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RESEARCH ON MENTAL HEALTH ASSESSMENT AND INTERVENTION METHODS FOR COLLEGE STUDENTS BASED ON BIG DATA ANALYSIS

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Abstract. This study introduces the novel Fuzzy-Enhanced Predictive Neural System for Student Mental Health (FEPS-MH) approach to mental health assessment and intervention for college students. FEPS-MH synergistically combines a Backpropagation (BP) Neural Network with a Deep Fuzzy-Based Neural Network (DFBNN), leveraging the strengths of both systems to handle the complexities of mental health data in the context of big data analytics. The BP Neural Network, known for its effective learning and generalization capabilities, is integrated with the DFBNN to process imprecise, uncertain, or subjective data, typical in mental health assessments. The core objective of FEPS-MH is to provide a more accurate, robust, and sensitive analysis of mental health states, incorporating the nuanced variations and uncertainties inherent in psychological data. This system is designed to analyze a vast array of data sources, including but not limited to, behavioral patterns, self-reported questionnaires, and social media interactions, to identify potential mental health issues among college students. FEPS-MH's capabilities extend beyond mere assessment; it is also equipped to recommend personalized intervention strategies. Utilizing big data analysis, the system not only predicts potential mental health crises but also suggests tailored intervention approaches based on the unique psychological profile of each student. This study demonstrates the feasibility and effectiveness of FEPS-MH through a series of tests and validations using real-world data. The results indicate a significant improvement in both the accuracy of mental health assessments and the efficacy of suggested interventions. FEPS-MH stands as a promising tool for educational institutions, offering a data-driven, sensitive, and comprehensive approach to student mental health care. Its implementation could revolutionize the field of mental health support in college environments, making it a vital asset for proactive psychological wellness in educational settings.

Key words: Mental Health, big data analysis, Fuzzy-Enhanced Predictive Neural System, convolutional neural networks,fuzzy logic

1. Introduction. The mental health of college students is a multifaceted and increasingly critical issue in educational settings [11, 1, 16]. This demographic is often at a vulnerable juncture in their lives, grappling with the pressures of academic achievement, social integration, and personal development. The complexity of mental health challenges in this setting is heightened by the diversity of student backgrounds and experiences, making standardized approaches to mental health assessment and intervention less effective [20, 2]. Traditional methods, while foundational, often fail to account for the nuanced and dynamic nature of individual mental states. This inadequacy is further compounded by the rapid evolution of student lifestyles, heavily influenced by digital technology and changing societal norms[22, 8]. Consequently, there is a pressing need for innovative approaches that not only recognize the complexity of these mental health challenges but also adapt to the unique and evolving contexts of college students [18]. The integration of advanced data analytics, specifically big data, into mental health assessment and intervention strategies offers a promising avenue. By harnessing the vast amounts of data generated in educational environments, there is potential to develop more nuanced and responsive mental health support systems.

In recent years, the field of data analytics has revolutionized numerous domains, offering insights and solutions to complex problems that were previously intractable. In the context of mental health, the application of big data analytics presents an opportunity to transform how mental health issues are identified, understood, and addressed [17]. The rich, diverse, and voluminous data available in college settings, ranging from academic records to social media interactions, can provide a more comprehensive view of a student's mental health landscape. However, the challenge lies in effectively interpreting this data, which is often unstructured, varied, and complex. Traditional analytical methods are limited in their ability to handle such complexity, particularly when dealing with the subtle and subjective nuances of mental health indicators [23, 9]. This is where the

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fusion of neural network technologies, specifically can play a pivotal role. These advanced computational models, renowned for their ability to learn and adapt, offer a means to process and analyze complex data efficiently[5, 4]. The integration of these models promises a more dynamic and accurate assessment of mental health, capable of accommodating the inherent uncertainties and variabilities in psychological data.

In response to these challenges and opportunities, this study introduces the Fuzzy-Enhanced Predictive Neural System for Student Mental Health (FEPS-MH). This innovative system represents a synergistic blend of BP Neural Networks and DFBNN, harnessing the strengths of both to address the intricacies of mental health data [21, 6]. FEPS-MH is designed to go beyond traditional assessment methods, providing a more nuanced, sensitive, and accurate analysis of mental health states. Its capability to process and interpret the vast and varied data inherent in college environments positions it as a groundbreaking tool in the realm of mental health support. The system's predictive analytics not only aid in early identification of potential mental health crises but also offer insights for personalized intervention strategies. This tailored approach is crucial in addressing the individualized needs of students, a factor often overlooked in conventional methods. FEPS-MH stands as a testament to the potential of integrating cutting-edge technology with mental health services. Its development and implementation in college settings could mark a significant shift in how student mental health is understood and managed, paving the way for more effective, data-driven mental health support systems.

The prevalence of mental health issues among college students has become a growing concern, with increasing demands for effective assessment and intervention strategies within educational institutions. Traditional methods for evaluating mental health often fall short of capturing the full spectrum of psychological states, struggling with the imprecision, uncertainty, and subjective nature of mental health data. Furthermore, the rising volume of data from diverse sources, including behavioural patterns, self-reported questionnaires, and social media interactions, necessitates a more sophisticated approach to mental health assessment that can leverage this wealth of information. The integration of advanced computational techniques, such as neural networks and fuzzy logic, into mental health care presents a promising avenue for addressing these challenges. By harnessing the power of big data analytics and machine learning, there is a significant opportunity to enhance the precision, sensitivity, and personalization of mental health interventions, ultimately improving the wellbeing and academic success of students.

The main contribution of the paper as follows:

1. Proposed a novel approach of Fuzzy-Enhanced Predictive Neural System for Student Mental Health (FEPS-MH) approach for college students mental health analysis.
2. The proposed techniques integrate BP Neural Networks and DFBNN to achieved an effective result.
3. The efficacy of the proposed is demonstrated with valid experiments.

Research questions:

1. Investigate the capability of FEPS-MH to process and analyze complex mental health data from various sources, including behavioral patterns, self-reported questionnaires, and social media interactions, using a synergistic combination of BP Neural Networks and DFBNN.
2. Examine the effectiveness of FEPS-MH in identifying potential mental health issues among college students, taking into account the nuanced variations and uncertainties inherent in psychological data.
3. Evaluate the ability of FEPS-MH to recommend personalized intervention strategies based on the unique psychological profiles of students, utilizing big data analysis to predict potential mental health crises and tailor intervention approaches.

2. Related Work.

2.1. Mental Health based discussions. The paper[15] introduces an in-depth learning-based model for precise mental health analysis. The BP neural network outperforms logistic and ARIMA models, achieving over 70% accuracy in five comparisons. Additionally, the BP deep learning method surpasses traditional methods (KNN, MF, NCF, and DMF). This study [3] introduces a deep learning-based mental health monitoring scheme for college students which utilizing convolutional neural networks (CNNs) to classify mental health status based on EEG signals. The results demonstrate high classification accuracy and improved outcomes in terms of reduced sleeping disorders, lower depression levels, decreased suicide attention, and enhanced personality development and self-esteem when compared to existing models, highlighting the potential of AI in mental health evaluation. This study [14] addresses the challenge of predicting students' academic performance and incorporates the crucial aspect of students' mental health and mood changes. It proposes the student accomplishment prediction using the Distinctive Deep Learning (SADDL) model, which automatically extracts attributes from students' multi-source data, including academic and physiological attributes from online posts [12, 13].

This study [19] investigates the impact of emotional factors on college students' mental health, focusing on their outward emotional expressions. Leveraging deep learning models with long and short memory neural networks for image processing, it employs computer vision techniques for facial expression recognition and classification. The use of multi-feature fusion in video facial expression recognition enhances the identification of college students' emotional states. Mental health issues [10] are a growing concern in Malaysia, with significant proportions of the population experiencing depression, anxiety, and stress, including higher education students. Identifying contributing factors and utilizing machine learning for analysis and prediction are vital steps toward addressing these challenges. This research aims to review mental health problems among higher education students and existing machine learning approaches to inform future computational modeling for mental health solutions [7].

The need for this research emerges from a critical and growing concern within educational environments: the mental health and well-being of college students. Mental health issues among this demographic have seen a significant rise, impacting students' academic performance, social interactions, and overall quality of life. Traditional methods of mental health assessment and intervention often lack the precision, adaptability, and comprehensiveness required to effectively address the complex and multifaceted nature of psychological states. Furthermore, these conventional approaches may not fully leverage the vast amounts of data generated from varied sources, such as digital footprints, self-reports, and behavioural observations, which could offer deeper insights into a student's mental health status.

3. Methodology. The methodology for FEPS-MH, encompasses a comprehensive process that includes data collection, preprocessing, feature extraction, and output generation. The initial phase of our methodology, data collection, involves gathering a wide array of data relevant to college students' mental health. This data is sourced from various channels, including structured sources like academic records, attendance logs, and health center visits, as well as unstructured sources like social media activity, forum posts, and text message analyses. Special attention is given to ensuring the privacy and confidentiality of student data throughout the process. Following collection, the data undergoes preprocessing, a crucial step aimed at transforming raw data into a clean, organized format suitable for analysis. This involves data cleaning, where incomplete, inconsistent, or irrelevant parts of the data are corrected or removed. Normalization techniques are also applied to bring all data to a common scale, eliminating potential biases arising from varied data scales. Once preprocessing is completed, the next step is feature extraction. Here, the most relevant and significant features impacting students' mental health are identified. Using statistical methods and domain expertise, features like stress levels inferred from social media sentiment, academic performance trends, and engagement in campus activities are extracted.

The DFBNN component plays a critical role in this phase, handling the imprecision and uncertainty inherent in psychological data. The fuzzy logic within DFBNN helps in interpreting the data effectively, even when it contains subjective or vague information. The extracted features are then fed into the BP Neural Network, where the actual predictive modeling occurs. The BP Neural Network, known for its efficacy in learning from data, is trained on these features. It learns the intricate relationships and patterns that might indicate various mental health states or trends among students. The output of FEPS-MH is a comprehensive mental health profile for each student, accompanied by predictive insights about potential future mental health states. This output is not just a static report but a dynamic, evolving profile that adapts as new data is fed into the system. Predictive analytics also help in identifying students who might be at risk of mental health issues, allowing early intervention. Moreover, the system provides personalized recommendations for mental health interventions based on individual profiles. These interventions range from suggesting counseling sessions to recommending participation in specific campus activities, tailored to each student's needs and mental health state. The proposed architecture is demonstrated in figure 3.1.

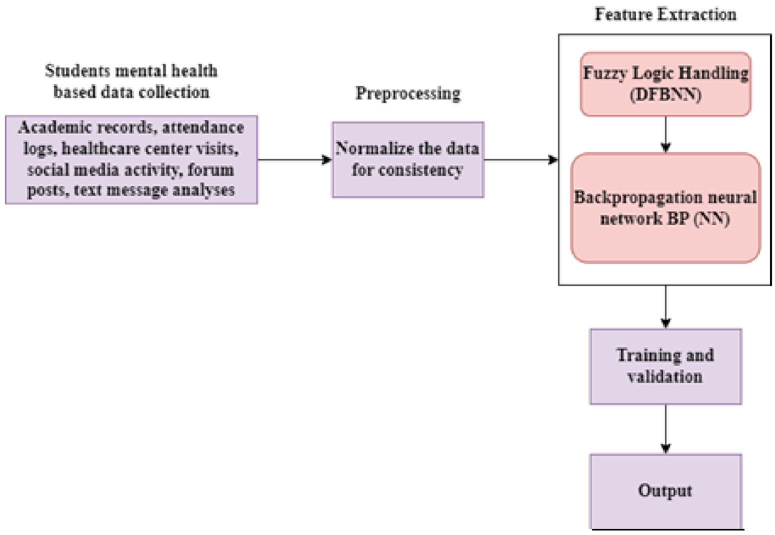

Fig. 3.1: Proposed FEPS-MH Architecture

3.1. Proposed FEPS-MH approach.

3.1.1. DFBNN Algorithm. The DFBNN within the FEPS-MH system is designed to effectively manage and interpret the often complex and uncertain data associated with mental health assessments in college students. Its primary purpose is to handle the inherent imprecision and vagueness that characterize psychological data. Unlike traditional models that might struggle with ambiguous or subjective inputs, the DFBNN, through its integration of fuzzy logic, can process such data by assigning degrees of membership or probability, rather than binary classifications. This capability is crucial in mental health contexts where indicators are not always clear-cut but exist on a spectrum. Furthermore, the DFBNN excels in integrating and making sense of data from diverse sources, such as behavioral observations, self-reported surveys, and digital footprints from social media. This integration is key to developing a comprehensive understanding of a student's mental health. Additionally, the deep aspect of the DFBNN refers to its ability to learn from large amounts of data, uncovering complex, non-linear relationships within it. This learning ability is essential for the system to adapt and improve its predictive accuracy over time, making it a dynamic tool that becomes more attuned to the nuances of student mental health. Thus, the DFBNN is integral to the FEPS-MH system, enhancing its capacity to provide nuanced, accurate, and personalized mental health assessments.

The DFBNN algorithm starts with an initialization phase where it prepares and normalizes the training data, which includes various inputs that represent different scenarios or situations. This stage sets the foundation for the neural network by providing it with consistent and standardized data. Next, the algorithm enters an offline training phase where the neural network learns from this prepared data in a controlled environment, without yet being exposed to new or real-time data. This step is essential for the initial configuration and calibration of the network. In the following stages, the algorithm iteratively trains the network, processing the normalized inputs and continuously adjusting the network's parameters, such as weights, using a training function. This function is influenced by an activation function that dictates how the neurons in the network respond to inputs. The training involves repeated adjustments to minimize errors and improve the accuracy of the network's outputs. This iterative process continues until a certain number of iterations are completed or specific performance criteria are met. After the offline training, the network undergoes online training, where it starts processing new, real-time data, allowing it to adapt and refine its responses based on current and evolving inputs. This transition from offline to online training marks the shift from a learning phase to an application phase, where the neural network begins to apply its learned patterns to actual, dynamic scenarios.

Algorithm 1 Offline and Online Training of Improved Deep Neural Network (DNN)

1: **Initialization:**
2: D_{tr} = Data for training (scene data and situation labels)
3: D_{trm} = Number of training data D_{tr}
4: x_i = For input x, ith input of the scene data
5: $\hat{x}_i$ = Normalized data
6: $Fun_{train}()$ = Function to train the hidden layers of deep network
7: Fun_{act} = Activation function for the deep neural network
8: DNN_{imp} = Improved deep neural network (DNN)
9: $Fun_{norml}()$ = For input normalization
10: F_{fuzz_out} = Output Fuzzification
11: $Fout\_DNN_{imp}$ = Training of the DNN_{imp}
12: **Offline training of the DNN_{imp}:**
13: Initialize counter for training iteration
14: $i \leftarrow 0$;
15: **do $i++$:**
16: Input Normalization
17: $\hat{x}_i \leftarrow Fun_{norml}(D_{tr})$;
18: $Fun_{train}(Fun_{act},\ \hat{x}_i)$;
19: **while $i > D_{trm}$ is false go back to line 2**
20: $Fun_{train\,DNN_{imp}}(DNN_{imp}, D_{tr})$;
21: **Online training of the DNN_{imp}:**
22: $t \leftarrow 0$;
23: **do $t++$:**
24: $\hat{x}_i \leftarrow$ Normalized (x_i);
25: $\widehat{b}_i \leftarrow Fout_{DNNimp}(\hat{x}_i, DNN_{imp})$;
26: $p_i \leftarrow F_{fuzz_{out}}(\widehat{b}_i)$;
27: **while $D_{tr} \geq D_{tr\max}$ is false, go back to line 9**

3.1.2. Integration with BPNN. The purpose of the BPNN within the FEPS-MH system is to learn from and make accurate predictions about college students' mental health. BPNN, a core component of many machine learning systems, is known for its ability to effectively process large amounts of complex data and identify underlying patterns. In the context of FEPS-MH, the BPNN takes the pre-processed and normalized data, which has already been refined by the DFBNN to handle uncertainties and ambiguities. It then applies its layers of interconnected neurons to analyze this data, learning from the inputs through a process of forward and backward propagation. In forward propagation, the BPNN makes predictions based on the input data, and in backward propagation, it adjusts its internal parameters to minimize the difference between its predictions and the actual data. This continuous process of prediction and adjustment allows the BPNN to refine its understanding of the complex factors that influence mental health in students. By doing so, it becomes increasingly proficient in predicting potential mental health issues, enabling timely and personalized interventions. The BPNN's ability to learn and adapt makes it an essential tool in the FEPS-MH system for providing accurate and actionable insights into student mental health.

The algorithm for integrating a BPNN within the FEPS-MH system begins by taking the output from a DFBNN as its input. This output, processed to handle uncertainties in the data, is then fed into the BPNN. The first step in the BPNN algorithm involves calculating the output of each neuron in every layer of the network. The output of a neuron is determined by the sum of the products of inputs and their corresponding weights, added to a bias, and then passed through an activation function like ReLU or tanh. These functions help to introduce non-linearity in the processing, allowing the network to handle complex patterns in the data. Once the forward pass is completed, the algorithm enters the backward propagation phase. This phase starts with the computation of errors at the output layer, comparing the network's predictions against actual data.

Algorithm 2 Backward Propagation in FEPS-MH Model

Input: Receive the output p_i from the DFBNN as the input to the BPNN
Forward Propagation:
Step 1: For each layer l in the BPNN, calculate the output of the neurons
Step 2: The output $o_{l,j} = f(\sum_k w_{l,jk}.o_{l-1,k} + b_{l,j})$
Step 3: Commonly used activation functions ReLU or tanh
Backward Propagation:
Step 4: Compute the error at the output layer, where the error e_k for the output neuron k is $e_k = (y_k - o_{l,k})$
Step 5: Propagate the error back through the network to update the weights and biases.
Step 6: The error is calculated using $\delta_{l,j} = f'(\text{net}_{l,j}) \sum_m \delta_{l+1,m}.w_{l+1,mj}$
Step 7: Update the weights and biases using gradients

$$w_{l,jk} \leftarrow w_{l,jk} + \Delta w_{l,jk}$$

$$b_{l,j} \leftarrow b_{l,j} - \eta.\delta_{l,j}$$

Prediction:
Step 8: Use the trained FEPS-MH model (including the BPNN with updated weights) to predict the mental health status of students based on new input data.
Step 9: Feed the new input data through the FEPS-MH model.
Step 10: The final output layer of the BPNN provides the predicted mental health status.
Analysis and Recommendations:
Step 11: Analyze the output to generate comprehensive insights and recommendations for interventions or further action.

The error for each output neuron is the difference between the expected result and the prediction made by the network. The next step involves backpropagating this error through the network. This backpropagation adjusts the network's weights and biases to minimize the error, effectively 'learning' from the discrepancies. The adjustments are made using gradients, calculated based on the error and the derivative of the activation function. This process iteratively adjusts the network to improve its accuracy. After the training is completed, the BPNN is ready to make predictions on new data. When new input data is received, it is fed through the trained FEPS-MH model, which includes the fine-tuned BPNN. The output layer of the BPNN provides the final prediction regarding the mental health status of the students. This output is not just a raw prediction; it's analyzed to generate comprehensive insights and actionable recommendations for interventions or further actions, providing a valuable tool for mental health professionals in understanding and addressing student mental health issues.

4. Results and Experiments.

4.1. Simulation Setup. The dataset used in the study for a psychological early warning system which is adapted from the study [6] is a comprehensive collection of various data points reflecting the mental health and behaviors of college students. It includes detailed records of students' class attendance and examination results, highlighting a general trend where consistent attendance correlates with higher academic performance. However, exceptions to this trend suggest the need for a deeper, more individualized analysis. The dataset also tracks dormitory access times, providing insights into students' daily routines, such as their sleep patterns and potential late-night activities, which can be indicators of stress or irregular lifestyle habits. Additionally, the study considers financial aspects, including students' spending habits through campus card usage and tuition fee payment status, to gauge their financial stability and related stress factors. Social media data from platforms like QQ, WeChat, and Weibo are also utilized to capture students' emotional expressions and concerns, offering a window into their mental states. The study acknowledges the different psychological challenges faced by students at various stages of their university journey, ranging from adaptation issues for freshmen to career-

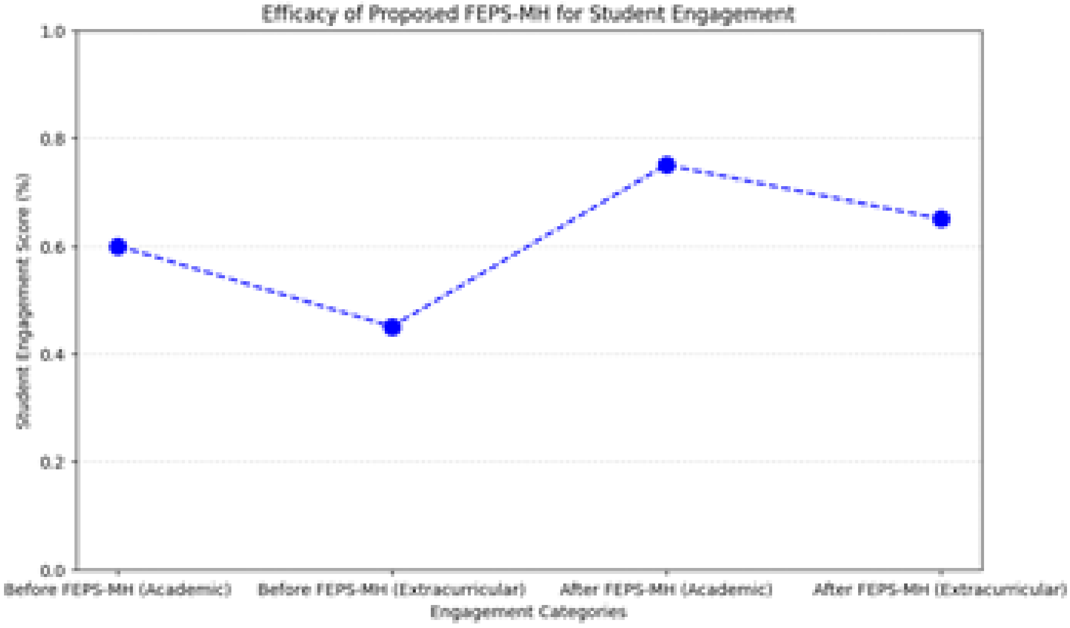

Fig. 4.1: Student Engagement

related anxieties for seniors. The result of proposed FEPS-MH is helps to accurately analyze the student's mental health, helping to identify early warning signs of distress and facilitating timely and personalized interventions. Such a multifaceted approach ensures that the mental health support provided is comprehensive and tailored to individual student needs.

4.2. Evaluation Criteria. In this section the proposed FEPS-MH is evaluated using the metrics in terms of student engagement score, wellness index and behavioral consistency score.

4.2.1. Student Engagement Score. Figure 4.1 illustrates the effectiveness of the proposed FEPS-MH system in enhancing student engagement. This evaluation categorizes FEPS-MH into two groups: before implementation and after implementation, focusing on both academic and extracurricular engagement. The figure clearly demonstrates that before the implementation of FEPS-MH, the scores in both academic and extracurricular engagement were relatively low. However, after the implementation of the proposed system, there was a significant improvement in the performance of both academic and extracurricular engagement categories. This improvement highlights the positive impact of FEPS-MH on enhancing student engagement compared to the pre-implementation phase.

4.2.2. Wellness Index. Figure 4.2 presents the efficacy of proposed regarding wellness index. Wellness index considered in key categories related to student well-being, specifically stress levels, mood patterns, and social interaction. Before the implementation of FEPS-MH, students exhibited moderate levels of stress (06), relatively lower mood patterns (05), and limited engagement in social interaction (04). These baseline scores indicated areas where students mental wellness could be enhanced. However, after the implementation of FEPS-MH, a notable transformation occurred. Stress levels significantly decreased to 0.3, indicating a reduction in students' stress and improved mental well-being. Mood patterns saw a substantial improvement, with a score of 0.7, suggesting that students experienced more positive and stable emotional states. Social interaction, a crucial aspect of overall well-being which significantly improved to a score of 0.8, indicating increased engagement and connectivity among students. Overall, the implementation of FEPS-MH resulted in a remarkable enhancement in stress management, mood stability, and social interaction among students. These improvements collectively contribute to a higher overall wellness index, reflecting the system's efficacy in promoting better mental health

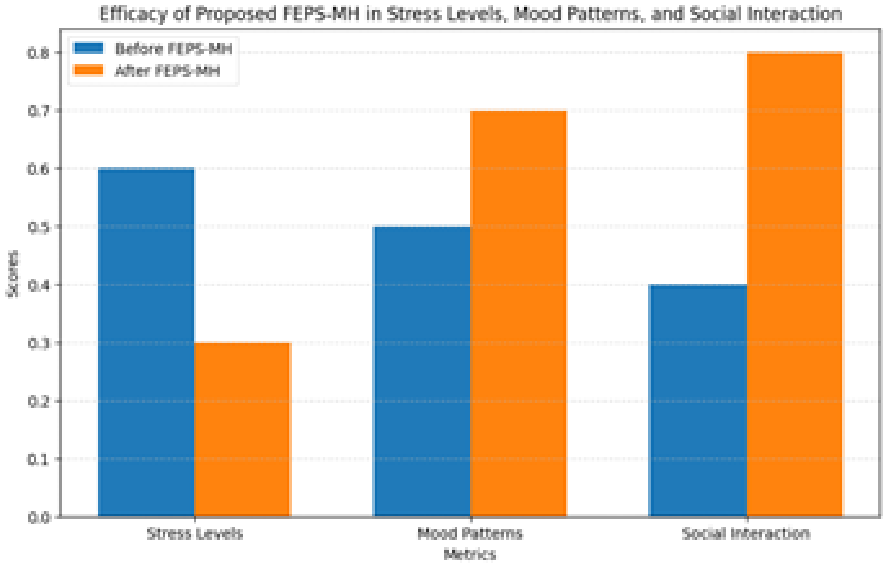

Fig. 4.2: Wellness Index

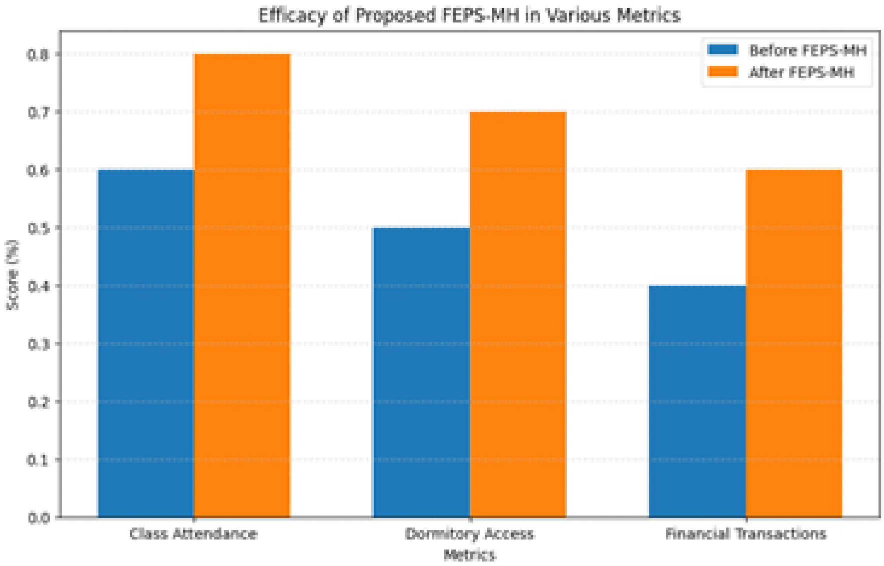

Fig. 4.3: Behavioral Consistency

and well-being in the student population.

4.2.3. Behavioral consistency. Figure 4.3 demonstrates the efficacy in terms of behavioral consistency. The efficacy of implementing FEPS-MH is clearly demonstrated through a comparison of key metrics before and after its implementation. These metrics encompass vital aspects of students daily lives and well-being, including class attendance, dormitory access, and financial transactions. Before implementing FEPS-MH, the scores for these metrics stood at 0.6, 0.5, and 0.4, respectively. However, after the implementation of FEPS-MH, remarkable improvements were observed, with scores rising to 0.8, 0.7, and 0.6 for class attendance, dormitory access, and financial transactions. These enhancements signify a positive transformation in student engagement, consistency in daily routines, and financial stability, all of which are essential components of mental health and well-being. The results clearly indicate the effectiveness of FEPS-MH in fostering better mental health and overall student wellness.

5. Conclusion. In conclusion this study introduces a novel approach called FEPS-MH which helps to analyse the mental health of the college students based on big data analytics. The proposed FEPS-MH integrates the strength of DFBNN and BPNN. By combining the strength of these effective techniques, the proposed demonstrates the efficacy in terms of the performance metrics called student engagement, wellness index and behavioral consistency in two categories called before implementing FEPS-MH and after implementing FEPS-MH. By analysing the student engagement score with the following categories such as academic and extracurricular activities. Next the wellness index under the terms of stress levels, mood patterns and social interactions. Finally, behavioral consistency based on class attendance, dormitory access and financial transactions. By analysing the above demonstrations, the results suggest that when compared with before implementation of FEPS-MH, after implementing will demonstrates the highest efficacy and efficiency in terms of overall metrics. This shows the efficacy of proposed under the mental health of the students which is highly trustable and an effective tool to improve the student wellness and acts as a crucial role to improve the mental health of the students.

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