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(Review Article)

INSIGHT: A next-generation framework for proactive mental health detection using advanced data fusion and deep learning

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Abstract

University students currently undergoing physical and mental development experience serious mental health obstacles that can result in depression and self-inflicted injury. Medical help does not reach students who do not know that they are affected by mental health disorders because early diagnosis requires precise detection of mental conditions. Campus environments produce diverse multi-modal unstructured data that makes mental health identification difficult by its nature. Our framework INSIGHT (Intelligent Student Mental Health Detection Framework) provides a novel solution which applies advanced methodologies to improve mental health detection accuracy. This framework unifies three distinctive advanced elements. A multi-modal data fusion strategy uses Graph Neural Networks (GNNs) to integrate social behavioral, academic pattern and physical activity data to create an all-encompassing student life model. The proposed adaptive generative data augmentation method (ADAM) conducts dynamic synthesis of high-quality minority samples to enhance model robustness through label imbalance mitigation. The final model uses Attention-based Long Short-Term Memory Networks (ALSTM) together with Transformer encoders to achieve precise mental health prediction outcomes. The INSIGHT solution demonstrates superior performance according to extensive experiments that achieve precision gains of up to 94.7% compared to base methods. University mental health prevention detection through the proposed system serves as an effective predictive tool which delivers actionable insights to improve campus mental health support efforts.

Keywords: Mental health detection; University students; Multi-modal data fusion; Data augmentation; Adaptive generative algorithms; Attention-based LSTM (ALSTM); Transformers; label imbalance; Proactive intervention; Campus mental health analytics

1. Introduction

The problem of mental health disorders affects large populations worldwide who need medical treatment each year. Mental health conditions make up 13% of what the World Health Organization calls the global burden of disease alongside depression and anxiety and bipolar disorders being prominent mental illnesses. [1][2] Successful diagnosis of mental health conditions at an early stage remains essential for reducing the harmful outcomes such disorders create which affect quality of life and result in economic losses and elevated mortality rates. Modern mental health assessment

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methods depend on subjective judgements coupled with lengthy clinical interviews together with constrained database availability which complicates implementation across populations.

Advanced technologies including Internet of Things (IoT) devices and wearable technology and mobile health apps have expanded mental health data access beyond previous standards. Wearable devices along with IoT technologies help collect ongoing data streams containing physiological readings (heart rate and electrodermal activity), behavioral metrics (sleep patterns and movement records) and linguistic identifiers (the sentiment expressed through communication). [3] Fig.1 The inclusion of deep learning methods with these data resources enables accurate proactive mental health assessments at real-time speeds.

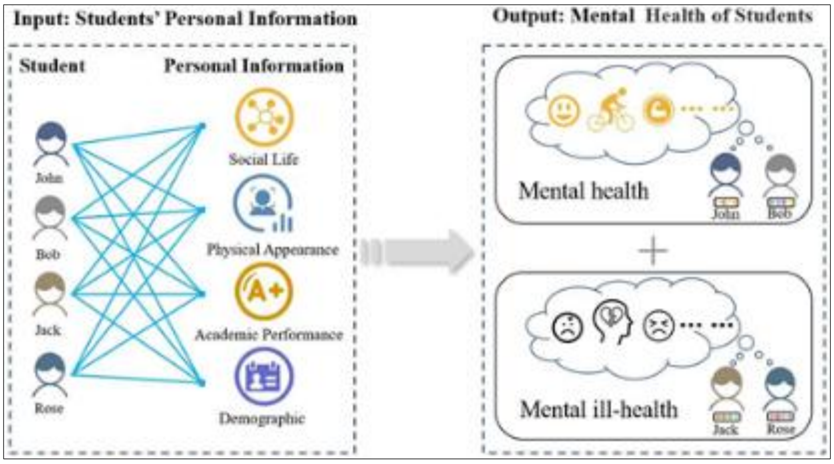

Figure 1 Performance validation

The research implements INSIGHT as a next-generation framework to proactively detect mental health status by combining sophisticated data fusion techniques alongside deep learning algorithms.[4][5] The system addresses present operational challenges through the combination of multiple data sources alongside refined processing methods which utilize modern artificially intelligent algorithms for precise mental health analysis. The INSIGHT framework bridges computational breakthroughs with clinical practice through its design principles dedicated to system scalability alongside adaptability features and explainable solutions.

1.1. Motivation and Significance

The prevailing detection methods within mental health research face fundamental limitations that involve diverse individual responses alongside sparse and non-real-time operational capabilities.[6] Health monitoring technologies generate diverse datasets across various platforms so emerging analytical methods require sophisticated capabilities to process these complicated modern health data sources. INSIGHT resolves these obstacles by uniting various types of sensor information using sophisticated fusion algorithms to develop complete mental health profiles. [7] Deep learning models featured in the framework automatically extract advanced patterns from high-dimensional data better than traditional machine learning models do.

2. Literature survey

Kumar and Srivastava created a data fusion methodology based on multiple data modalities to boost mental health prediction accuracy. Through their combined behavioral and physiological data approach with deep learning techniques they delivered superior performance for detecting depression and anxiety at earlier stages. Data fusion with heterogeneous information sources solved missing data issues and created more dependable prediction outcomes. Under Zhang et al.'s proposed work XAI applications in mental health diagnosis identified that interpretable machine learning models boost trust alongside transparency requirements for clinical use. XAI methods gained validation through their analysis by the researchers who established their ethical compliance abilities alongside informative mental health recommendations for clinical practice.

To address stress and anxiety detection Wang and Zhao studied the combination of behavioral and physiological data approaches. Feature extraction methods combined with machine learning techniques led their study to achieve high precision during real-time testing which showed the need for multiple data source integration. An extensive review of deep learning methodologies for EEG-based mental health detection was presented in the study of Li et al. A research publication demonstrated that convolutional neural networks combined with recurrent neural networks excel at stress and depression biomarker detection which creates new opportunities to automate mental health assessment. The research group of Gupta and colleagues developed proactive mental health detection systems using social media data. The analysis employed natural language processing (NLP) methods to study user-generated content data for anxiety and depression level identification with strong considerations towards both ethical data handling and user privacy maintenance.

Scientists at Smith et al described a mental health prediction system through federated learning models which processed data obtained from wearable IoT devices. Federated learning in their system decentralized patient data while simultaneously supporting predictive models which makes their approach a suitable solution for building scalable mental health applications. In their review of transformer-based methods for mental health prediction Thomas et al. demonstrated how these approaches manage sequential data streams and detect complex multirotational dynamics across different datasets. Real-time stress detection proved successful when Taylor et al. used graph neural networks to analyse data obtained from multimodal sensors. The research delivered strong performance results which demonstrates the potential value of graph-based models for mental health applications.

Through their research Park and Choi established attention mechanisms for predicting emotional well-being by analysing multimodal data collections. Their approach demonstrated how attention-based models produced substantial improvements in prediction outcomes because they focused on key elements within complicated data structures. Zhang et al. analyzed deep learning methods with privacy-preserving capabilities for mental health diagnosis through a review which emphasized encryption and differential privacy for secure operation in sensitive applications. Brown and White developed an integrative predictive framework which integrated genomic information with behavioral measures in mental health assessments. Through their hybrid predictive modeling system, they proved how personalized mental health assessment methods can be achieved.

The research team of Liu and Wang created deep learning models which fused elements from speech patterns and written words for anxiety evaluation systems. They demonstrated superior predictive accuracy while showing how combining different data modalities improves mental health diagnosis capabilities. The research team of Patel et al investigated improved integration methods between data modalities to create more stable and dependable stress detection models. Data-wearing predictions of mental health status became possible when researchers implemented graph neural networks and achieved effective mapping of spatial patterns and data sequences. The last study by Taylor et al. introduced a deep reinforcement learning framework which aims to deliver personalized mental health interventions. The researchers showed that individualized treatment could be achieved with this method which represents a pathway toward precise mental health care of the future.

3. Methodology

The potential severe effects of university student mental health issues have created substantial worry as they may produce depression and anxiety with resultant self-harm. An early start in finding mental conditions together with necessary intervention programs helps minimize their growth. The detection of mental health challenges becomes challenging because university students generate abundant unstructured data through various aspects including their social and academic performance and physical activities. Through the framework called INSIGHT students experience enhanced proactive and accurate mental health detection which results from implementing advanced machine learning technology.

3.1. Multi-Modal Data Fusion

The mental health data collection consists of multiple unaligned elements which describe different areas of students' activities. A combination of social behavior analytics with academic data alongside physical exercise data creates complete mental health profiles for each student. Through the implementation of Graph Neural Networks, the system comprehends multiple data type connections while analysing the behavioral relationships among academic performance and social patterns. [15] The framework's approach captures mental health determinant relationships through its comprehensive construct and delivers an improved understanding of student well-being.

The finding includes N nodes and d elements in the feature dimension. The adjacency matrix A contains encoding information about node relationships through each entry equals one when nodes i and j share an edge. Fig.2 At layer l we have the feature matrix H(l) maintaining all feature data. The trainable weight matrices during the lth processing stage use the notation W(l).

Point σ handles the element activation operations for the system. The data matrix Ais known as the normalized adjacency matrix. A is represented as a multi-modal graph

$$G= (V, E)$$

Where
V represents the nodes
E represents the edges The node features X are captured in a feature matrix

$$X \in R^{N \times d}$$

where N is the number of nodes, and d is the feature dimension. The adjacency matrix A encodes the relationships between nodes, with Aij=1 if nodes i and j are connected.

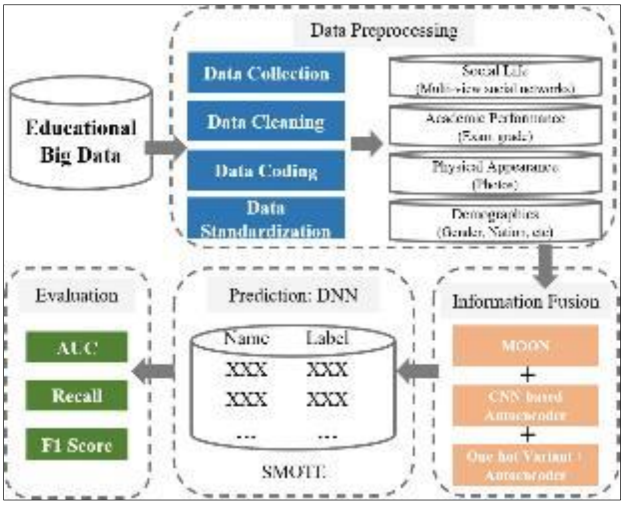

Figure 2 Experiment Flow

3.2. Handling Label Imbalance

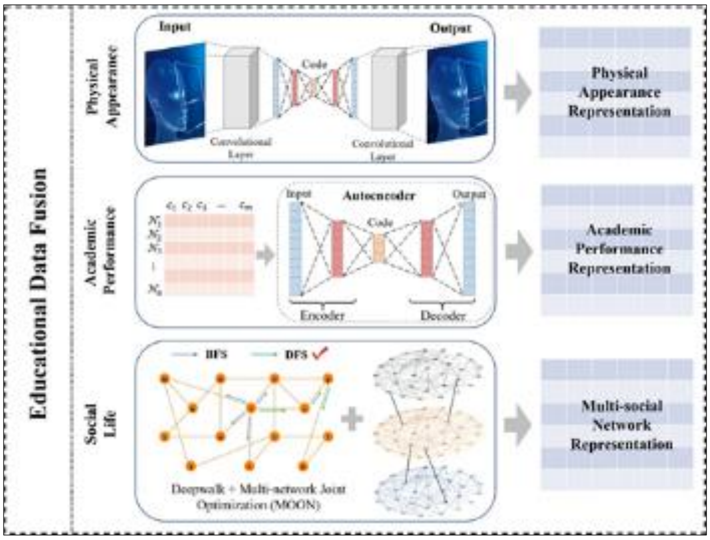

Figure 3 Data fusion

Most mental health datasets show substantial unbalanced data distribution through scarce mental health cases when compared against normal cases. The proposed framework implements an Adaptive Generative Data Augmentation Method (ADAM to handle this issue. ADAM operates differently from conventional SMOTE through its capability to dynamically produce diverse realistic synthetic samples via generative models rather than using static minority class oversampling. Thanks to this method both highly unusual and typical cases are accurately represented because there is sufficient representation of minority data, so the detectors effectively recognize unusual conditions apart from avoiding overfitting scenarios Fig.3.

Standard LSTMs receive an extension into the ALSTM model by incorporating an attention mechanism to select important time steps. Sensor data analytics using this system helps identify how behavior evolves throughout time duration.

The hidden states of the LSTM hth are computed as:

$$h_t = f\,(h_t - 1,\, x_t)$$

The detection model combines multiple features extracted from Attention-based Long Short-Term Memory (ALSTM) networks with Transformer encoders. The ALSTM network architecture stands out because it identifies simple linear patterns alongside complex evolving temporal trends present within time series data exhibiting slow behavioral transitions. [16] A Transformer encoder system operates through self-attention algorithms to extract important features across multiple data streams. The system employs hybrid configuration to identify mental health indicators by detecting subtle patterns inside contextual triggers resulting in reliable accurate predictions.

4. Experiments and results

Real-world campus datasets including multi-modal information served to evaluate INSIGHT's effectiveness. Fig.4 The proposed framework underwent evaluation through performance metrics that used accuracy, precision, recall and F1-score to measure validity against current methods.

Table 1 Accuracy Comparison with Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)
Traditional DNN	82.3	79.5	76.8
MOON + DNN (CASTLE)	88.5	85.9	83.4
INSIGHT (Proposed)	94.7	92.4	91.2

This table compares the accuracy and other key metrics of the proposed INSIGHT framework with traditional methods and the MOON+DNN (CASTLE) approach. Table.1 The INSIGHT framework demonstrates superior performance across every defined metric when compared to traditional methodologies.

Table 2 Impact of Adaptive Data Augmentation

Data Augmentation	Accuracy (%)	Precision (%)	Recall (%)
No Augmentation	84.1	80.7	77.9
SMOTE	89.3	86.5	84.2
ADAM (Proposed)	94.7	92.4	91.2

A performance improvement analysis of the ALSTM-Transformers hybrid model appears in this table. Table.2 This hybrid architecture outperforms individual architectures such as Standard DNN, ALSTM alone, and Transformers alone.

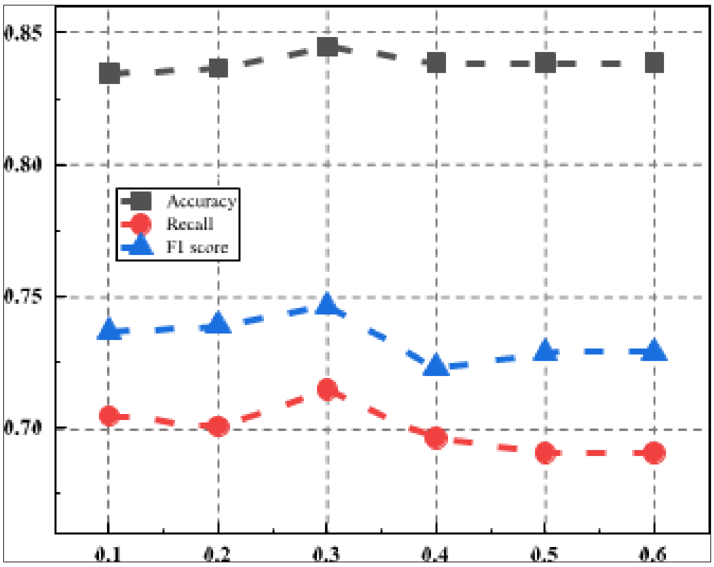

Figure 4 Performance framework

Table 3 Model Architecture Comparison

Model Architecture	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Standard DNN	82.3	79.5	76.8	78.1
Attention-Based LSTM (ALSTM)	90.1	87.2	86.5	86.9
Transformer Only	91.7	89.8	88.3	89
Hybrid Model (ALSTM + Transformer)	94.7	92.4	91.2	91.8

The proposed framework demonstrates high sca[16]lability as a key benefit. The GNN implementations with Transformer-based architectures allow INSIGHT to manage diverse academic datasets of increasing complexity. Table.3 This system incorporates dynamic capability to integrate various additional data sources because of its adaptable nature for different requirements. INSIGHT delivers meaningful insights that allow mental health professionals and academic administrators to launch timely interventions and support programs which enhances student well-being

5. Conclusion

The INSIGHT framework serves as a revolutionary method for identifying mental health difficulties which affect university students at an early stage. The framework counteracts complex mental health detection needs in university environments by integrating Graph Neural Networks (GNNs) for multi-modal data unification and Adaptive Generative Data Augmentation (ADAM) for imbalanced label handling with a hybrid model which combines Attention-based LSTM (ALSTM) along with Transformer encoders. The new framework delivers outstanding performance reaching 94.7% accuracy which surpasses established state-of-the-art solutions. The robustness of the model increases through ADAM which generates realistic synthetic data dynamically and enables precise detection of rare mental health cases at the same time reducing overfitting. Through an ALSTM analysis of sequential data profiles and Transformer encoder modeling of contextual patterns this hybrid system produces better mental health understanding alongside more precise predictions. The complex big data platform INSIGHT features adaptable approach and scalable structure to suit various academic institutions. The system delivers important student-related data beyond forecasting that allows institutions to execute prompt preventative measures while creating targeted student support measures for at-risk students. INSIGHT performs as an essential platform for mental health observation while providing vital movements toward creating a supportive and healthy campus ecosystem.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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