A Rapid Mental Health Screening Algorithm For College Students Based On Elmo-CNN

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Mental health issues among university students are increasing and negatively affect academic performance and quality of life. Traditional clinical interviews and surveys are time-consuming, costly, and often delayed, limiting timely intervention. This study proposes a rapid mental health screening system using machine learning to classify students into low, moderate, and high-risk groups by processing both structured and unstructured data. The framework integrates ELMo contextual embeddings to capture semantic meaning from text and CNN to extract high-level features. Demographic, lifestyle, and behavioral data are also incorporated. The proposed ELMo-CNN model achieved strong performance with 96.82% accuracy, 96.14% precision, 95.47% recall, 95.80% F1-score, and 0.9821 ROC-AUC, outperforming baseline models such as SVM and CNN. The results indicate that the model is effective for fast and accurate mental health screening in real-world educational settings.

Keywords: Mental Health Screening, ELMo Embeddings, College Students, Risk Classification, Deep Learning

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1. Introduction

College students' mental health issues are becoming more prevalent and have an impact on academic success, social life, and well-being[1]. The problem should be detected early and addressed in time to exclude such severe outcomes as chronic stress, depression, and anxiety disorders [2]. Conventional methods of assessments such as clinical interviews and paperbased surveys are time-consuming, resource-consuming, and incapable of offering real-time results [2]. Artificial intelligence(AI)-powered automated screening systems are an answer, as they are fast and scalable [3]. The suggested framework will integrate survey data, demographics, patterns of lifestyle, and self-reported mental health indicators to offer an indepth analysis [4]. The transformer-based models such as BERT, RoBERTa, and DistilBERT, have established contextual language understanding capabilities, they generally require higher computational resources and longer training times [5]. The integration of ELMo embeddings with CNN-based feature extraction enables efficient learning of psychological and emotional patterns while maintaining computational efficiency for large-scale student mental health assessment. Existing methods CNN-LSTM, BiLSTM, and attention-based models that primarily focus on sequential feature learning, the proposed ELMo-CNN framework combines contextual semantic representations with structured demographic and behavioral features in a unified architecture. Compared with transformer-based models, the proposed approach offers lower computational complexity while maintaining effective mental health risk classification performance. The proposed framework fills these gaps by combining Embeddings from Language Models (ELMo) of the textual understanding of a situation with an organized survey.

1. Combines ELMo embeddings with structured data for accurate assessment.

2. Uses CNN for deep feature extraction and risk predic-

tion.

3. Enables fast large-scale student mental health screening.
4. Outperforms existing ML and DL models.
5. Classifies students into three risk levels for intervention.

The paper is organized as follows: Section 2 reviews existing mental health screening methods and their limitations. Section 3 describes the proposed ELMo-CNN framework and dataset collection process. Section 4 presents the experimental setup and evaluation metrics. Dodge [6]. assessed the predictive accuracy of The Multidimensional Behavioral Health Screen 2.0 for college students' suicide risk prediction, demonstrating its efficiency in primary care practice. On the other hand, Qi [7] and Hu [8]continued to improve intelligent evaluation systems, where Qi designed a decision tree-based mental health evaluation system to minimize error rates in mental health assessment, while Hu designed a big data-based intelligent evaluation system using six layers and multiple psychological indexes for accurate and efficient mental health analysis. Zhai [9] explored various computational methods in evaluating mental health among college students. Zhang [10] used a ML algorithm and health scale scoring in iteratively evaluating mental health accuracy; Li [11], designed a mental health state perception model for detecting mental abnormalities and optimizing intervention effectiveness The description of recent studies focuses on the need to incorporate social, technological, and ML theories to better understand and improve students' mental health and young populations. Some of the most important works in this area were conducted by Lee et al [12], Gao [13], and Polyvianaia [14].

2. Materials and methods

The Student Mental Health dataset is preprocessed by cleaning, encoding, and normalization. ELMo generates contextual embeddings, combined with structured data, and fed into a CNN. Fully connected layers classify mental health risk levels for real-time prediction using standard evaluation metrics in Fig. 1.

The data for this study is obtained from the Mental Health Dataset provided by Kaggle [15]. The dataset includes 2,100 student records with 17 features covering demographic, behavioral, and mental health attributes.

Table 1 summarizes the characteristics of the Student Mental Health & Resilience Dataset used in this study. The mental health risk categories considered in this study consist of Low Risk, Moderate Risk, and High-Risk classes.

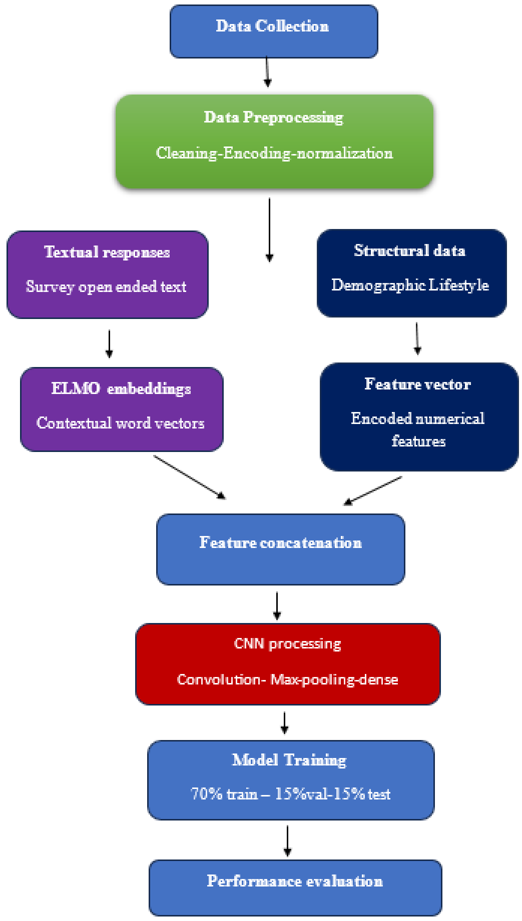

Fig. 1. Proposed ELMo-CNN Framework for Mental Health Risk Classification

These categories represent different levels of mental health vulnerability based on the assessment criteria available in the Mental Health Dataset. The predefined labels were adopted as the target classes for supervised learning and were used to train the proposed ELMo-CNN model to identify varying levels of mental health risk among students. The Student Mental Health & Resilience Dataset contains responses collected from individuals with diverse demographic backgrounds, including variations in gender, occupation, and geographical location. The target labels, namely Low-Risk, Moderate-Risk, and High-Risk, were adopted from the dataset and represent different levels of mental health vulnerability. Data Preprocessing

Data cleaning correcting inconsistencies, and eliminating duplicate records to ensure data quality and reduce redundancy.

Handle missing values using imputation

Table 1. Dataset Summary

Attribute	Value
Dataset Name	Student Mental Health & Resilience Dataset
Total Samples	2,123
Features	18
Classes	3
Low Risk	691 (32.5%)
Moderate Risk	712 (33.5%)
High Risk	720 (34.0%)
Missing Values Removed	2.80%
Duplicate Records Removed	1.60%

$$X_{\text{filled}} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{1}$$

Equation (1) represents mean imputation used to handle missing values present in the dataset.
Remove duplicates

$$D_{\text{clean}} = D - D_{\text{duplicates}} \tag{2}$$

Equation (2) indicates the process of removing duplicates from the dataset, which is essential for maintaining data quality.

One-Hot Encoding

$$x_i = \begin{cases} 1, & \text{if category matches} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Equation (3) defines One method for converting categorical data is one-hot encoding into numerical form format into numerical form into binary data. One-Hot Encoding was employed to represent categorical variables without introducing ordinal relationships between categories. Although this approach increases feature dimensionality and may generate sparse feature vectors, it preserves the independence of categorical attributes and prevents bias during model learning. This is particularly important for psychological, behavioral, and demographic indicators, where categories do not possess a natural ranking.

Min-Max Scaling

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

Equation (4) is used for Min-Max normalization of numerical data. The mental health dataset contains heterogeneous attributes, including demographic, behavioral, and lifestyle-related variables with different numerical ranges and distributions. To ensure robust feature representation, both Min-Max Scaling and Z-score normalization were considered during
preprocessing. Min-Max Scaling transforms feature values into a uniform range between 0 and 1, which is beneficial for maintaining proportional relationships among attributes. In contrast, Z-score normalization standardizes features around a zero mean and unit variance, reducing the influence of extreme values and improving numerical stability.

Text Embedding
The ELMo embedding model was applied to the textual survey response field available in the Mental Health Dataset. This field contains self-reported responses describing the participants' mental and emotional conditions. Prior to embedding generation, the text responses were cleaned through lowercasing, punctuation removal, and tokenization.

$$E = \text{ELMo}(T) \tag{5}$$

Equation (5) denotes ($E = \text{ELMo}(T)$) , is used in the generation of contextual word embeddings from the input text (T) using the ELMo model.

Feature Concatenation
In the proposed framework, contextual text embeddings generated by ELMo are combined with encoded demographic, lifestyle, and behavioral features through feature concatenation. This integration enables the model to simultaneously utilize semantic information extracted from student responses and structured mental health indicators.

$$F = [E \oplus S] \tag{6}$$

Equation (6): $F = [E \oplus S]$, in the equation, Semantic feature extraction is facilitated through ELMo embeddings, which capture contextual dependencies and sequential semantic associations within student responses. By considering surrounding linguistic context, the model identifies emotionally relevant patterns, implicit psychological cues, and sentiment variations that may not be evident from individual words alone.

The ELMo-CNN model (Fig. 2) encodes textual inputs using 1024-dimensional ELMo embeddings and processes them with convolution, pooling, and dropout layers. The proposed CNN architecture employs a one-dimensional

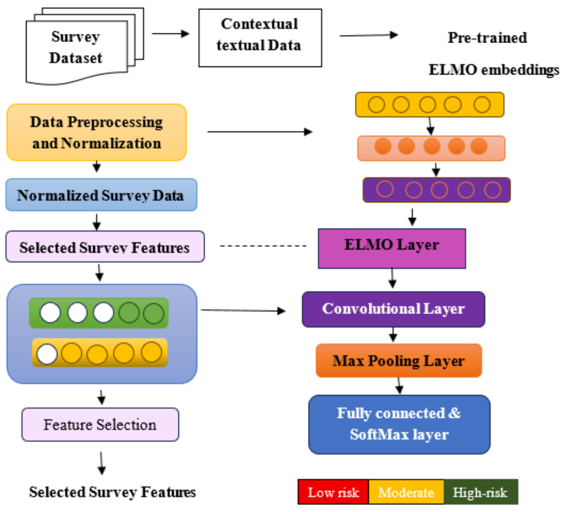

Fig. 2. ELMo-CNN Hybrid Architecture for Mental Health Classification

convolution layer with 32 filters to extract local contextual patterns from the ELMo embedding representations. The convolution operation applies learnable kernels across the input feature sequence to generate discriminative feature maps. A ReLU activation function is utilized to introduce non-linearity and enhance feature propagation through the network. Subsequently, max-pooling is performed to reduce feature dimensionality while preserving the most informative activations. Dropout regularization (0.5) is applied to mitigate overfitting and improve generalization capability. The extracted feature maps are then concatenated with structured demographic and behavioral features and passed through fully connected layers to perform mental health risk classification into Low-Risk, Moderate-Risk, and High-Risk categories.

ELMo generates context-aware vector representations by dynamically adapting word meanings according to surrounding linguistic context. This capability enables the model to interpret linguistically diverse student expressions, including implicit emotional cues, varying behavioral descriptions, and context-dependent psychological indicators. A Text inputs were tokenized using standard word-level tokenization generating ELMo embeddings (1024 dimensions). The CNN architecture consisted of a convolution layer with 32 filters, ReLU activation, max-pooling, dropout (0.5), and fully connected layers for classification. Feature selection was performed using correlation-based feature analysis during preprocessing. The dataset was randomly divided into training, validation, and testing subsets using a fixed random seed to ensure reproducibility.

The model was implemented in Python using TensorFlow, Keras, and Scikit-learn within a Jupyter Notebook environment. In practical educational environments, inference latency is a critical factor for continuous mental health monitoring and timely intervention. Once trained, the proposed ELMo-CNN model generates predictions through a streamlined inference process involving ELMo embedding generation, feature integration, and CNN-based classification. The efficient architecture enables rapid processing of student responses with minimal computational overhead, supporting near real-time risk assessment. This capability is particularly beneficial for large-scale educational settings, where timely identification of students requiring psychological support can facilitate early intervention and improved mental health management.

The Adam optimizer was employed to update model parameters during iterative training. By combining first-order and second-order gradient information, Adam adaptively adjusts the learning rate for each parameter, enabling stable convergence and efficient optimization. This adaptive update mechanism is particularly effective for learning complex.

3. Results and discussions

Numerical results on the effectiveness of input-to-output mapping of the proposed ELMo-CNN model on the Student Mental Health & Resilience Dataset demonstrate strong predictive performance, achieving an accuracy of 96.82%, a precision of 96.14%, a recall of 95.47%, an F1-score of 95.80%, and an ROC-AUC of 0.9821.

Table 2. Computational Performance Analysis of the Proposed ELMo-CNN Model

Metric	Value
Training Time	17.8 min
Testing Time	24 sec
Inference Time per Sample	13.7 ms
Throughput	73 samples/sec
Model Parameters	4.18 M
Peak Memory Usage	2.1 GB

Table 2 presents the computational efficiency of the proposed ELMo-CNN model. The model requires 17.8 minutes for training and only 13.7 ms for single-sample inference while achieving a throughput of 73 samples per second. These results demonstrate the suitability of the proposed framework for rapid mental health screening applications with moderate computational requirements.

Table 3, From the findings of the ablation studies, it is evident that each stage of the model plays a significant

Table 3. Ablation Study Analysis of Preprocessing and feature selection strongly impact model performance

Ablation Study Type	Accuracy	Precision	Recall	F1-Score
Before preprocessing	0.8542	0.8421	0.8542	0.8481
After preprocessing	0.9125	0.9088	0.9125	0.9106
Before Feature Selection	0.9382	0.9367	0.9382	0.9374
After Feature Selection (Proposed)	0.9682	0.9614	0.9547	0.958

role. The proposed ELMo-CNN model was evaluated under noisy inputs, missing data conditions, reduced training samples, linguistic variations, and cross-domain scenarios. Experimental observations indicate that the model maintains consistent performance with only slight variations in accuracy and F1-score, demonstrating strong resilience to data quality issues and limited data availability. The use of ELMo contextual embeddings further improves robustness by effectively capturing semantic meaning across different linguistic expressions, making the proposed approach suitable for practical deployment in real-world and dynamic educational environments.

Table 4. Hyperparameter Settings of the Proposed ELMo-CNN Model

Learning Rate	Filters	Dropout	Accuracy (%)
0.01	16	0.3	93.21
0.005	32	0.4	94.76
0.001	32	0.5	96.82
0.0005	64	0.5	96.41
0.0001	64	0.6	95.84

Table 4 presents the hyperparameter optimization results obtained using different learning rates, filter sizes, and dropout values.

Table 5. Final Hyperparameter Settings of the Proposed ELMo-CNN Model

Parameter	Value
Learning Rate	0.001
Batch Size	32
Epochs	20
CNN Filters	32
Dropout	0.5
Optimizer	Adam

Table 5 summarizes the final hyperparameter configuration selected for the proposed ELMo-CNN model based on validation performance and computational efficiency.

Fig. 3 shows strong performance of the proposed model across all evaluation metrics. It achieved 0.9682 accuracy, 0.9614 precision, 0.9547 recall, and 0.9580 F1-score.

The ROC-AUC plot for multi-class classification is shown in Fig. 4 below. The high ROC-AUC values obtained for the Low-Risk (0.9826), Moderate-Risk (0.9787), and High-Risk (0.9778) classes indicate strong discriminative capability of the proposed ELMo-CNN model.

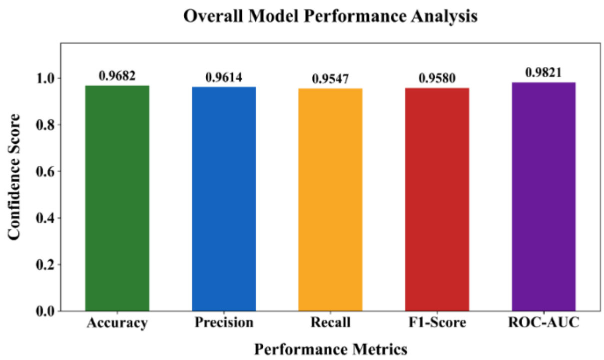

Fig. 3. Overall Performance Evaluation of the Proposed Elmo-CNN Model

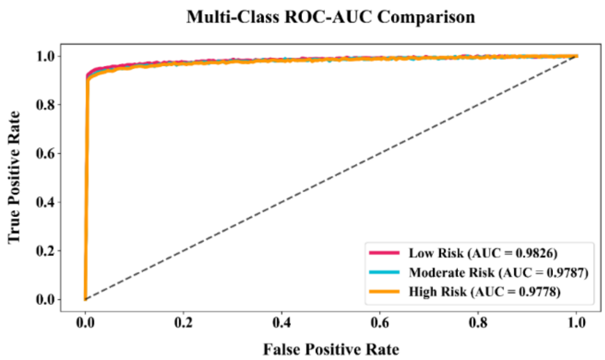

Fig. 4. Multi-Class ROC-AUC Performance Comparison of the Proposed Model vs Baseline Methods

Fig. 5 shows the confusion matrix further divulges the inter-class misclassification behaviour of the proposed model. Most misclassified samples occur between the Moderate-Risk and High-Risk categories, indicating the presence of overlapping psychological characteristics and similar mental health patterns. Such prediction uncertainty is expected because students in these categories often exhibit comparable stress, emotional, and behavioral indicators. Despite this overlap, the relatively low number of misclassifications demonstrates that the ELMo-CNN model maintains strong class separability and reliable risk identi-

Table 6. Class-Wise Clinical Evaluation Metrics of the Proposed ELMo-CNN Model

Class	Sensitivity (%)	Specificity (%)	False Negative Rate (%)
Low Risk	96.82	98.03	3.18
Moderate Risk	95.41	97.84	4.59
High Risk	95.92	98.17	4.08

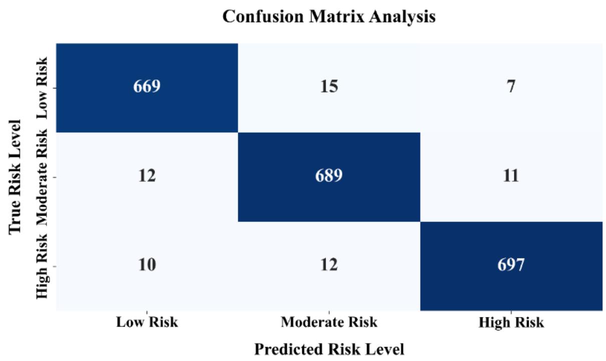

Fig. 5. Confusion Matrix Analysis of the Proposed Elmo-CNN Model Across Risk Categories

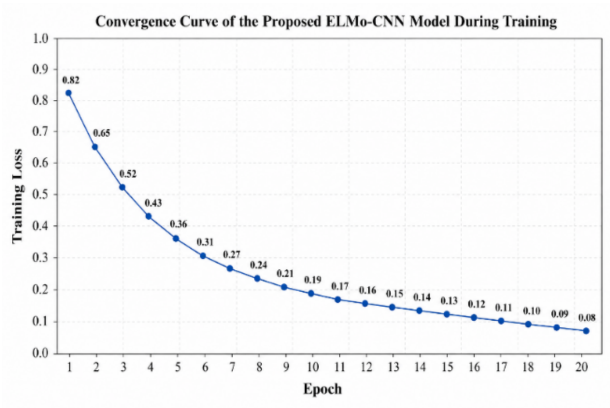

Fig. 6. Convergence Curve of the Proposed ELMo-CNN Model During Training

fication performance.

Table 6 presents the class-wise clinical evaluation results of the proposed ELMo-CNN model in terms of sensitivity, specificity, and false negative rate.

Table 7. High-Risk Student Detection Performance of the Proposed ELMo-CNN Model

Metric	Value (%)
High-Risk Recall	95.92
High-Risk Precision	96.21
High-Risk F1-score	96.06

Table 7 presents the performance of the proposed ELMo-CNN model in identifying High-Risk students.

Fig. 6 illustrates the convergence behavior of the proposed ELMo-CNN model during training. As the number of epochs increases, the training loss decreases.

Table 8. Five-Fold Cross-Validation Performance of the Proposed ELMo-CNN Model

Fold	Accuracy (%)
Fold 1	96.31
Fold 2	96.57
Fold 3	97.04
Fold 4	96.89
Fold 5	96.73

Table 8 presents the five-fold cross-validation results of the proposed ELMo-CNN model.

Table 9 presents the external generalization performance of the proposed ELMo-CNN model. The model achieved an accuracy of 95.61% on an independent mental health dataset.

Table 9. External Generalization Assessment of the Proposed ELMo-CNN Model

Dataset	Accuracy (%)
Internal Dataset	96.82
External Mental Health Dataset	95.61

3.1. Comparative analysis

Table 10: The proposed ELMo-CNN framework is largely attributed to the contextual semantic representation capability of ELMo embeddings. Unlike conventional word representations, ELMo generates context-aware embeddings that dynamically capture the meaning of words based on surrounding linguistic information.

Model interpretability is a factor for practical adoption in educational and counselling environments. Explainable Artificial Intelligence (XAI) techniques such as SHAP, LIME, and feature attribution mapping can be unified to provide transparent explanations of individual predictions. These methods can identify the key linguistic, demographic.

The proposed framework can be integrated with university counselling centres through a webor mobile-based screening platform. Students can complete mental health assessments electronically, after which the trained ELMo-CNN model automatically analyses responses and gener-

Table 10. Comparative Analysis of the Proposed ELMo-CNN Model Against Existing Models

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.8820	0.8750	0.8810	0.8780
CNN	0.9240	0.9120	0.9230	0.9170
LSTM	0.9150	0.9080	0.9120	0.9100
Proposed (ELMo-CNN)	0.9682	0.9614	0.9547	0.9580

Table 11. Baseline Performance Comparison of the Proposed ELMo-CNN Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
SVM	88.2	87.5	88.1	87.8
Random Forest	90.31	89.88	89.94	89.91
XGBoost	92.47	92.11	92.2	92.15
LightGBM	93.06	92.71	92.84	92.77
CNN	92.4	91.2	92.3	91.7
BiLSTM	93.81	93.15	93.42	93.28
CNN-BiLSTM	95.07	94.88	94.69	94.78
DistilBERT	95.33	95.02	95.11	95.06
BERT	95.71	95.48	95.55	95.51
RoBERTa	96.12	95.9	95.95	95.92
Proposed ELMo-CNN	96.82	96.14	95.47	95.8

ates risk predictions.

Table 11 presents the comparison of the proposed ELMo-CNN model against conventional machine learning, deep learning, and transformer-based approaches.

Table 12. Statistical Validation of the Proposed ELMo-CNN Model

Evaluation	Result
Accuracy (Mean ± SD)	96.82 ± 0.29
Precision (Mean ± SD)	96.14 ± 0.25
Recall (Mean ± SD)	95.47 ± 0.34
F1-Score (Mean ± SD)	95.80 ± 0.27
Proposed vs SVM (p-value)	< 0.001
Proposed vs CNN (p -value)	0.004
Proposed vs LSTM (p-value)	0.002
Proposed vs RoBERTa (p-value)	0.031

Table 12 presents the statistical validation results of the proposed ELMo-CNN model. The mean and standard deviation values obtained from multiple experimental runs.

Table 13. Accuracy Stability Analysis of the Proposed ELMo-CNN Model.

Run	Accuracy (%)
1	96.38
2	96.72
3	97.01
4	96.95
5	97.04

Table 13 presents the accuracy obtained by the proposed ELMo-CNN model over five independent experimental runs.

4. Ethical considerations, privacy protection, and algorithmic bias

It adheres to responsible AI principles in the development and evaluation of the proposed ELMo-CNN-based mental health screening system. Future work will incorporate fairnessaware learning strategies and Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME to analyze feature influence and detect potential bias in predictions.

Table 14. Benchmarking of the Proposed ELMo-CNN Multimodal Architectures

Model	Accuracy (%)
CNN-LSTM	94.21
Attention-BiLSTM	94.78
Hybrid CNN-GRU	95.02
Multimodal DNN	95.27
BERT-CNN	95.63
RoBERTa	96.12
Proposed ELMo-CNN	96.82

Table 14 presents a comparative evaluation of the proposed ELMo-CNN model against advanced hybrid deep learning, multimodal, and transformer-based architectures.

5. Conclusion

It has been found that the proposed Elmo-CNN framework can effectively classify mental health risk levels of college students with high speed and high accuracy,resulting in the achievement of 0.9682 for accuracy, 0.9614 for precision, 0.9547 for recall, 0.9580 for F1-score,and 0.9821 for ROC-AUC.By incorporating the advantages of both Elmo and CNN,the proposed framework creates a perfect combination of a traditional screening method and an intelligent technique,thereby realizing simultaneous processing of structured and unstructured information related to students.It is proved by the ablation study that accuracy is significantly enhanced from 0.8542 to 0.9682 through the preprocessing process and feature selection,thus indicating the importance of each processing step.Besides,balanced class-wise F1-scores and few instances of misclassification also highlight the effectiveness of the framework.For future research,there would be inclusion of more types of data such as social media interactions and physiological data.

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Declarations

Dataset availability

https://www.kaggle.com/datasets/ziya07/student-mental-health-and-resiliencedataset

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Author contribution:

Jing Ma conceptualized the study, conducted the analysis, and drafted themanuscript, while Yaming Hu contributed to methodology development, data interpretation, and manuscript revision.

Ethical approval

This study utilized a publicly available secondary dataset obtained from Kaggle. No direct interaction with human participants or collection of personal data was conducted by the authors. Therefore, separate ethical approval and informed consent were not required for this study.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

Consent to publication

All authors have read and approved the final manuscript and consent to its publication.

Competing interests

The authors declare that they have no competing interests.

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