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Enhancing Mental Health Support in Engineering Education with Machine Learning and Eye-Tracking

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ABSTRACT: Mental health concerns are increasingly prevalent among university students, particularly in engineering programs where academic demands are high. This study builds upon previous work aimed at improving mental health support for engineering students through the use of machine learning (ML) and eye-tracking technology. A framework was developed to monitor mental health by analyzing eye movements and physiological data to provide personalized support based on student behavior. In this extended study, baseline data were analyzed to explore the correlations between emotions and physiological biomarkers. Key findings indicate that emotions such as Anger and Fear are positively correlated with increased physical activity, while Sadness is associated with elevated respiratory rates. A strong positive correlation between Electrodermal Activity (EDA) and Happiness was also identified, indicating physiological markers linked to positive emotional states. Temporal patterns were observed, with heightened emotional tagging occurring more frequently in the evening. These findings deepen the understanding of how emotional states manifest through physiological changes, providing a foundation for enhancing real-time, personalized mental health interventions. The results contribute to a more comprehensive framework for supporting student well-being and academic performance within engineering education.

KEYWORDS: Mental Health, Philosophy of Engineering Education, Data Correlation, Factor Analysis, Machine Learning, Electrodermal Activity

1. Introduction

Mental health concerns have become increasingly prominent among university students, especially within engineering programs, where students are subject to intense academic demands and pressure [1, 2]. Traditionally, engineering education has focused on the development of technical knowledge and skills [3, 4], often placing limited emphasis on the physical and mental well-being of students. As a result, many students in engineering experience high levels of stress, which can negatively impact their academic performance, personal lives, and overall professional growth.

Current methods for assessing mental health, such as surveys and self-reported questionnaires, have limitations in terms of accuracy and bias. These methods may not fully capture the extent of students' mental health challenges, as some may feel reluctant to disclose personal issues due to stigma, fear of judgment, or concerns about potential academic consequences [5]. While initiatives like counseling services, awareness campaigns, and stress management workshops have been introduced to address these issues , there is a pressing need for more objective and effective methods to monitor and improve the mental health of engineering students [6].

Predictive analytics, particularly when applied through machine learning (ML) models, presents a promising solution for addressing mental health challenges. In healthcare, ML techniques have shown potential to transform mental health assessment and intervention by providing objective insights into emotional and psychological states. Building on this, the conference paper Improving Mental Health Support in Engineering Education Using Machine Learning and Eye-Tracking introduced a framework leveraging ML and eye-tracking technology to monitor student well-being. This innovative approach aimed to fill gaps in mental health monitoring by providing data-driven insights and personalized interventions.

This study introduces insights based on data from a 10-week study involving 18 participants. It includes detailed correlations between emotional states—such as Anger, Fear, Happiness, and Sadness—and physiological markers, including physical activity (actigraphy), respiratory rate, and Electrodermal Activity (EDA). Results reveal that increased actigraphy counts are associated with Anger and Fear, while Sadness correlates with elevated respiratory rates. Furthermore, a strong positive relationship between EDA and Happiness is observed. These findings offer a deeper understanding of the physiological responses to emotional states, improving the system's ability to provide real-time, personalized mental health support.

This paper is structured as follows: the next section provides background information on machine learning algorithms and mental health prediction. The methodology section outlines the strategy used for data collection and analysis. The results section presents detailed findings on the emotional and physiological correlations, followed by a discussion of the potential impact on future mental health interventions. The paper concludes by summarizing the findings and offering recommendations for future research directions.

2. Background

2.1. Machine Learning

Machine learning (ML) refers to the application of statistical and probabilistic methods to build systems that can learn and improve from experience [7, 8]. This capability makes ML a powerful tool for predicting mental health outcomes by analyzing large amounts of complex data, leading to the development of intelligent automated systems that can offer personalized insights. Several algorithms such as support vector machines (SVM), random forests, and artificial neural networks (ANNs) have proven effective in predicting future outcomes and categorizing data. In the healthcare sector, ML is widely applied in various forms, including supervised learning, unsupervised learning, and deep learning. There are also hybrid methods like semi-supervised learning, which combines elements of both supervised and unsupervised learning, as well as reinforcement learning [9].

Supervised learning (SL) is commonly used in healthcare for disease prediction, where the algorithms are trained on a dataset that is pre-labeled with known outcomes. These models are then tested on unseen data to evaluate their predictive performance. On the other hand, unsupervised learning (UL) works without labeled data and is designed to detect patterns and clusters in datasets. Techniques such as k-means clustering, hierarchical clustering, and principal component analysis (PCA) are commonly employed to identify meaningful patterns within the data. In healthcare, UL is valuable for uncovering hidden structures in medical imaging or genetic data, which can help identify subtypes of diseases and facilitate personalized treatment strategies. Additionally, UL is useful for anomaly detection and feature reduction, contributing to more accurate medical diagnoses.

2.2. Deep Learning

Deep learning (DL) [10] is a subset of ML that uses artificial neural networks with multiple layers of nodes to learn intricate representations from raw data. This approach mimics the way the human brain processes information, enabling the discovery of complex relationships within high-dimensional datasets like electronic health records (EHRs). While DL models are highly effective in finding patterns, their multi-layered structure can make it difficult to interpret the decision-making process behind their outputs. Despite this challenge, DL has shown great potential in analyzing vast amounts of healthcare data.

2.3. Reinforcement Learning

Reinforcement learning (RL) is an area of ML where intelligent agents learn to make decisions by interacting with their environment and receiving feedback in the form of rewards or penalties. RL has been successfully applied in areas like robotics [11, 12, 13], gaming [14, 15], education [16] and finance. Recently, RL has gained attention as a promising method for developing personalized mental health interventions [17, 18, 19]. Mental health disorders, being a major source of disability worldwide, often require tailored treatments. RL can create individualized interventions by adapting to patient needs over time based on continuous feedback. One key strength of RL is its ability to work with dynamic and complex data, such as EHRs and wearable device outputs. It is particularly effective in handling incomplete or noisy data, which is frequently encountered in mental health studies. However, implementing RL in mental health care poses challenges related to privacy, transparency, and the interpretability of models. Despite these obstacles, RL holds great promise for creating adaptive, patient-centered treatment plans.

3. Methodology

In recent years, continuous and real-time monitoring technologies have gained significant traction due to the potential to enhance cognitive and behavioral performance while reducing healthcare costs. With the increasing need to monitor mental health, researchers have been investigating different technologies to develop efficient monitoring systems [20, 21]. Among these, eye-tracking technology has shown promise for its ability to track mental health indicators [22]. By applying computational methods to the extensive physiological data collected through eye-tracking, intelligent systems like IntelEye [23] can extract meaningful patterns by analyzing eye movement data such as pupil dilation, fixation points, and blink rates. IntelEye specifically uses the K Nearest Neighbor (KNN) algorithm to classify eye movement patterns into stress levels. The system processes this data by first segmenting the video-watching experience into different scenes, identifying the moments when stress indicators (e.g., dilation of pupils, rapid blinking) are detected. These stress-related signals are then correlated with the specific scenes, allowing IntelEye to detect when stress occurs and to identify the exact content that triggered it. This dual capability, detecting stress and linking it to specific triggers, makes IntelEye a powerful tool for monitoring mental health.

3.1. Study Selection

This section discusses three typical studies conducted over the past decade that explore the advancements in machine learning algorithms for mental health assessment. The focus is on research published from 2015 to 2023, although the review is not systematic and does not cover every possible study meeting the broader criteria. Relevant research was identified using PubMed, ScienceDirect, IEEE, and Google Scholar, with a focus on clinical studies applying machine learning to mental health. Studies involving untested or theoretical ML applications were excluded. The selected studies represent key original research efforts, as outlined in Table 1.

3.2. Review of Selected Studies

Researchers explored a method for automatically assessing depression severity by analyzing facial landmarks

Table 1: Typical ML and Mental Health Studies

Authors	Sample Size	Method	Performance
Anis Kacem et al. [24]	49	SL	84%
Subhagata Chattopadhyay et al. [25]	302	DL	95.5%
Fabian Wahle et al. [26]	28	SL	62%

and 3D head motion using barycentric coordinates and Lie-algebra rotation matrices [24]. Key features were extracted, processed, and encoded using Gaussian Mixture Models (GMM) and Fisher vector encoding. The study, which involved adults with chronic depression, achieved classification accuracy comparable to state-of-the-art deep learning models, while providing interpretable clinical insights.

Building on these computational approaches, a mathematical model was developed to reflect how psychiatrists evaluate depression symptoms [25]. Fourteen symptoms of adult depression were considered, in line with the Diagnostic and Statistical Manual (DSM-IV-TR). Principal Component Analysis (PCA) was used to reduce the number of symptoms to seven key features, which were then input into a hybrid system that combined Mamdani's fuzzy logic controller with a feed-forward multilayer neural network (FFMNN). The system was further refined using a backpropagation neural network (BPNN). This model, validated on 302 real-world depression cases and 50 controls, achieved an average diagnostic accuracy of 95.50

As technological interventions in mental health continue to evolve, [26] investigated the potential of smartphone-based interventions to support individuals with depressive symptoms by collecting data through the Mobile Sensing and Support (MOSS) app. The app gathered context-sensitive sensor data from participants and provided real-time, personalized interventions based on cognitive behavior therapy. Over an eight-week period, participants regularly completed self-reported depression surveys (PHQ-9). For those with clinical depression and high adherence, significant reductions in PHQ-9 scores were observed, indicating the effectiveness of the system in reducing depressive symptoms.

3.3. Results and Future Directions

After reviewing various works in the field, it is clear that eye gaze measures have been employed by multiple models to detect emotions, stress, cognitive load, mental fatigue, and other mental states [27, 28, 29]. This study builds upon these methodologies by developing a system to collect and analyze students' eye movements and physiological responses during remote learning activities, such as attending online lectures. Using machine learning (ML) algorithms, the data will be analyzed to identify patterns and anomalies that indicate changes in mental health, such as stress, anxiety, depression, or distraction. The model will be trained using a combination of eye-tracking data and mental health survey results. The system will then provide real-time feedback to both students and instructors, offering personalized support strategies, such as relaxation exercises or mindfulness training.

The system will be developed and tested in two phases. In the first phase, participants will watch videos designed to elicit both positive and negative emotions while their eye movements are tracked. The gathered data will then be used to train a reinforcement learning (RL) model, which will learn to identify emotional states based on eye movements. In the second phase, the trained model will be integrated into an online platform that provides personalized mental health interventions based on the detected emotional states. This could include relaxation exercises, motivational messages, or other interventions aimed at improving student well-being.

To evaluate the system's performance, participants will complete mental health assessment questionnaires before and after using the platform, focusing on anxiety, depression, and stress. The accuracy, sensitivity, and specificity of the RL model in identifying emotional states will be assessed, along with changes in the participants' mental health scores. The study's overall effectiveness will be evaluated through a series of experiments and surveys, measuring changes in self-reported mental health and academic performance before and after the intervention. The results are expected to improve mental health support for engineering students by offering personalized, real-time interventions tailored to individual needs.

The bar chart in figure 1 summarizes the count of different emotions across all participants, providing an overview of the most to least frequently recorded emotions. Anger: Most frequently observed with 24 instances. Fear: Notably present, accounted for 17 instances. Happiness: Identified 14 times. Surprise and Disgust: Both emotions were less frequently detected, with 6 and 7 instances each. Sadness: Least frequent, with only 3 occurrences. These insights are based on the emotion label mapping which categorizes the emotions as Anger (0), Disgust (1), Fear (2), Happy (3), Sad (4), and Surprise (5).

Figure 2 Heatmap depicting the correlation between Emotion Day Mean and Overall Mean for various physiological markers (e.g., actigraphy counts, EDA, MET). Warmer colors indicate positive correlations, while cooler colors reflect negative correlations.

3.3.1. Key Findings

The analysis of the relationship between emotional states and physiological markers was conducted by comparing the differences between the emotion day mean and the overall mean across various biometric measures. The results are visualized in the heatmap (Fig.2.), which illustrates the correlations between emotional states (Anger, Fear, Happiness, Disgust, Surprise, and Sadness) and physiological variables, including actigraphy counts, electrodermal activity (EDA), respiratory rate, and other measures.

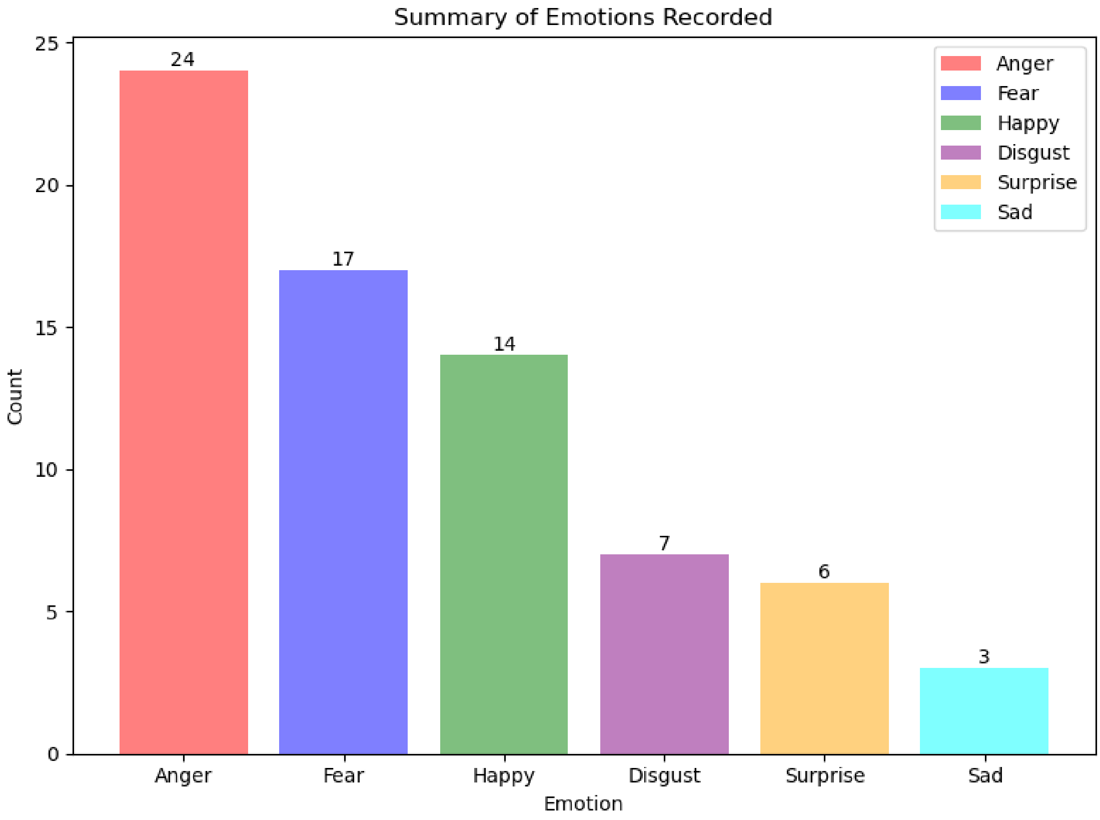

Figure 1: Summary of Emotions Recorded

1. **Electrodermal Activity (EDA)**: A strong positive correlation was observed between EDA and Anger ($r = 0.30$, $p = 0.013$), suggesting increased EDA levels during emotional episodes characterized by anger. Conversely, a significant negative correlation was found between EDA and Fear ($r = -0.26$, $p = 0.031$), indicating lower EDA levels during fearful states.

2. **Metabolic Equivalent (MET)**: Sadness showed a strong positive correlation with MET ($r = 0.32$, $p = 0.008$), suggesting higher energy expenditure on days when participants reported feeling sad.

3. **Activity Counts**: Activity counts demonstrated moderate positive correlations with Anger ($r = 0.24$, $p = 0.046$) and Surprise ($r = 0.24$, $p = 0.051$), implying increased physical activity during moments of these emotions.

4. **Respiratory Rate**: Sadness also correlated positively with respiratory rate ($r = 0.30$, $p = 0.015$), indicating that respiratory rates tended to be higher on days marked by sadness.

5. **Actigraphy Counts**: While most correlations involving actigraphy counts were non-significant, moderate correlations were observed for Sadness across different actigraphy measures, particularly on the Z-axis ($r = 0.25$, $p = 0.038$) and the vector magnitude ($r = 0.24$, $p = 0.051$), suggesting that emotional states may influence overall body movement.

Overall, the heatmap indicates that physiological changes are indeed associated with distinct emotional states. Anger and Sadness, in particular, exhibit stronger relationships with biometric markers such as EDA, MET, and respiratory rate. These findings demonstrate the potential of using physiological signals to track and identify emotional states in real-time, thus informing targeted mental health interventions for students.

3.4. Limitations of ML and Mental Health

While ML and eye-tracking technologies show significant potential in monitoring mental health, there are some notable limitations. One challenge is the lack of clinical validation, which could hinder its readiness for real-world decision-making in clinical settings. The quality and size of the dataset are also critical factors affecting the performance of ML algorithms. Small sample sizes could lead to overfitting, and if models are only tested within a specific dataset, their generalizability may be limited. Furthermore, ML models often rely heavily on specific input features, meaning their predictions may only be accurate under certain conditions. Studies using binary classifiers also tend to oversimplify conditions and overlook their severity. Additionally, imbalanced datasets often lead to models that predict the majority class while missing rare events.

Future research must focus on recruiting larger, high-quality, and diverse datasets to address the challenges of participant retention and engagement. In this study, although initially recruited 50 participants, the complexity of maintaining engagement throughout the study resulted in 18 active participants by the end. While larger sample sizes might enhance the generalizability of findings, human factors, particularly in mental health studies, introduce complexities that make such generalizations difficult. The current findings should be viewed as a starting point, and

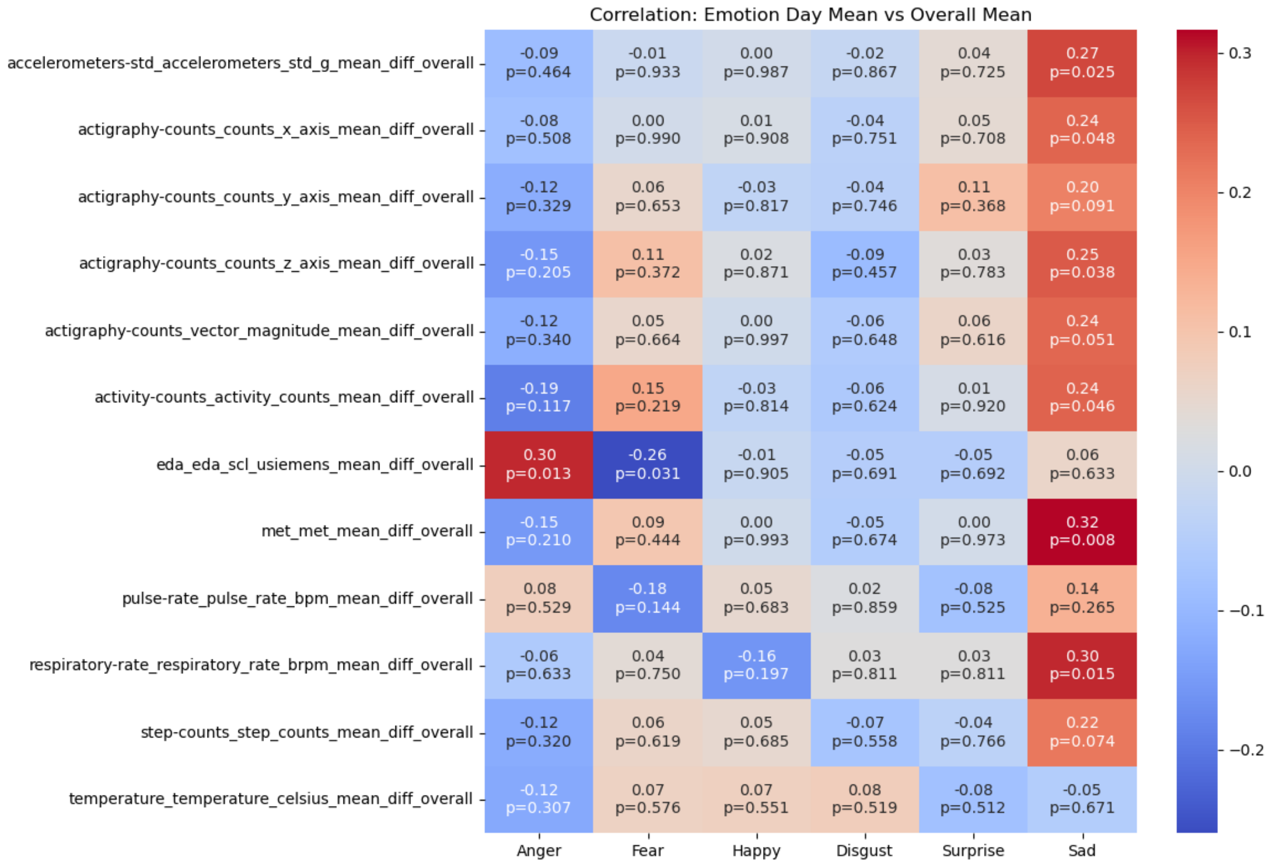

Figure 2: Emotion Day Mean vs. Overall Mean

future research should explore more diverse and larger populations to validate and extend these insights.

Collaboration among institutions for robust data sharing is essential to achieving larger, more representative datasets. Deep learning (DL) methods will become increasingly important in handling complex data, but ensuring that models remain interpretable is crucial. Transfer learning may also be beneficial in improving model performance, especially when working with diverse datasets. Researchers must consider the heterogeneity in input data and develop machine learning models capable of continuous learning to prevent "catastrophic forgetting." Interdisciplinary collaborations between data scientists and clinicians will likely yield the best results for mental health applications, helping to ensure the scalability and reliability of the findings.

3.5. Future Research Directions

Further research should explore a larger sample size and a longer study duration to enhance the generalizability of findings. Larger datasets will allow for more rigorous statistical analysis and reveal insights into the long-term impact of interventions. Personalized feedback and adaptive interventions based on individual stress levels would also improve the system's effectiveness. Expanding the range of physiological measures to include heart rate variability and electrodermal activity could provide a more comprehensive mental health assessment. Finally, researchers should investigate the scalability of the system for broader educational environments, identifying any practical challenges that may arise in larger-scale implementations.

Machine learning is increasingly becoming a cornerstone of digital medicine, with promising applications for mental health. However, to fully unlock its potential, collaboration across disciplines is critical. Clinicians, scientists, and data experts must work together to ensure that ML models are valid, reliable, and free from bias. Moreover, ethical considerations must be addressed, especially when deploying ML technologies in mental health care.

3.6. Recommendations

In conclusion, ML and eye-tracking technologies hold great promise in enhancing mental health support in engineering education. By delivering real-time feedback and personalized interventions, these technologies can help students better manage stress, anxiety, and other emotional challenges, leading to improved academic outcomes and overall well-being. However, further research is necessary to broaden the application of these techniques to other fields and student populations. Ethical concerns, particularly around the use of sensitive personal data in ML applications, must also be addressed. By fostering collaboration between engineers, data scientists, and mental health professionals, the potential benefits of ML in improving student mental health can be fully realized.

Conflict of Interest The authors declare no conflict of interest.

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