

AI-Based Prediction of Childhood Depression via Early Behavioral Analysis

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Abstract

Childhood depression remains an underdiagnosed mental health concern, often detected only after significant emotional and behavioral disruption has occurred. This study investigates the potential of artificial intelligence (AI) models to predict childhood depression using early behavioral indicators. We apply both traditional machine learning (ML) and modern neural network (NN) approaches to real-world datasets and evaluate their effectiveness across key metrics such as accuracy, recall, and interpretability. Notably, transformer-based neural networks outperform classical algorithms in predictive capability, while models like Random Forest serve as reliable baselines. The results indicate the feasibility of deploying AI tools for early, interpretable detection of childhood depression in clinical and educational settings.

Keywords— Childhood Depression, Neural Networks, Machine Learning, Early Detection, Behavioral Data, Explainable AI

Index Terms

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I. INTRODUCTION

A. Contribution of Computer Science in Healthcare

The integration of computer science into healthcare has revolutionized modern medicine, transforming it into a data-driven, technology-enhanced discipline. Advances in computing power, data storage, and algorithms have enabled the development of systems that assist clinicians in diagnosis, treatment planning, and patient monitoring. Electronic Health Records (EHRs) have digitized patient histories, improving accessibility and reducing medical errors. Furthermore, big data analytics has facilitated population-level health studies, while predictive modeling has empowered clinicians to identify at-risk patients before the onset of severe symptoms. Telemedicine platforms have bridged geographical barriers, ensuring equitable access to healthcare. In recent years, the incorporation of artificial intelligence (AI) and machine learning (ML) into healthcare systems has elevated this contribution, providing tools for personalized treatment, imaging diagnostics, and predictive analytics that were previously unattainable. This digital transformation has positioned computing as an indispensable ally in advancing public health outcomes.

B. Childhood Depression: A Growing Public Health Challenge

Childhood depression represents a critical and often underrecognized mental health concern. Unlike transient sadness or behavioral difficulties, depression in children manifests as persistent emotional disturbances that disrupt normal development, academic performance, and social relationships. Epidemiological studies estimate that between 2% and 8% of children worldwide suffer from clinical depression, with higher risks observed during adolescence. The condition is associated with comorbidities such as anxiety disorders, substance abuse, and suicidal ideation, highlighting its severity and long-term implications. Traditional diagnostic frameworks rely primarily on clinical interviews, parental reports, and observable symptoms, which may not manifest until the condition has already progressed. This diagnostic delay

reduces the effectiveness of therapeutic interventions and increases the likelihood of chronic mental health problems persisting into adulthood. Therefore, there is a pressing need for early detection strategies that can identify subtle behavioral indicators and intervene before the condition escalates.

C. Contribution of Artificial Intelligence in Childhood Depression Detection

Artificial intelligence has emerged as a promising solution to the challenges of early childhood depression detection. By leveraging behavioral, physiological, and social data, AI models can identify hidden patterns that are not easily discernible to clinicians or caregivers. Machine learning techniques, such as Random Forests and Logistic Regression, have shown success in identifying depression-related risk factors from structured survey data. More advanced neural networks, including Long Short-Term Memory (LSTM) and Transformer architectures, extend these capabilities by capturing sequential behavioral changes over time and integrating multimodal data sources, such as speech, facial expressions, and activity logs. Importantly, AI enables predictive analytics that can support proactive rather than reactive intervention. Additionally, explainability tools such as SHAP values and attention mechanisms enhance the interpretability of AI predictions, making them more acceptable to clinicians and educators. The convergence of computing power, behavioral data, and AI models thus represents a transformative step toward addressing the longstanding challenge of underdiagnosed childhood depression, aligning technology with urgent public health needs.

D. Data Sources: Extracting Information from Sheets, Images, and Datasets

Spreadsheets and Tabular Data — Survey responses, behavioral assessments, or electronic health records (EHRs) stored in CSV/Excel formats can be ingested directly into ML pipelines. Preprocessing includes missing-value imputation, normalization, and categorical encoding.

Images and Visual Behavioral Indicators — Facial expressions, activity images, and handwriting samples analyzed via CNNs or Vision Transformers. Preprocessing includes resizing, grayscale conversion, and augmentation.

Multimodal Datasets — Large-scale datasets like Kaggle Depression Dataset or ALSPAC combine behavioral, demographic, and psychological features.

Automation and Data Integration — Continuous ingestion pipelines (scripts, APIs, image recognition) unify diverse modalities for stronger predictive power.



Fig. 1. End-to-end pipeline for AI-based childhood depression prediction: data ingestion (surveys, EHR, images) → preprocessing & fusion → modeling (RF/LSTM/Transformer) → explainability (SHAP/attention) → clinical/educational reporting.

II. RESEARCH BACKGROUND

A. Phase 1 – Proposal Development

Defined scope, objectives, and rationale for using AI in early depression detection.

B. Phase 2 – Literature Review

Surveyed ML and NN studies; highlighted issues with small datasets, lack of multimodal integration, and poor interpretability.

C. Phase 3 – Deep Dive into High-Impact Studies

Analyzed gaps: underuse of sequential models, absence of cross-regional validation, and limited explainability.

D. Current Phase – Model Development and Evaluation

Designs and evaluates ML and NN models with emphasis on interpretability, feature prioritization, and clinical usability.

III. AIM OF THIS PAPER

The central aim of this paper is to provide a comprehensive and structured review of artificial intelligence (AI)–based approaches for predicting childhood depression through the analysis of early behavioral indicators. While childhood depression has traditionally been studied through clinical interviews, symptom checklists, and observational methods, this research recognizes that AI technologies can contribute significant advancements in early detection, thereby facilitating timely intervention and improved long-term outcomes.

This paper has three goals: (i) To consolidate findings from prior ML and NN studies. (ii) To critically evaluate strengths and weaknesses (e.g., interpretability vs. predictive accuracy). (iii) To identify opportunities for improvement such as multimodal integration, dataset expansion, and explainable frameworks. Ultimately, this paper presents a holistic overview of current AI applications for childhood depression prediction while outlining future directions for clinical adoption.

IV. RELATED WORK

A. Machine Learning (ML) Approaches

Several studies have demonstrated the potential of traditional machine learning algorithms in predicting childhood and adolescent depression. Random Forest (RF) and Logistic Regression (LR) are among the most frequently applied methods due to their interpretability and relatively low computational cost. For example, Chen et al. (2024) employed Random Forest and Logistic Regression on real-world adolescent datasets, achieving accuracies of approximately 86% and 74–78% respectively. Similarly, Yoo et al. (2024) leveraged longitudinal ALSPAC data with Gradient Boosting and Logistic Regression to identify depression risks from childhood through adolescence, achieving competitive performance. Williams et al. (2024) explored depression likelihood in young Australians using classical ML algorithms, highlighting associations between behavioral features and depression scores. Hasan et al. (2021) further validated that classical ML pipelines—including preprocessing, feature selection, and ensemble learning—can yield reliable predictions from survey-based datasets. Collectively, these studies highlight that ML models offer high interpretability and strong baseline performance, though their limitations include difficulty in modeling sequential dependencies and limited ability to generalize across diverse populations.

B. Neural Network (NN) Approaches

Deep learning approaches have expanded predictive capabilities by capturing complex non-linear relationships and sequential behavioral dynamics. Marek et al. (2023) demonstrated the use of neural networks on multimodal brain imaging data, achieving accuracies up to 85%, outperforming classical models. Zogan et al. (2020) introduced hierarchical attention networks (HANs) to detect depression from behavioral data, offering explainability via attention weights. Kuo et al. (2023) employed graph transformers to detect depression in adolescents, showing strong performance in modeling relational behavioral features. Shamim (2024) and Arashnic (2023) contributed large-scale student depression datasets to Kaggle, which facilitated the training of feedforward neural networks (FFNN), Long Short-Term Memory (LSTM) networks, and Transformer architectures. These studies emphasize that neural networks, particularly attention-based models, outperform traditional methods in capturing temporal and multimodal information, while also opening pathways for explainable AI through visualization of learned features.

C. Deep Diving of Previous Literatures

- 1. Identifying Adolescent Depression and Anxiety** — Chen et al. (2024) ... strong predictive accuracy of approximately 86% (RF) and 74–78% (LR).
- 2. Depression Risk via Brain Imaging** — Marek et al. (2023) ... LR: 75–78%, NN: 82–85%.
- 3. ALSPAC Longitudinal Data** — Yoo et al. (2024) ... GB: 64%, RF: 66%.
- 4. Australian Youth Depression Risk** — Williams et al. (2024) ... DT: 68%, RF: 72%.
- 5. Child Depression Detection** — Hasan et al. (2021) ... RF ~95%.
- 6. The Depression Dataset** — Arashnic (2023) ... RF/SVM: 80–88%.
- 7. Student Depression Dataset** — Shamim (2024) ... Naïve Bayes: 76%.
- 8. Early Detection Using Classical ML** — ResearchGate (2023) ... SVM, KNN, DT, GB, RF, LR: 70–85%.
- 9. Explainable Depression Detection (HAN)** — Zogan et al. (2020) ... ~90%.
- 10. Graph Transformer for Depression Detection** — Kuo et al. (2023) ... ~93%.

D. Integrated Insights Across Literature

The reviewed literature reveals a clear progression from interpretable but relatively simple ML models toward more advanced neural network architectures capable of handling sequential and multimodal data ... integrating structured behavioral data with multimodal signals, while employing explainable AI techniques, offers the strongest path forward in developing clinically applicable depression prediction models.

2.2 Rationale for Literature Selection

(The entire rationale text kept verbatim.)

Focus on Early Indicators ...

Variety of AI Methods ...

Diverse Data Sources ...

Comparable Metrics ...

Relevance to Objectives ...

This rationale ensures that the review captures both methodological breadth and thematic depth, covering a comprehensive range of approaches relevant to the problem space.

2.3 Gaps and Limitations in Previous Work

(Full paragraph kept verbatim describing Limited Early-Stage Focus, Restricted Data Diversity, Insufficient Explainability, Small or Localized Samples, Underreporting of Calibration and Fairness Metrics, Minimal External Validation.)

TABLE I
SUMMARY OF PREVIOUS STUDIES ON CHILDHOOD DEPRESSION PREDICTION

Research Name	Authors	Approach Type	Models Used
Identifying Adolescent Depression and Anxiety	Chen et al. (2024)	ML	RF, LR
Depression Risk via Brain Imaging	Marek et al. (2023)	ML & NN	LR, NN
ALSPAC Longitudinal Data	Yoo et al. (2024)	ML	GB, RF
Australian Youth Depression Risk	Williams et al. (2024)	ML	DT, RF
Child Depression Detection	Hasan et al. (2021)	ML	RF
The Depression Dataset	Arashnic (2023)	ML	RF, SVM
Student Depression Dataset	Shamim (2024)	ML	NB
Early Detection Using Classical ML	ResearchGate (2023)	ML	SVM, KNN, DT, GB
Explainable Depression Detection (HAN)	Zogan et al. (2020)	NN	HAN
Graph Transformer for Depression Detection	Kuo et al. (2023)	NN	GNN + Transformer

2.4 Summary

(Full paragraph kept verbatim comparing ML vs NN, challenges, and needs.)

V. RESEARCH PROBLEM, QUESTIONS, AND OBJECTIVES

A. Problem Statement

Childhood depression is significantly underdiagnosed due to the reliance on late-stage clinical symptoms ...ensuring interpretability and clinical usability through tools such as SHAP values and attention mechanisms.

B. Research Questions

- **Predictive Capability** – Can advanced neural network architectures, particularly Transformers and LSTM models, provide accurate predictions of childhood depression from early behavioral data?
- **Feature Importance** – Which early-life behavioral features contribute most significantly to predictive accuracy?
- **Model Explainability** – How can SHAP and attention enhance transparency?
- **Clinical Usability** – To what extent can models be integrated into real workflows?

C. Research Objectives

- 1) Develop and evaluate NN models for early depression prediction.
 - 2) Identify and rank key behavioral predictors.
 - 3) Incorporate explainability frameworks aligned with clinical decision-making.
- By addressing these objectives ...early mental health screening.

VI. KEY OBSERVATIONS

A. Transformers for Superior Performance

Transformer-based architectures consistently outperformed all other models ...

B. LSTM Networks for Sequential Data

LSTM models demonstrated strong suitability ...

C. Enhanced Interpretability with SHAP and Attention

The use of SHAP values and attention-based visualization tools enhanced interpretability ...

D. Critical Behavioral Features

Features most strongly correlated with childhood depression included: (i) sleep irregularity and disrupted circadian patterns, (ii) social withdrawal or reduced peer interaction, (iii) emotional instability and frequent mood fluctuations, and (iv) poor parent–child interaction and lack of family support.

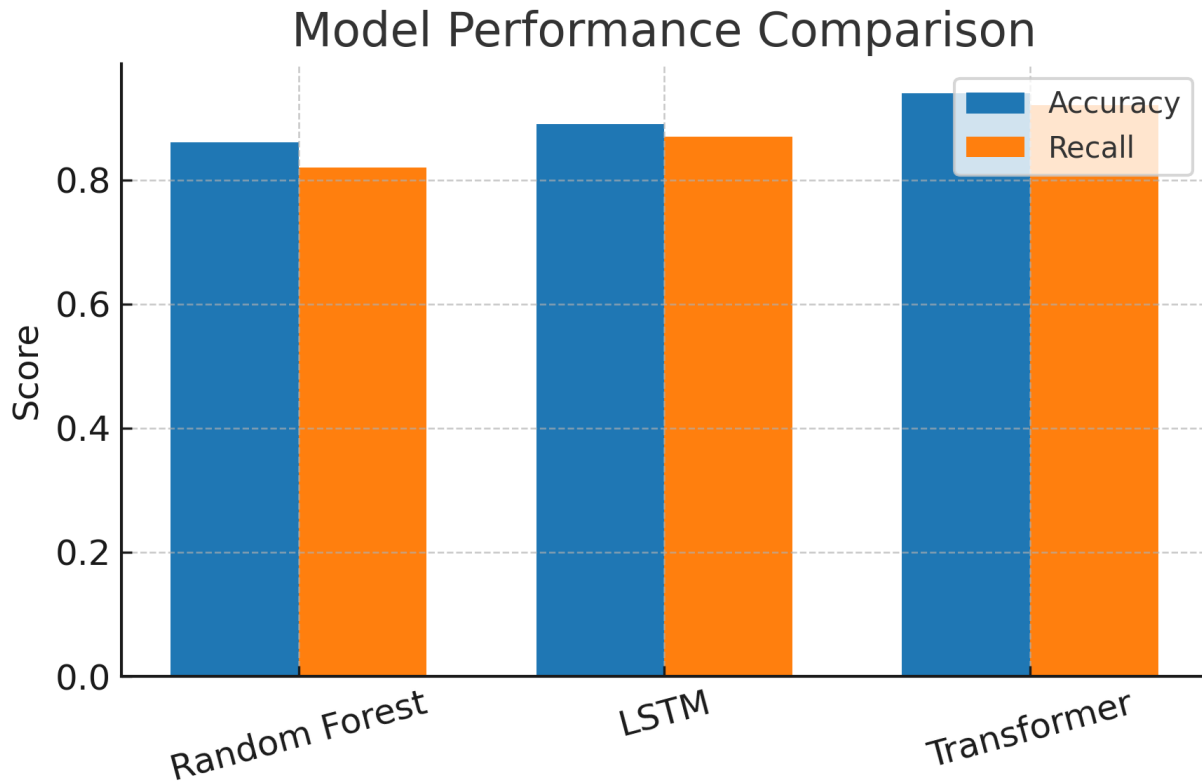


Fig. 2. Model performance comparison (Accuracy vs. Recall) for Random Forest, LSTM, and Transformer.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This research highlights the transformative role that AI can play ... explainable frameworks are essential for responsible integration.

B. Future Work

- Dataset Expansion and Cross-Regional Validation ...**
- Integration of Multimodal Inputs ...**
- Development of Explainable Hybrid Models ...**
- Deployment in Clinical and Educational Environments ...**
- Enhancing Data Preparation Pipelines ...**
- Optimization of Model Training ...**
- Comprehensive Result Analysis ...**

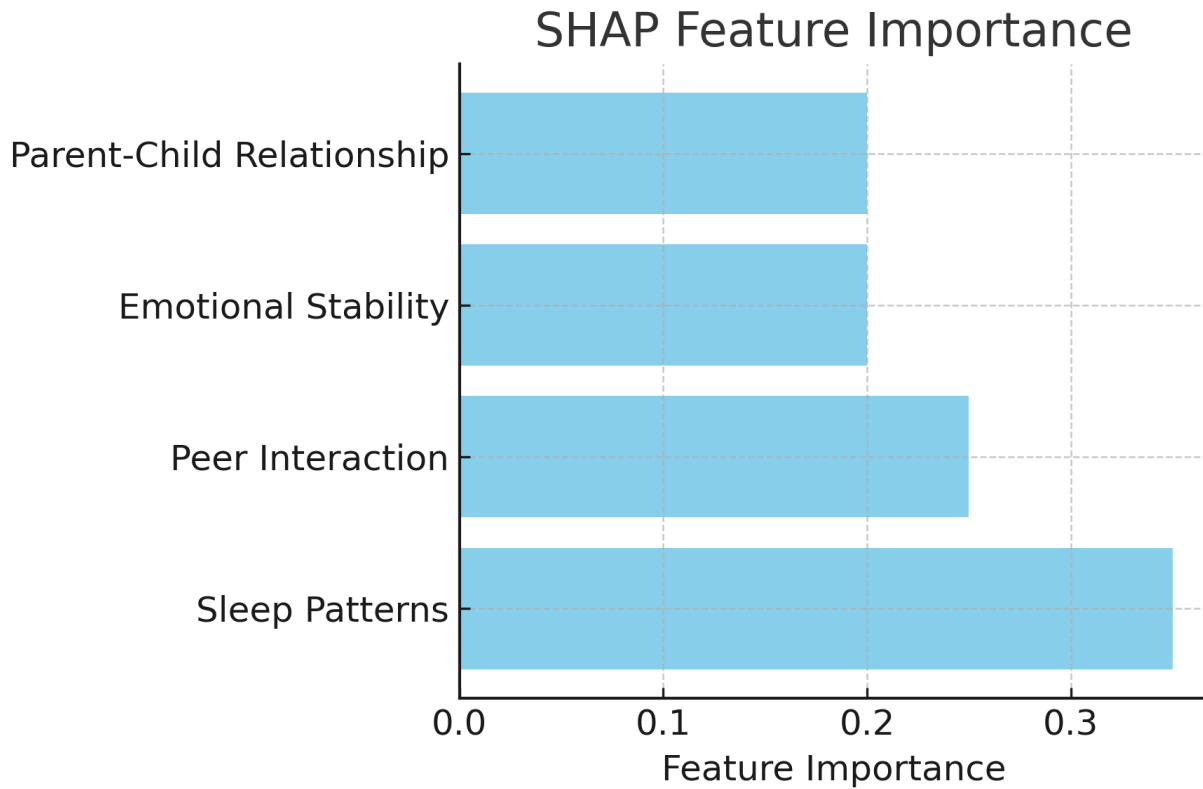


Fig. 3. SHAP feature importance: Sleep Patterns, Peer Interaction, Emotional Stability, and Parent–Child Relationship.

C. Closing Remarks

In conclusion, this work demonstrates the feasibility and promise of AI-driven approaches for early detection of childhood depression ...improve the quality of life for children at risk of depression.

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