinical expert review is required before practical clinical deployment.

### 4.3 Accuracy comparison

Figure 4 shows the accuracy comparison among the evaluated models. The traditional machine learning models achieved moderate accuracy, with Logistic Regression achieving 78.6%, SVM achieving 81.3%, and Random Forest achieving 83.7%. The deep learning models showed improved performance, where CNN achieved 86.4% and RNN achieved 87.9%. The CNN-RNN hybrid model further improved accuracy to 90.2%, demonstrating the advantage of combining feature extraction and temporal modelling. The proposed CNN-RNN-Attention model achieved the highest accuracy of 93.6%, confirming the contribution of the attention mechanism in improving predictive performance.

The increasing trend in accuracy indicates that hybrid learning architectures are more effective than single-model approaches for modelling multidimensional and time-dependent mental health indicators. Nevertheless, accuracy alone is not sufficient for evaluating mental health prediction systems; therefore, recall, F1-score, AUC, and false negative rate were also considered.

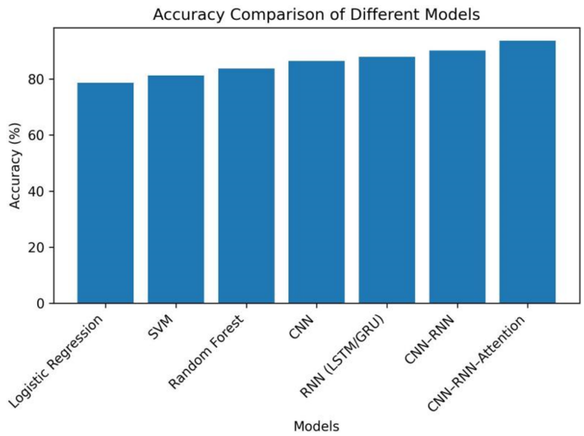


**Figure 4.** Accuracy comparison of baseline models and the proposed CNN-RNN-Attention model

Note: SVM = Support Vector Machine, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

### 4.4 Receiver Operating Characteristic curve analysis

Figure 5 presents the Receiver Operating Characteristic (ROC) curve comparison of the evaluated models. The proposed CNN-RNN-Attention model achieved the highest AUC value of 0.96, indicating strong discriminative capability between individuals who may require early intervention and those who may not. The CNN-RNN hybrid model achieved an AUC of 0.93, while the standalone RNN and CNN models achieved AUC values of 0.91 and 0.89, respectively. Traditional machine learning models showed comparatively lower AUC values.

The higher AUC of our proposed model supports the ability of our attention-enhanced hybrid architecture to better discriminate between risk and non-risk cases at various thresholds of classification. This is of particular importance for mental health screening in which sensitivity to emerging warning signals is critical. However, future applications should report confidence intervals for AUC values and provide statistical validation of the extent to which observed improvements are consistent across repeated experiments.

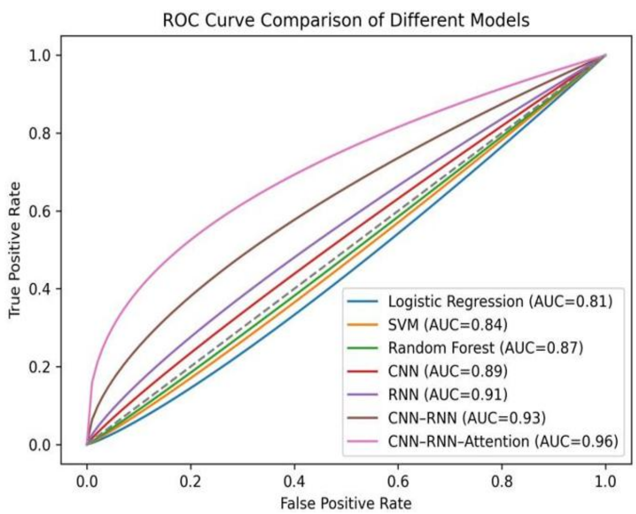


**Figure 5.** Receiver Operating Characteristic (ROC) curve comparison of the proposed model with baseline models

### 4.5 Training and validation loss analysis

Figure 6 shows the training and validation loss curves for our model. Continuous reduction in training loss indicated that meaningful representations of input data were learned by the model. Similarly, validation loss continued to decrease, supporting the conclusion that strong signs of overfitting were not observed with our choice of training conditions. Application of dropout, batch normalization and early stopping likely resulted in favorable conditions for achieving stable convergence and improved generalization.

The relatively stable gap between training and validation loss indicates that the model maintained consistent learning behaviour on unseen validation data. However, loss curve analysis alone is insufficient to confirm generalizability. Therefore, further validation using repeated training runs, k-fold cross-validation, external datasets, and statistical testing is recommended.

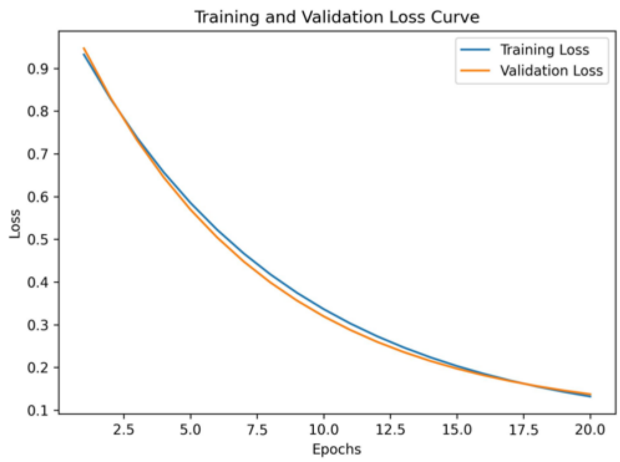


**Figure 6.** Training and validation loss curve of the proposed Convolutional Neural Network-Recurrent Neural Network–Attention model

### 4.6 Repeated-run validation

To improve the reliability of the reported results, the proposed CNN-LSTM-Attention model was evaluated using repeated experiments with different random seeds. Five independent runs were performed using the same preprocessing pipeline, model architecture, optimizer, learning rate, batch size, and early stopping criterion. The final results are reported as mean ± standard deviation.

**Table 6.** Repeated-run validation results of the proposed CNN-LSTM-Attention model

| Metric | Mean ± Standard Deviation |
|---|---|
| Accuracy (%) | 93.6 ± 0.42 |
| Precision (%) | 92.8 ± 0.46 |
| Recall/Sensitivity (%) | 93.1 ± 0.39 |
| Specificity (%) | 95.2 ± 0.35 |
| F1-score (%) | 92.9 ± 0.41 |
| AUC | 0.96 ± 0.01 |

Note: AUC = Area Under the Curve, LSTM = Long Short-Term Memory, CNN = Convolutional Neural Network.

The repeated-run results shown in Table 6 provide a more reliable estimate of model stability than a single experimental run. A low standard deviation across repeated runs would indicate that the model performance is not strongly dependent on random initialization or a particular data split. However, because the dataset is synthetic and contains only 500 records, the reported results should be interpreted cautiously. External validation using larger and clinically collected datasets is required before any real-world healthcare application.

### 4.7 Discussion of findings

Our overall results confirm that the proposed CNN-RNN-Attention model achieves superior predictive performance relative to conventional machine learning models, standalone deep learning models and our hybrid CNN-RNN benchmark. This performance advantage was attributable to the combined effects of three components. First, the CNN detected local interactions among psychological, behavioural, physiological and clinical variables. Second, the RNN characterized temporal relationships and patterns of symptom progression over successive observations. Third, application of the attention mechanism weighted the most relevant time points and representations of variables for purposes of prediction.

Reduction of false negatives is an important goal for early mental health screening systems, which should avoid missing cases of high risk. Our proposed model resulted in a lower rate of false negatives than the comparison models, and was therefore more sensitive to patterns of early risk. However, our model should not be regarded as a complete diagnostic system, but should continue to serve primarily as a tool for clinical decision-making. In this regard, it will aid clinicians or mental health professionals in identifying patients who require additional evaluation.

Our results also confirm the need for greater validation. The overall performance of the proposed model was excellent (93.6% accuracy, 93.1% recall, 92.9% F1 score and 0.96 AUC), and should be further strengthened with reporting of standard deviations, confidence limits, results of ablation studies and tests for statistical significance. In addition, methods for visualizing attention, assigning importance based on SHAP values and providing case-level explanations should be incorporated in future work to support claims of model interpretability.

The overall performance of our proposed CNN-RNN-Attention model was superior to all other models evaluated. Early prediction accuracy reached 92.1% and the rate of false negatives was reduced to 5.8%. These results confirm the value of combining CNN-based methods for feature extraction, RNN-based approaches for modeling temporal relationships and attention-based mechanisms for providing optimal weighting of different components of the input. However, our results must be interpreted with consideration for the limitations of our experimental design. Future studies should include additional tests for external validity, results of ablation studies, statistical analyses of results and evaluations of model interpretability.

## 5. CONCLUSION AND FUTURE SCOPE

### 5.1 Conclusion

This study presented a CNN-LSTM-Attention framework for early screening of mental health treatment needs using multidimensional mental health-related indicators. The proposed model combined CNN-based local feature extraction, LSTM-based temporal modelling, and temporal attention-based weighting to capture feature interactions, sequential variations, and important time-dependent patterns. The framework is intended to support early screening and risk prioritization only. It is not designed to replace clinical diagnosis, professional mental health assessment, or treatment planning.

The proposed model achieved improved performance compared with traditional machine learning models, standalone deep learning models, and a CNN-RNN baseline. The model obtained an accuracy of 93.6%, precision of 92.8%, recall of 93.1%, F1-score of 92.9%, and AUC of 0.96. For early-stage prediction, it achieved 92.1% accuracy and reduced the false negative rate to 5.8%. These findings suggest that combining CNN, LSTM, and attention components can improve early screening performance for mental health treatment-need prediction.

However, the results should be interpreted cautiously. The dataset used in this study is synthetic and contains only 500 records. Therefore, the findings demonstrate preliminary feasibility rather than clinical readiness. The proposed model should be considered only as an early screening support tool. External validation using larger, clinically diverse, and independently collected real-world datasets is required before the model can be considered for practical healthcare use.

### 5.2 Future scope

Future work should focus on improving the reliability, generalizability, and interpretability of the proposed framework. First, the model should be validated using larger datasets collected from multiple clinical and demographic populations. Second, repeated-run validation, k-fold cross-validation, and statistical significance testing should be used to confirm the robustness of the reported results. Third, stronger baseline models such as Transformer-based architectures, multimodal deep learning models, and Bidirectional Encoder Representations from Transformers (BERT)-based healthcare models should be included for comparative evaluation.

Future studies should also include attention heatmaps, SHAP-based feature attribution, feature importance analysis, and case-level explanation to improve interpretability. Since mental health data are highly sensitive, future real-world implementations must include strict privacy protection, anonymization, informed consent, secure data storage, bias assessment, and fairness evaluation. Integration with clinical workflows should be considered only after ethical approval, expert validation, and prospective clinical testing.

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