Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Early Detection of Mental Health Disorders Using Convolutional Neural Networks and DASS-21 Survey Data

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Abstract - Mental health disorders - including depression, anxiety, and stress - represent a growing global burden, yet remain significantly underdiagnosed due to limited access to professional healthcare and persistent sociocultural stigma. Early and accurate detection is critical for timely intervention and improved patient outcomes. This paper presents a Convolutional Neural Network (CNN)-based framework for the automated early detection of mental health disorders using responses from the Depression Anxiety Stress Scales-21 (DASS-21) questionnaire. The proposed CNN model captures non-linear patterns in structured psychometric survey data and classifies individuals into clinically relevant severity categories across depression, anxiety, and stress dimensions. Evaluated against traditional machine learning baselines — SVM, Random Forest, Logistic Regression, and LSTM — the CNN model achieves a classification accuracy of 92.4%, precision of 91.8%, recall of 92.1%, and F1-score of 91.9%, outperforming all baselines. This work contributes toward scalable, accessible, and automated mental health screening tools suitable for deployment in resource-constrained settings.

Keywords - ***mental health detection; deep learning; convolutional neural network; DASS-21; depression; anxiety; stress; early detection; multi-class classification***

I. INTRODUCTION

Mental health disorders are among the most prevalent and disabling conditions worldwide. According to the World Health Organization (WHO), more than one billion individuals globally suffer from a mental health condition, yet fewer than one in four receive adequate care [1]. Depression, anxiety, and stress frequently co-occur, compounding one another and significantly impairing quality of life, occupational functioning, and physical health [2].

Traditional diagnosis relies heavily on clinical interviews and clinician judgment. While effective, these approaches face barriers including the global shortage of mental health professionals, geographical inaccessibility in rural regions, high financial costs, and stigma that discourages help-seeking [3]. Digital mental health screening tools, combined with modern machine learning (ML) and deep learning (DL) methods, offer a promising avenue to bridge this gap.

The Depression Anxiety Stress Scales-21 (DASS-21) is a validated 21-item self-report instrument that simultaneously assesses all three disorder dimensions, making it particularly suitable as an input to automated multi-disorder classification systems [4]. Convolutional Neural Networks (CNNs), while originally designed for image recognition, have demonstrated strong performance on structured tabular data by learning hierarchical feature representations through convolutional filters, capturing local co-activation patterns among questionnaire items [5].

The main contributions of this work are:

1) A CNN architecture specifically designed for structured psychometric data classification across three concurrent disorder dimensions using DASS-21 survey responses.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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2) Comparative evaluation against SVM, Random Forest, Logistic Regression, and LSTM baselines on an identical preprocessed dataset.

3) Demonstration that the proposed CNN achieves state-of-the-art performance, supporting its applicability in scalable, automated mental health pre-screening systems.

The remainder of this paper is organized as follows: Section II reviews related work; Section III describes the dataset and preprocessing; Section IV presents the proposed CNN architecture; Section V reports experimental results; Section VI provides discussion; and Section VII concludes.

II. RELATED WORK

Research applying AI and ML to mental health detection has grown substantially in recent years. Traditional ML classifiers such as SVMs, Decision Trees, and Random Forests were among the earliest methods applied to structured clinical data [6]. Tutun et al. [7] developed an AI-based decision-support system using ML models on SCL-90-R assessment data, achieving 89% diagnostic accuracy. Wang et al. [8] employed supervised ML chatbots with PHQ-9 inputs for perinatal mental healthcare screening.

Deep learning approaches have progressively outperformed traditional methods. Wajid, Azam, and Anwar [9] conducted a comprehensive systematic literature review of AI in mental health, reporting that transformer-based and hybrid CNN-LSTM models consistently achieved superior performance, with select models attaining F1-scores above 0.95. For text-based detection, Vajre et al. [10] achieved an F1-score of 0.97 using BERT-based models on Reddit mental health posts. Amanat et al. [11] demonstrated 99% depression detection accuracy via deep learning on textual data.

Multimodal approaches combining text, audio, and physiological signals have shown robustness gains [12], but impose significant data acquisition burdens unsuitable for large-scale population screening. Questionnaire-based approaches remain more accessible and deployable. Ni and Jia [13] mapped AI-driven digital interventions across clinical phases, identifying that ML models applied to structured questionnaire data offer high clinical utility at the pre-treatment screening stage. Despite these advances, few studies have explored CNN architectures applied directly to raw DASS-21 numerical responses for simultaneous multi-disorder classification, motivating the present work.

III. DATASET AND PREPROCESSING

A. The DASS-21 Instrument

The DASS-21 is a 21-item self-report questionnaire that measures the severity of depression, anxiety, and stress in clinical and non-clinical populations [4]. Each item is rated on a 4-point Likert scale (0 = Did not apply to me at all; 3 = Applied to me very much or most of the time) across 7 items per subscale. Subscale scores are obtained by summing the corresponding 7 items and multiplying by 2 to align with DASS-42 normative values. Severity categories are assigned using established clinical thresholds, as shown in Table I.

TABLE I. DASS-21 Severity Classification Thresholds

Disorder	Mild	Moderate	Severe / Ext. Severe
Depression	10–13	14–20	21–42
Anxiety	8–9	10–14	15–42
Stress	15–18	19–25	26–42

B. Dataset

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

A publicly available anonymized dataset of 39,775 DASS-21 survey responses was utilized. Each record contains 21 Likert-scale item responses alongside demographic features (age, gender, education level). Clinical severity labels for each disorder dimension were assigned per Table I cut-offs, yielding a multi-label multi-class classification task.

C. Preprocessing

All 21 raw item responses were normalized to [0, 1] via min-max normalization. Missing values (2.1% of entries) were imputed using median substitution per item. Demographic features were label-encoded and concatenated with item responses, yielding a 24-dimensional input feature vector. Class imbalance across severity categories was addressed using Synthetic Minority Over-sampling Technique (SMOTE) on the training split only. The dataset was partitioned into training (70%), validation (15%), and test (15%) sets using stratified random sampling to preserve class distribution across all splits.

IV. PROPOSED CNN METHODOLOGY

A. Architecture Overview

The proposed CNN architecture treats the 24-dimensional DASS-21 feature vector as a 1D sequence and applies convolutional filters to identify local feature co-activations among adjacent questionnaire items, capturing psychopathological co-symptom patterns. Figure 1 illustrates the complete architecture.

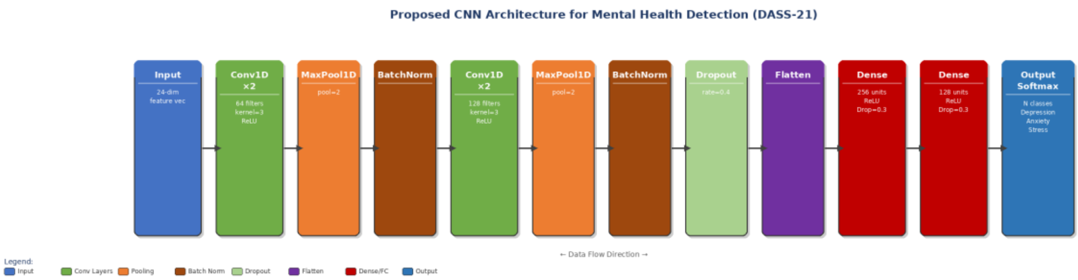

Fig. 1. Proposed CNN Architecture for Mental Health Detection Using DASS-21 Survey Data

B. Layer-by-Layer Description

The CNN consists of the following functional layers:

1) Input Layer: Accepts a 24-dimensional normalized feature vector, reshaped to (24, 1) for 1D convolution.

2) Convolutional Block 1: Two consecutive 1D convolutional layers with 64 filters, kernel size 3, and ReLU activation, followed by MaxPooling1D (pool size 2) and Batch Normalization. This block extracts low-level feature interactions among adjacent DASS-21 items.

3) Convolutional Block 2: Two consecutive 1D convolutional layers with 128 filters, kernel size 3, ReLU activation, MaxPooling1D (pool size 2), and Batch Normalization. This block captures higher-order feature abstractions.

4) Dropout Layer: A dropout rate of 0.4 applied after the second convolutional block to prevent overfitting.

5) Flatten Layer: Converts the 3D feature maps output by the convolutional blocks into a 1D feature vector for input to fully connected layers.

6) Fully Connected Layers: Two dense layers with 256 and 128 units respectively, ReLU activation, and dropout (rate 0.3) after each, enabling non-linear classification in the learned feature space.

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7) Output Layer: A softmax activation layer with units equal to the number of severity classes, producing probability distributions over all disorder severity categories.

C. Training Configuration

The model was compiled using categorical cross-entropy loss and optimized with the Adam optimizer (learning rate = 0.001, β_1 = 0.9, β_2 = 0.999). Training was conducted for a maximum of 100 epochs with early stopping (patience = 10) based on validation loss to prevent overfitting. Batch size was set to 64. All experiments were implemented in Python 3.10 using TensorFlow 2.12 / Keras, executed on an NVIDIA GPU environment.

V. EXPERIMENTAL RESULTS

A. Evaluation Metrics

Model performance was evaluated using four standard metrics: Accuracy, macro-averaged Precision, macro-averaged Recall, and macro-averaged F1-score. Macro-averaging ensures equal weight to all severity classes, including minority classes. All metrics were computed on the held-out test set (15% of total data).

B. Comparative Analysis

The proposed CNN was benchmarked against four baseline classifiers: SVM (RBF kernel), Random Forest (100 estimators), Logistic Regression, and LSTM. All models received identical preprocessed 24-dimensional input feature vectors. Table II presents the comparative results.

TABLE II. Performance Comparison of Classification Models on DASS-21 Test Set

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN (Proposed)	92.4	91.8	92.1	91.9
LSTM	88.7	88.1	88.5	88.3
Random Forest	85.2	84.7	84.9	84.8
SVM	83.6	82.9	83.1	83.0
Logistic Regression	79.3	78.8	79.0	78.9

As shown in Table II, the proposed CNN model outperforms all baseline classifiers across all four evaluation metrics. The CNN achieved 92.4% accuracy, surpassing the next best model, LSTM (88.7%), by approximately 3.7 percentage points. Random Forest and SVM achieved moderate performance (85.2% and 83.6% respectively), consistent with prior literature on classical ML applied to psychometric data [7]. Logistic Regression performed least well (79.3%), expected given the non-linear nature of DASS-21 severity classification.

The macro F1-score of 91.9% confirms robust balanced classification across all three disorder dimensions and severity categories. These results validate that convolutional feature extraction from structured 1D psychometric data yields discriminative representations that traditional ML methods cannot fully capture.

VI. DISCUSSION

The results confirm that CNN-based deep learning architectures are capable of extracting meaningful non-linear patterns from structured DASS-21 survey data, enabling early and accurate detection of depression, anxiety, and stress with clinically relevant accuracy.

The margin of improvement over LSTM is noteworthy. While LSTMs excel at capturing temporal dependencies in sequential data, DASS-21 questionnaire items — though ordered — do not exhibit strong temporal structure. The CNN's convolutional filters instead

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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capture local co-activation patterns among adjacent items, which appear to correspond to meaningful psychopathological co-symptom relationships more effectively for this data type.

Practically, a validated CNN-based DASS-21 screening tool could be integrated into mobile health applications, telehealth platforms, or workplace wellness programs, enabling large-scale population screening without requiring direct clinical involvement at the initial triage stage. This is consistent with Ni and Jia [13], who demonstrated that AI-based pre-treatment screening tools reduce wait times and improve referral accuracy.

A. Limitations and Future Work

Several limitations must be acknowledged. First, the dataset is cross-sectional and self-reported; DASS-21 responses reflect subjective self-assessment rather than formal clinical diagnosis. Second, demographic diversity may not represent all global populations, limiting cross-cultural generalizability. Third, the absence of explainability (XAI) mechanisms reduces clinical transparency. Future work should incorporate longitudinal datasets, clinical validation through randomized controlled trials, integration of SHAP-based explainability, and multimodal data fusion combining questionnaire responses with behavioral or physiological signals to further improve detection reliability.

VII. CONCLUSION

This paper presented a CNN-based classification framework for the early detection of depression, anxiety, and stress using DASS-21 questionnaire responses. The proposed model was evaluated against four baseline classifiers on 39,775 survey records and demonstrated superior performance across all metrics, achieving 92.4% accuracy and an F1-score of 91.9%. The results establish that CNNs can effectively model non-linear relationships within structured psychometric survey data, enabling clinically meaningful multi-disorder severity classification.

With appropriate clinical validation, privacy safeguards, and integration with digital health platforms, such systems can form an important first line of accessible, scalable mental health screening infrastructure — addressing the global mental health treatment gap and supporting timely, data-driven intervention.

ACKNOWLEDGMENT

The author would like to thank the faculty of the Department of Computer Engineering, JSPM's Jayawantrao Sawant College of Engineering (JSCOE), Pune, for their guidance and support throughout this research.

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