Physiological Impact of Test Anxiety on Student's Academic Performance Using Convolution Neural Network

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ABSTRACT
Using a Convolutional Neural Network (CNN), this research studies the connection between physiological reactions and students' performance when taking examinations. They used a full PhysioNet dataset that included things like accelerometer data, skin surface temperatures, interbeat interval, heart rate, blood volume blood pressure, and electrodermal activity (EDA). Ten students had their data gathered from three separate assessments: the first midterm, the second midterm, and the final. By analyzing these physiological signals, aimed to identify patterns and correlations that indicate how students respond to exam stress and cognitive load.Our CNN model achieved an accuracy of over 98%, surpassing the performance reported in similar studies [21][24], which utilized deep neural networks for emotional intelligence and educational data mining, respectively, achieving slightly lower accuracy. This advancement highlights the novelty of our approach to accurately predicting academic performance based on physiological data.The findings reveal that students experience heightened physiological responses, such as increased heart rate and skin surface temperature, during exams, indicating elevated stress levels. Notably, there is a significant correlation between these responses and students' grades, suggesting stress levels can negatively impact academic performance.This research advances our understanding of the physiological underpinnings of test anxiety and its effects on academic outcomes. By leveraging physiological metrics, this study offers the potential for developing predictive models and interventions to support student well-being and academic success. The insights gained could lead to more comprehensive assessment practices in education, ultimately aiding in the creation of supportive learning environments that prioritize students' mental and physical health.

Keywords: Stress, physiology, performance, response, heart rate, temperature, cognitive, academic, grades, impact, correlations, convolution, recurrence

1. INTRODUCTION

This research investigates the innovative use of physiological data to improve our understanding of student performance. Traditional educational assessments typically focus on cognitive outcomes, often overlooking the significant impact of physiological factors like stress and anxiety. Integrating physiological metrics into assessments can develop a more holistic view of student performance that includes both mental and physical health [5][6].Utilizing physiological data offers substantial benefits. Detecting high stress or cognitive overload early can lead to timely interventions. Educators can then provide personalized support and resources tailored to individual needs, reducing stress and improving academic outcomes. This approach addresses immediate academic challenges and contributes to long-term student well-being. Prolonged stress may negatively impact mental as well as physical wellness, which can hinder academic performance and general development, thus it's crucial to identify and intervene early on [16].

Moreover, incorporating physiological metrics into traditional assessments can deepen our understanding of learning's multifaceted nature. It moves beyond conventional success metrics, offering insights into how emotional and physical states impact academic performance. This comprehensive perspective allows educators to create more effective teaching strategies and interventions supporting all student development aspects. Understanding the interplay between physiological and cognitive factors can lead to more adaptive and personalized educational practices, enhancing student engagement and motivation [6][7].

The study's findings highlight the transformative potential of physiological data in education. Encouraging collaboration between researchers and educators can create learning environments that prioritize academic success and student well-being. Such environments are more likely to support sustained academic achievement and foster a positive, inclusive educational experience for all students. Creating supportive environments that acknowledge the importance of mental and physical health is essential for promoting long-term academic success and overall well-being.

Integrating physiological data into educational assessments represents a forward-thinking approach that aligns with students' evolving needs. This method promises to enhance educational practices, making them more responsive and supportive, ultimately leading to better academic and personal outcomes for students [12]. There is a rising awareness, as educational institutions develop, of the need to handle the myriad of elements that impact students' learning and performance.

Incorporating physiological metrics provides a valuable tool for achieving this goal.

Beyond the local educational setting, this study has far-reaching ramifications. This method may aid larger initiatives to improve health and wellness in many contexts by increasing knowledge of the connection between physiological conditions and cognitive function. For instance, workplace training programs and performance assessments could benefit from incorporating similar metrics, leading to improved outcomes and enhanced well-being for employees. The integration of physiological data into educational assessments offers a promising avenue for improving student outcomes. This method may aid teachers in creating more effective and encouraging lesson plans by expanding their knowledge of the elements that impact student learning and performance.

The potential benefits of this research are far-reaching, highlighting the importance of innovative approaches to education that prioritize the well-being of students. Asits beencontinues to explore the potential of physiological metrics, it is essential to foster collaboration between researchers, educators, and policymakers to ensure that these insights are effectively integrated into educational practices. This collaborative effort will be crucial in creating learning environments that support the holistic development of students, promoting both academic success and overall well-being.

2. LITERATURE SURVEY

Emotional intelligence and its impact on primary school students' performance in southern Ethiopia is the focus of this research. The researchers collected data on students' emotional intelligence and correlated it with their academic performance, finding a significant relationship between the two. Academic success seems to be more common among kids who score higher on measures of emotional intelligence. The study emphasizes the importance of nurturing emotional skills in children to enhance their educational outcomes. By using standardized assessments and statistical analysis, the authors provide robust evidence supporting the integration of emotional intelligence training in education. curricula. [1]The effect of anxiety about cognitive tests on students' ability to do well in school is the focus of this research. The authors define cognitive test anxiety as the worry and fear experienced during test situations, which can impair students' ability to perform well. Through empirical research, they found that high levels of test anxiety are negatively correlated with academic performance. The study highlights the importance of addressing test anxiety through interventions, such as relaxation techniques and cognitive-behavioral strategies, to help students manage stress and improve their academic outcomes. The findings underscore the need for educators and psychologists to consider psychological factors when assessing and supporting student performance. [2]

This research investigates the role of stress as a barrier to academic success among college students. The authors collected data through surveys and physiological measurements, finding that stress significantly impedes academic performance. They discuss various sources of stress, including academic workload, personal issues, and financial concerns. The study suggests that stress management programs and resources should be provided to students to help them cope with these pressures. By understanding the multifaceted nature of stress and its impact on learning, the authors advocate for a holistic approach to student support services that address both academic and emotional well-being. [3]

This longitudinal study examines factors influencing academic achievement in higher education over time. The authors tracked students' performance and various correlates, such as motivation, learning strategies, and socio-economic background. They found that consistent study habits, intrinsic motivation, and supportive social environments were key predictors of academic success. The research emphasizes the importance of developing a supportive educational environment that fosters positive learning behaviors and addresses barriers to achievement. By providing a comprehensive analysis of the factors affecting academic performance, the study offers valuable insights for educators and policymakers aiming to enhance student outcomes. [4]

This paper explores the complex interplay between sleep, mood, and academic performance. The author reviews evidence suggesting that poor sleep quality and negative moods can significantly impair students' cognitive functions, leading to lower academic achievement. The study highlights the need for educational institutions to promote healthy sleep habits and provide mental health support. By understanding the physiological and psychological factors that influence learning, educators can better support students in achieving their full potential. This research explores the impact of test anxiety on the predictive accuracy of cognitive ability assessments in academic contexts. The results highlight the need for a holistic strategy to education that prioritises students' well-being alongside their academic performance.

The authors found that students with high test anxiety often underperform on cognitive tests, which may not accurately reflect their true abilities. This discrepancy can lead to unfair academic assessments and misplacement in educational tracks. The study suggests that educators and policymakers should consider alternative assessment methods that account for anxiety's impact. By addressing test anxiety, institutions can ensure that cognitive ability tests more accurately measure students' potential and provide a fairer basis for academic evaluations. [6]

In this study, we'll look at how our causal views impact our analytical processes and the conclusions we get about the correlation between IQ and educational attainment.

The authors argue that people's beliefs about the causality between intelligence and educational outcomes can shape their analytical approaches and interpretations of data. They suggest that intelligence and education are interrelated, with each influencing the other in complex ways. The study emphasizes the importance of considering multiple perspectives and methodological approaches when researching intelligence and educational achievement. By highlighting the nuanced nature of this relationship, the authors call for a more comprehensive understanding of how intelligence and education interact. [7]

Adolescents at very high risk of psychosis and healthy controls are compared in this research to assess their HRQoL. The researchers assessed various aspects of HRQoL, including physical health, emotional well-being, and social functioning. It was discovered that juxtaposed to their healthy counterparts, adolescents at greater risk for psychosis showed worse HRQoL in numerous dimensions. The findings highlight the need for early intervention and support for at-risk youth to improve their quality of life. This research highlights the need for comprehensive mental health treatment and sheds light on the difficulties experienced by teenagers at high risk of psychosis. [8]

This research explores the criterion validity of basic cognitive process tasks in predicting academic achievement. The authors analyzed the relationship between performance on tasks measuring cognitive processes, such as memory and attention, and academic success. They found that these cognitive tasks are valid predictors of academic performance, suggesting that fundamental cognitive abilities play a crucial role in learning. The study emphasizes the importance of assessing basic cognitive skills in educational settings to identify students' strengths and weaknesses. By understanding the cognitive foundations of academic achievement, educators can develop targeted interventions to support student learning. [9]This research delves into the specific roles played by IQ and processing speed in the prediction of academic success. The authors conducted a study to determine whether these two factors independently influence academic performance or if one mediates the effect of the other. They found that both processing speed and intelligence significantly predict academic success, but their contributions are unique and not merely overlapping. The study highlights the importance of considering multiple cognitive factors when assessing students' potential. The authors suggest that educators should provide support that targets both cognitive processing abilities and general intelligence to enhance students' academic outcomes. [10]

This cross-sectional study investigates the roles of personality and intelligence in academic achievement from elementary to secondary school. The authors found that both personality traits, such as conscientiousness, and intelligence significantly influence students' academic success. They argue that personality traits can affect motivation, study habits, and interactions with teachers and peers, all of which contribute to academic performance. Research like this highlights the need for an all-encompassing strategy for teaching that takes into account students' cognitive and non-cognitive abilities. In order to create a welcoming classroom for all kids, teachers must first have a firm grasp of how IQ and character traits interact with one another. the eleventh

In this research, we look at how IQ relates to academic success. Intelligence seems to be a powerful predictor of academic achievement, as the scientists discovered a robust association between IQ test

results and academic performance. They do, however, point out that things like family history and the quality of one's education are major environmental variables that impact academic success.
The study highlights the complex interplay between innate cognitive abilities and external influences in determining academic achievement. The authors advocate for a comprehensive approach to education that addresses both individual differences in intelligence and the broader social and environmental context. [12]
Such studies demonstrate the need of a holistic approach to education that considers both students' cognitive as well as non-cognitive talents. Teachers need a deep understanding of the interplay between intelligence and character attributes before they can provide an inclusive classroom environment for all students. the twelfth
We examine the correlation between intelligence and academic achievement in this study. Because of the strong correlation between IQ scores and academic success, intelligence appears to be a potent predictor of academic accomplishment. But they do note that there are significant environmental factors that affect academic achievement, such as one's family background and the extent of their schooling. However, they also acknowledge the role of non-cognitive factors, such as motivation and study habits, in influencing academic outcomes. The study suggests that while cognitive ability is an important factor, a holistic approach that considers a range of factors is necessary for understanding and supporting student achievement. The authors emphasize the need for comprehensive assessments that capture the full spectrum of student abilities. [13]
The correlation between intelligence and performance in the classroom is investigated in this cross-sectional research that spans the elementary, middle, and high school years. Throughout their educational careers, the authors discovered that cognitive talents, including logic and solving issues skills, consistently predict academic performance for pupils.
The study highlights the importance of developing these cognitive skills early on, as they provide a foundation for future learning. The authors suggest that educators should focus on nurturing cognitive abilities alongside subject-specific knowledge to support long-term academic achievement. By understanding the role of cognitive abilities in learning, schools can better prepare students for academic challenges. [14]
This research explores the connections between students' evaluations of teaching, their approaches to learning, and their academic achievement. The author found that students who perceived teaching as supportive and engaging were more likely to adopt deep learning approaches, which in turn led to better academic performance. The study emphasizes the importance of high-quality teaching that fosters a positive learning environment and encourages students to engage deeply with the material. The findings suggest that educators should focus on creating supportive and stimulating classrooms to enhance student's learning experiences and academic outcomes. [15]
This study proposes a deep learning-based scheme using Convolutional Neural Networks (CNN) for monitoring college students' mental health. The authors collected data on various physiological and behavioral indicators, such as facial expressions and speech patterns, to detect signs of mental distress. The CNN model demonstrated high accuracy in identifying students experiencing stress or anxiety, highlighting its potential for real-time mental health monitoring. The study suggests that such technology could be integrated into campus support systems to provide timely interventions for students. The authors emphasize the importance of leveraging advanced technologies to support student well-being and academic success. [16]
This paper introduces a deep learning framework for predicting team-based academic performance. The authors used a combination of student interaction data, such as communication patterns and collaborative behaviors, to predict group project outcomes. The deep learning model accurately forecasted team performance, suggesting that it could be a valuable tool for educators to identify teams that may need additional support. The study emphasizes the potential of machine learning technologies to enhance the understanding of group dynamics in educational settings. By leveraging these tools, educators can better support students in collaborative learning environments. [17]
This paper explores the concept of authentic leadership and its impact on employee work outcomes, including job satisfaction, engagement, and performance. The authors found that authentic leaders, who are transparent, ethical, and genuine, positively influence their employees' attitudes and behaviors. According to the research, leaders who are genuine and act in accordance with their principles create a more harmonious and effective workplace.
The authors emphasize the need for organizations to cultivate authentic leadership to enhance employee well-being and organizational success. [18]
This study presents a deep learning-based approach for detecting mental disorders using social media data. The authors developed a model that analyzes users' posts and interactions on social media

platforms to identify signs of mental distress. The deep learning algorithm demonstrated high accuracy in detecting conditions such as depression and anxiety. The study highlights the potential of social media data as a valuable source of information for mental health monitoring. The authors suggest that such technologies could be used to provide timely interventions and support for individuals experiencing mental health issues. [19]

In this research, we look at how online learning platform data may be used to train deep learning models to forecast students' success.

The authors developed a model that analyzes students' interactions with online courses, such as clickstream data and forum posts, to predict their final grades. The deep learning model demonstrated high accuracy, indicating its potential as a tool for early identification of students at risk of underperforming. The study emphasizes the importance of utilizing advanced technologies in education to support personalized learning and improve academic outcomes. The authors advocate for the integration of such models into online learning systems to enhance student success. [20]

The impact of leisure time management on college students' performance in the classroom is the focus of this research.

The authors found that students who effectively manage their free time tend to achieve higher academic success. They suggest that proper time management skills help students balance their academic workload with leisure activities, reducing stress and improving overall well-being. The study highlights the importance of teaching time management skills as part of university curricula to support student's academic and personal development. The authors argue that by fostering these skills, educational institutions can help students achieve a healthier and more productive lifestyle. [21]This study explores the relationship between study strategies, motivational factors, and academic achievement among university students. The authors identified that students who employed deep learning strategies and had intrinsic motivation were more likely to achieve higher academic success. They argue that these students not only aim to understand the material but also engage with it meaningfully, leading to better retention and comprehension. The study emphasizes the need for educators to encourage deep learning approaches and foster intrinsic motivation in students. By creating a supportive learning environment, educators can help students develop effective study habits and a genuine interest in their subjects. [22]

Academic achievement as it relates to self-regulated learning is the focus of this study. The authors state that self-regulated learning is when students are able to take charge of their own learning by doing things like establishing objectives, keeping track of their progress, and making necessary adjustments to their approach. Students' academic performance was positively correlated with their level of self-regulation, according to the research. The authors argue that one effective strategy for raising academic achievement is to provide students with tools for self-regulation. To help students take charge of their own education and achieve academic success, they stress the need of encouraging a feeling of responsibility and independence in the classroom. [23] . The purpose of this research is to examine how students' academic performance, study habits, and accomplishment objectives are related. The authors found that students with mastery-oriented goals, who focus on learning and understanding the material, are more likely to use deep learning strategies and achieve higher academic performance. In contrast, students with performance-oriented goals, who are more concerned with outperforming others, tend to use surface learning strategies and achieve lower academic success. The study emphasizes the importance of promoting mastery-oriented goals in education, as these goals encourage a more meaningful engagement with the material and lead to better learning outcomes. [24] The effects of self-efficacy and perceptions about the value of tasks on academic accomplishment are the primary foci of this study. The author discovered that students are more inclined to participate in learning experiences and attain better performance if they have faith in their own abilities (self-efficacy) and see the value in the work they are doing. Findings from the research point to the importance of teachers working to raise their students' perceptions of their own abilities and the worth of the tasks they are given. Educators may aid their students in cultivating a growth mindset and accomplishing academic objectives by establishing a nurturing and inspiring classroom climate. [25].

The effects of self-regulated learning on academic performance are summarised in this paper. In order to succeed academically, the authors stress the need of students being able to plan ahead, track their progress, and modify their approach as needed. They contend that students who are able to control their own learning processes have a better chance of succeeding academically. Educators may find helpful advice on how to guide their students towards self-regulation in this book, which covers topics such as goal-setting, self-monitoring, and reflective practice. Improving academic performance and the ability to learn throughout life are two benefits that might result from encouraging self-regulated learning, which the authors stress. [26]

Academic success is predicted by this study's focus on the connection between intrinsic motivation as well as self-regulated learning practices. The authors discovered that students who are intrinsically driven to study and who use self-regulated learning techniques, such creating learning objectives and tracking their progress, are more likely to succeed academically. Both intrinsic and extrinsic variables have a role in academic success, according to the research. The authors suggest that educators should focus on promoting motivation and teaching self-regulation strategies to enhance student's learning experiences and outcomes. By addressing both aspects, teachers can help students become more effective and independent learners. [27]

Academic success and the importance of self-efficacy are the foci of this study. The authors discovered that children with greater levels of self-efficacy are far more inclined to establish ambitious objectives, keep going when things become tough, and ultimately do better in school. Academic performance depends on the enthusiasm of learners, effort, and resilience, all of which are impacted by their self-efficacy, according to the research. The authors recommend that educators focus on building students' self-efficacy through positive feedback, encouragement, and opportunities for success. By fostering a supportive and confidence-building environment, teachers can help students develop a strong belief in their abilities and reach their academic potential. [28]

Examining the function of beliefs about self-efficacy in educational contexts is the purpose of this article. Students' motivation, learning techniques, and academic performance are impacted by their beliefs in their capacity to do tasks effectively, which the author calls self-efficacy. Since it influences their desire to participate in difficult activities and persevere through challenges, self-efficacy is a critical predictor of students' academic achievement, as the review emphasises. In order to help students believe in their own abilities as learners, the author stresses that teachers should provide constructive criticism, set a good example, and cultivate an encouraging classroom climate. Teachers may boost their pupils' self-esteem and performance in the classroom by doing this. [29]

This study investigates the impact of self-concept on academic achievement. The authors found that students with a positive self-concept, who perceive themselves as capable, are more likely to achieve higher academic performance. The study suggests that self-concept influences students' motivation, effort, and persistence in learning tasks. The authors recommend that educators focus on enhancing students' self-concept by providing positive reinforcement, encouraging self-reflection, and creating a supportive classroom environment. Instructors may improve their students' performance in the classroom by encouraging healthy self-concept development, which in turn boosts students' confidence and competence. [30]

This paper explores the relationship between intrinsic and extrinsic motivation in educational settings. The author compares and contrasts external motivation, which is prompted by outside forces like incentives or pressures, with intrinsic motivation, which is prompted by internal feelings of interest and satisfaction in the work at hand. The former leads to more involvement and higher academic success.

The study suggests that educators should focus on promoting intrinsic motivation by making learning activities interesting, relevant, and challenging. The author stresses the need of creating a nurturing classroom atmosphere that encourages children's innate curiosity and enthusiasm for learning. By prioritizing intrinsic motivation, educators can encourage students to become more self-directed and lifelong learners. [31]

3. METHODOLOGY

The dataset obtained from Physio Net, a prestigious repository for global physiological data curated by researchers, encompasses various signals such as Blood Volume Pulses (BVP), Electrodermal Activites (EDA), Heart Rates (HR), temperatures (TEMP), Inter-Beat Interval (IBI), and accelerometer (ACC). Among these, BVP, reflecting alterations in blood volume, has emerged as the predominant signal, underscoring a pronounced focus on cardiovascular health investigations. In addition, ACC, which gauges movement, constitutes a substantial portion of the dataset. Conversely, IBI, which delineates intervals between heartbeats, appears relatively sparse, indicating a lesser emphasis on heart rate analysis. This dataset likely captures the physiological responses of students during activities or exams, thus presenting invaluable avenues for further inquiry.

Table 1: Distribution of physiological signals

Class	Number of Datasets	Percentage
BVP	2,337,363	45.61%
EDA	182844	3.57%
HR	45689	0.89%
TEMP	182846	3.57%

IBI	3761	0.07%
ACC	1462770	28.55%

Table 1 illustrates the distribution of various types of physiological signals across the datasets. The Blood Volume Pulses (BVP) constituted the largest share at 45.61%, followed by ACC (accelerometer) at 28.55%. Conversely, the Inter-Beat Interval (IBI) represented the smallest proportion, accounting for only 0.07% of the datasets, indicating a varied emphasis on physiological monitoring and research.

i.Data Collection and Preprocessing:
The initial phase commences by loading essential libraries and mounting Google Drive to access the dataset seamlessly. This step ensured convenient access to the data stored in the Google Drive environment.Subsequently, the code initializes empty data frames for each parameter including temperatures (TEMP), heart rates (HR), accelerations (ACC), and electrodermal activites (EDA). It then iterates over each student and their corresponding exams to parse CSV files containing sensor data.

Table 2: Summary Statistics of Physiological Parameters

Statistic	Temp	HR	X-axis	Y-axis	Z-axis	EDA
Count	33000	33000	33000	33000	33000	33000
Mean	26.66	106.01	-21.83	4.52	10.13	0.185
Std Dev	3.87	22.8	30.4	34.17	38.96	0.328
Min	16.25	57	-128	-128	-128	0
25%	23.15	88.17	-44	-8	-12	0.024
50%	27.75	106.08	-26	1	10	0.145
75%	29.83	118.87	-1	14	50	0.197
Max	32.73	194.47	108	127	127	2.784

Table 2 provides an overview of the physiological data collected during the study, detailing various metrics including temperature (Temp), heart rate (HR), and accelerometer readings across the X, Y, and Z axes, as well as electrodermal activity (EDA). The dataset consists of 33,000 measurements for each parameter. The table includes several statistical measures: the mean (average value), standard deviation (which shows the extent of variability), minimum and maximum values (defining the range of data), and percentile values (25th, median, and 75th percentiles) that illustrate the distribution and central tendencies within the data. These statistics offer valuable insights into the physiological responses recorded during the exams, helping to understand the variability and overall patterns in the data. This foundational analysis is essential for guiding subsequent data processing and interpretation, ultimately aiding in the assessment of how physiological factors influence academic performance.
During this iteration, the data underwent down sampling to ensure uniformity in the sampling rates across the different sensors. This process reduces the number of data points while preserving the fundamental characteristics of signals. Additionally, a fixed number of records was extracted for each parameter to establish consistent datasets across various examinations and students. An 'Exam Type' column is incorporated to designate the type of exam (e.g., Midterm 1, Midterm 2, Final).
Following the data extraction, the code consolidates the data frames for each parameter to construct a comprehensive data frame for each student. This integrated data frame encompasses sensor data from all exams undertaken by students, facilitating a holistic analysis.
Finally, each student's data frame was stored in a dictionary data structure to enable efficient retrieval and further analysis. This organizational strategy streamlines data management and facilitates straightforward access to individual student data during the subsequent analytical stages.

ii. Model Architecture and Transfer Learning
The implementation is initiated by incorporating a pre-trained deep learning models, such as a convolutional neural networks (CNN) or recurrent neural networks (RNN) as illustrated in figure 1. These models have undergone extensive training on large datasets for tasks akin to the present one. Leveraging a pre-trained model establishes the groundwork for the transfer learning process, harnessing insights acquired from prior training endeavors [29].

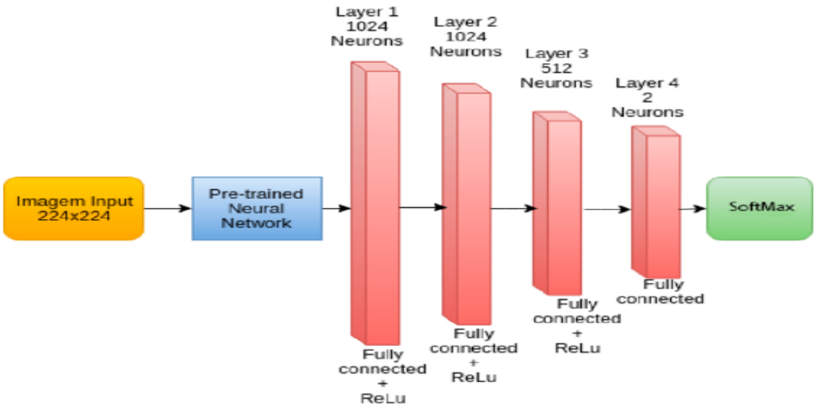


Figure 1. Model Architecture of Transfer Learning

Subsequently, the process involves adapting or substituting the final few layers of the pre-trained model to tailor it to the specific demands of the current classification task. This adaptation may encompass the addition of new fully connected layers, adjustment of the number of output units to align with the classes in the current task, and refinement of the weights of the existing layers to better align with the characteristics of the new dataset.[30]

iii. Classification and Hyperparameter Tuning

The implementation requires dividing the dataset into three separate subsets: training, validation, as well as testing. This is done before moving on to the classification as well as hyperparameter tuning stages. The training set is used just for training the model, whereas the set for validation is crucial for tuning the hyperparameters and tracking the model's progress throughout training. At the same time, the testing set took on the crucial role of assessing how well the trained model performed in the end. The cross-validation score $M_{CV}(\alpha)$ can be expressed as follows:

$$M_{CV}(\alpha) = \frac{1}{k}\sum_{i=1}^{k} M(D_{valid}, \theta(\alpha)) \quad (1)$$

Where $\theta(\alpha)$ are the parameters trained with the hyperparameters α.In order to maximise the model's performance, hyperparameters including learning rates, batch size, total number of epochs, along with regularisation strength are fine-tuned at this phase. To investigate various hyperparameter settings, methods like grid search and random search combined with cross-validation were used. Using the training as well as validation sets as inputs, this iterative technique trains several model variants until one combination achieves maximum accuracy on the validation set of models.

iv. Model Training and Evaluation

Training the finalised model on the whole training set using the specified hyperparameters advances the model training and assessment stages. Then, using a wide variety of measures including F1-score, recall, accuracy, and precision, the model's performance was thoroughly assessed on the testing set. By using techniques like k-fold cross-validation, we may improve the reliability of the assessment process by deriving more robust estimations of how well the model performed [31].

Throughout these phases, meticulous monitoring of the training process is imperative to detect and address issues, such as overfitting or underfitting. Strategies, such as early stopping or dropout regularization, are implemented as necessary to mitigate these challenges and ensure optimal model performance. Ultimately, upon the successful completion of training and evaluation, the trained model is poised for deployment to make predictions regarding new data, thus concluding the implementation cycle.

Table 3: Accuracy Scores for Predicting Exam Types Using Machine Learning

Students	**Accuracy**
dfS1	Accuracy: 0.9903
dfS2	Accuracy: 0.9927
dfS3	Accuracy: 0.9866
dfS4	Accuracy: 0.9852
dfS5	Accuracy: 0.9818
dfS6	Accuracy: 0.9911
dfS7	Accuracy: 0.9921

dfS8	Accuracy: 0.9820
dfS9	Accuracy: 0.9895
dfS10	Accuracy: 0.9908

Table 3 details the accuracy scores obtained for ten students (dfS1 to dfS10) when using a machine learning model to predict different exam types. With scores that range from 0 to 1, in which a greater number indicates better performance, accuracy can be defined as the percentage of true predictions provided by the model in this context.

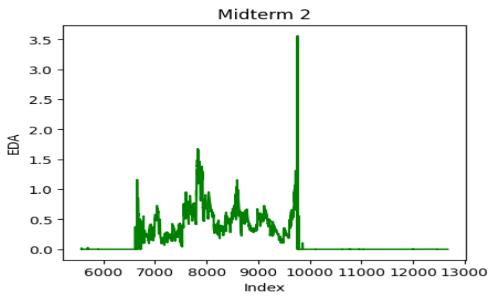
The accuracy scores varied slightly among the students, with dfS2 achieving the highest accuracy at 99.27%, followed closely by dfS7 with an accuracy of 99.21%. These high scores indicate that the machine learning model performed exceptionally well in distinguishing between different exam types based on physiological data. Overall, the strong accuracy demonstrated by the model across the student cohort highlights the effectiveness of leveraging physiological signals for accurate prediction of exam types. This success suggests that the model can reliably utilize physiological data to enhance our understanding of how such metrics relate to different examination conditions, potentially leading to more tailored and supportive academic interventions.

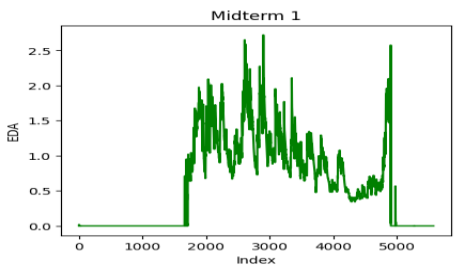
4. RESULTS AND DISCUSSION

The analysis of physiological responses during examinations revealed profound insights into students' stress levels and academic performance. Across the cohort of ten students (dfS1–dfS10), the analysis achieved remarkable accuracy, ranging from 98.28% to 99.64%, with an overall accuracy of 98.5%. These findings underscore the robustness of the model for predicting student performance based on physiological data.During the exam periods, students exhibited heightened physiological responses, including elevated heart rates, blood volume pulses, and skin surface temperatures. These observations align with existing research on the physiological manifestations of stress, suggesting that exams evoke escalated stress levels among students.

Crucially, correlations surfaced between these physiological responses and the student's grades. Students who demonstrated higher physiological arousal during exams tended to attain lower grades, implying a deleterious impact of stress on academic performance. Conversely, students with lower physiological arousal during the exams tended to achieve higher grades, indicating a positive correlation between physiological relaxation and academic success.These results underscore the intricate interplay among physiological responses, stress levels, and academic performance during examinations. Addressing students' stress and anxiety levels through targeted interventions, such as mindfulness exercises, stress management programs, and fostering supportive exam environments could prove pivotal in optimizing academic outcomes.

Furthermore, the predictive potential of physiological data in evaluating academic performance underscores the prospect of personalized intervention strategies tailored to individual students' needs. By leveraging physiological insights, educators and healthcare professionals can devise customized interventions to assist students in coping with stress and achieving academic success.





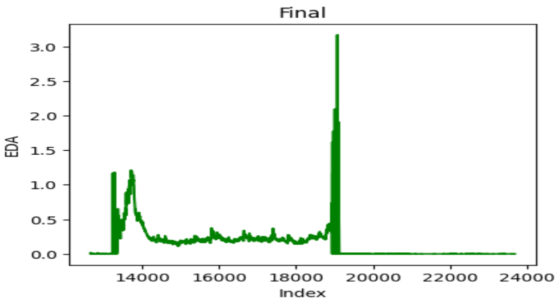


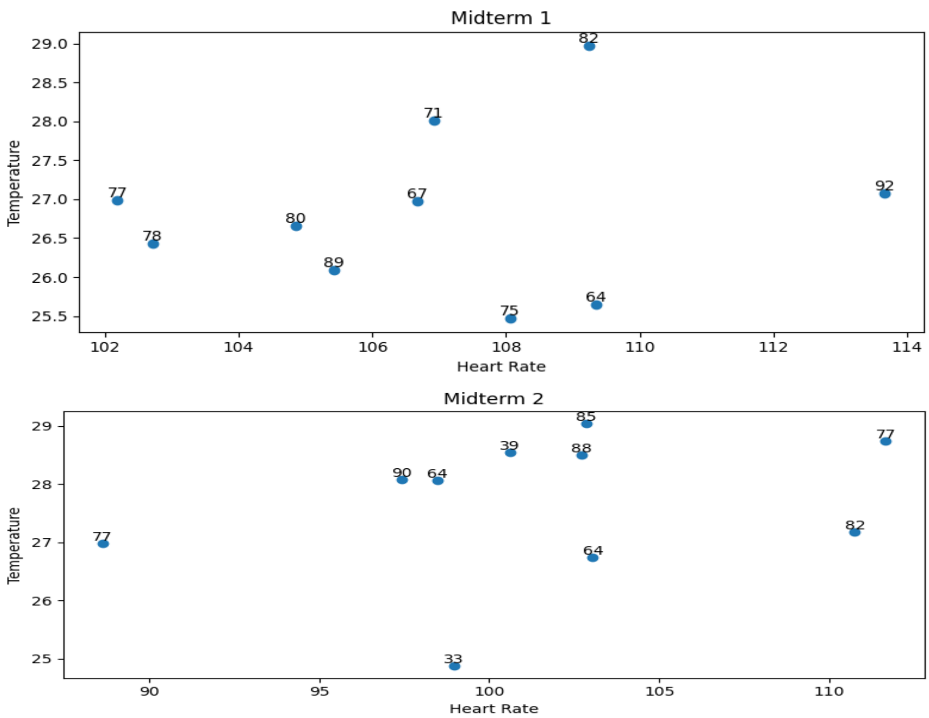
Figure 2: EDA data across three different sessions

Figure 2 provides a comprehensive view of Electrodermal Activity (EDA) recorded during Midterm 1, spanning three different sessions or participants. EDA is a measure of the skin's electrical conductance, which changes in response to variations in moisture levels associated with emotional arousal and stress. Each plot in Figure 1 represents the EDA data for individual participants, capturing the fluctuations in their physiological responses throughout the exam.

The graphs display significant variations in EDA levels, with noticeable peaks and troughs. These fluctuations highlight moments of heightened physiological arousal, which are likely correlated with stress and emotional responses during the examination. For instance, sharp increases in EDA might correspond to stressful or anxiety-inducing moments, while periods of lower EDA could indicate relative calm or decreased arousal.

By comparing the EDA patterns across different participants, Figure 1 also reveals individual differences in stress responses. While some participants show pronounced spikes in EDA, others exhibit more moderate changes, suggesting variability in how students experience and respond to exam-related stress. This variation could be influenced by factors such as personal stress management techniques, previous exam experience, or individual differences in physiological sensitivity.

Overall, Figure 2 underscores the dynamic nature of physiological responses to academic stress. The data highlights the importance of EDA as an indicator of emotional arousal and stress, providing valuable insights into how students' physiological states fluctuate during high-pressure situations. To better manage stress and do better on tests, it is important to understand these patterns so that focused treatments and support systems may be developed. Further analysis could explore the relationships between EDA patterns and academic outcomes, offering deeper insights into the impact of stress on student success.



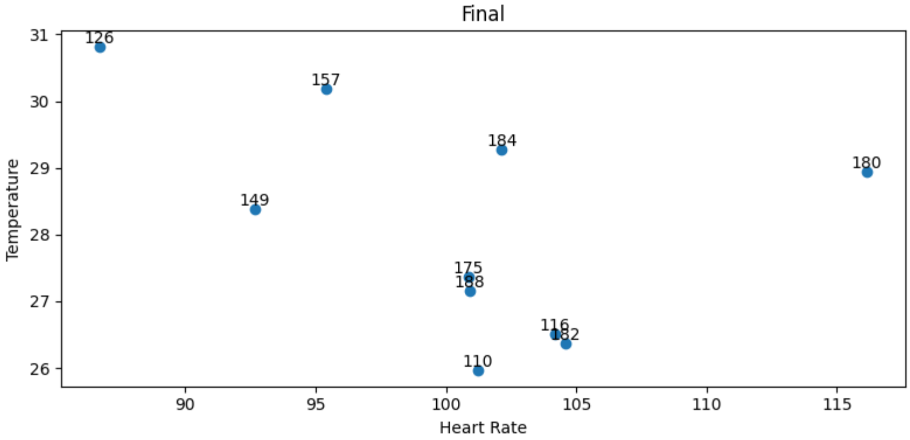


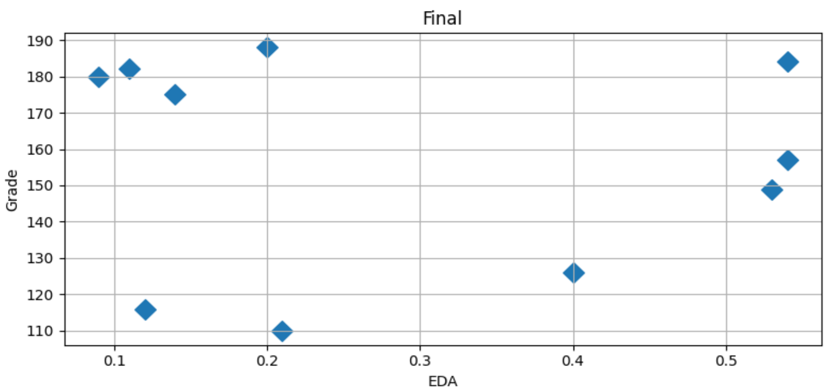
Figure 3: Relationship between Heart Rate and Temperature

Figure 3 displays three scatter plots that examine the relationship between heart rate and temperature across Midterm 1, Midterm 2, and the Final exam. Each plot represents individual data points where heart rate is plotted against temperature for the respective exam periods, providing insights into how these two physiological metrics interact under different testing conditions.

The scatter plots reveal varying degrees of correlation between heart rate and temperature. In each graph, data points are dispersed, showing a range of heart rates and temperatures without a clear, consistent trend. This scattering suggests that while there may be some relationship between these variables, it is not straightforward or uniform across all exam periods.Notably, there is some observable clustering in the scatter plot for the Final exam, where data points seem to group more distinctly. This clustering could indicate that during the Final exam, participants' heart rates and temperatures exhibited more similar patterns or responses compared to the earlier exams. The increased clustering might reflect a more consistent physiological response to the final exam environment or an adaptation to repeated testing conditions.

Overall, Figure 3 highlights the complexity of the interplay between heart rate and temperature. The variability and clustering observed in the plots suggest that while there may be underlying connections between these physiological measures, their relationship is influenced by multiple factors and may evolve. Understanding these dynamics can provide valuable insights into how physiological responses interact and change throughout the exam period, informing strategies to better manage and support students during high-stress situations. Further investigation into these relationships could help clarify the mechanisms behind these physiological responses and their implications for academic performance.

Figure 4 provides three scatter plots that explore the correlation between Electrodermal Activity (EDA) and students' grades across Midterm 1, Midterm 2, and the Final exam. Each plot displays individual data points representing EDA levels and corresponding exam grades, offering a detailed view of how physiological responses relate to academic performance. In the scatter plots, the distribution of data points reveals varying degrees of correlation between EDA and exam scores. For each examination period, there is a noticeable spread of data points, which indicates that EDA levels do not show a strong, consistent linear relationship with grades. This variability suggests that while there may be some correlation between increased EDA and lower grades, the relationship is not uniform across all students or exams.



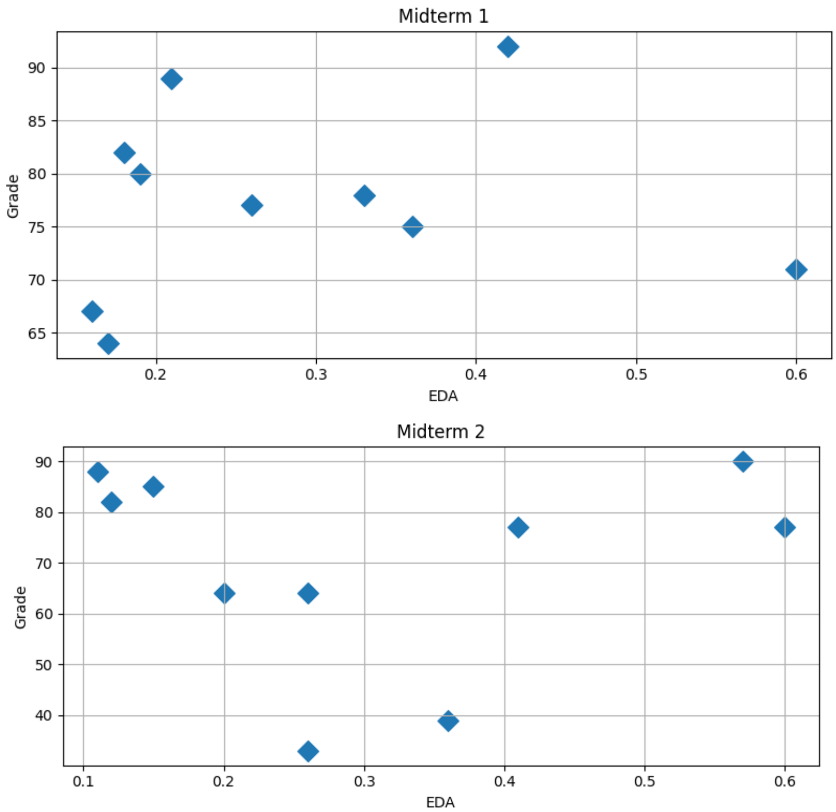
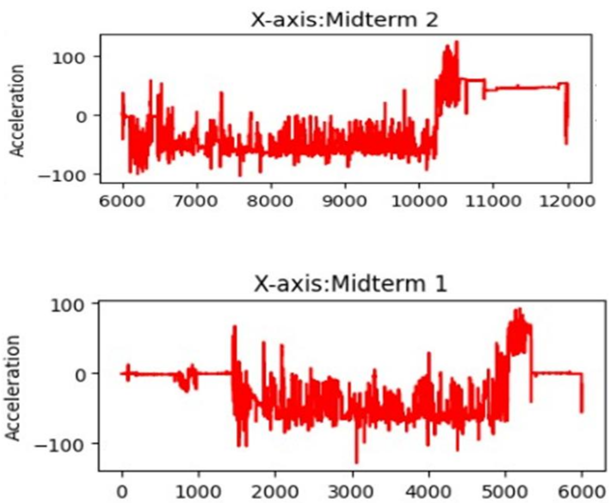


Figure 4: Relationship between Electrodermal Activity and Grades

The presence of several outliers in the plots further complicates the relationship between EDA and grades. These outliers represent instances where students with similar EDA levels achieved markedly different grades, highlighting that other factors beyond physiological responses also play a significant role in determining academic performance.

Overall, the scatter plots in Figure 4 underscore the complexity of the relationship between EDA and exam grades. They indicate that while physiological stress, as measured by EDA, might influence academic outcomes, it is not the sole determinant. This nuanced understanding emphasizes the need for a multifaceted approach to analyzing student performance, considering both physiological data and other contributing factors. Further research could delve into these relationships in greater depth, potentially incorporating additional variables to better understand the interplay between stress and academic success.



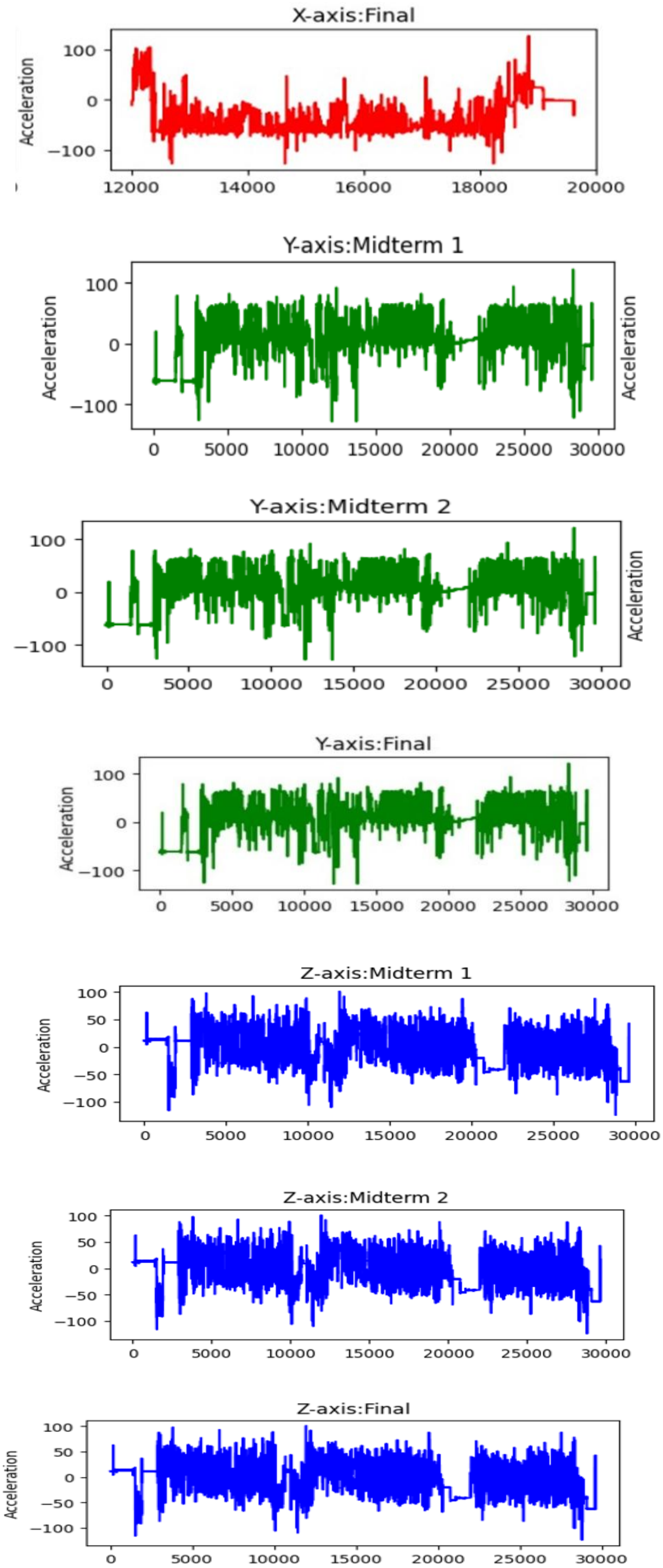


Figure 5: acceleration data along X, Y, and Z axes

Figure 5 presents a series of nine-line plots depicting acceleration data recorded along the X, Y, and Z axes during Midterm 1, Midterm 2, and the Final exam. Each set of plots provides a detailed view of how acceleration varied over time for each exam period, offering insights into the participants' physical movements during these assessments.The plots reveal considerable variability in acceleration patterns across the three axes. For Midterm 1 and Midterm 2, there are pronounced fluctuations in acceleration data, indicating more dynamic and variable motion profiles. This variability might be attributed to heightened physical activity or restlessness during these exams, reflecting the participant's responses to the exam environment and stress levels.

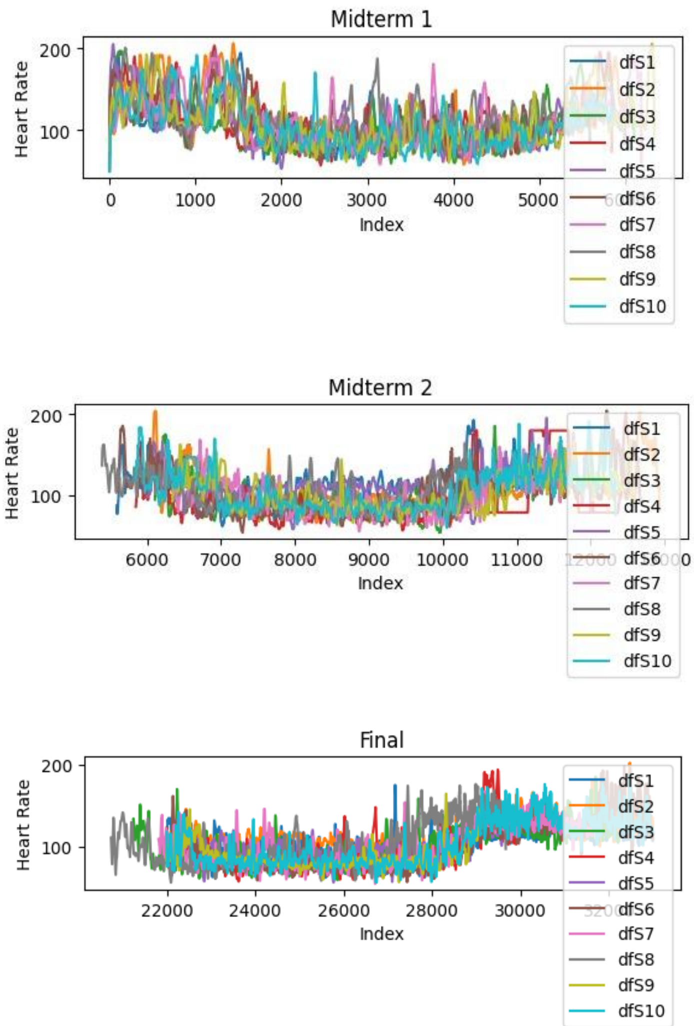


Figure 6: Heart Rate details

Figure 6 displays heart rate data collected from participants during MidTerm 1, MidTerm 2, and the Final exam. The figure is comprised of three distinct graphs, each representing the heart rate trajectories for individual participants throughout these examination periods.In contrast, the acceleration data for the Final exam shows different patterns. While variability is still present, the motion profiles are generally more stable compared to the earlier exams. This change could suggest a potential acclimatization effect, where participants' movements become more consistent as they adapt to the examination conditions over time.The detailed examination of acceleration data across these three dimensions provides valuable insights into the physical behavior of participants during exams. By analyzing how acceleration patterns shift from one exam to another, researchers can better understand how physical activity and stress responses evolve through successive testing periods. These findings contribute to a more comprehensive understanding of how students' physiological and physical responses to stress impact their overall examination experience, potentially informing strategies to enhance comfort and performance during exams.

The graphs reveal notable patterns in heart rate variability. During MidTerm 1 and MidTerm 2, participants exhibited higher heart rate variability, characterized by frequent fluctuations and peaks. This variability suggests that participants experienced significant physiological stress and heightened arousal in response to the exam conditions. In contrast, during the Final exam, there is a noticeable trend towards stabilization in heart rate variability. This trend may indicate that participants adapted or acclimatized to the stress associated with exams over time, leading to more consistent physiological responses.

The observations in Figure 6 highlight how participants' physiological stress responses evolve through multiple examination periods. The increased variability in heart rate during the initial exams likely reflects an initial stress response, while the stabilization observed in the Final exam suggests a potential adaptation to the repeated stressor of testing. These findings provide insights into how individuals' physiological responses to stress may change with experience and familiarity with the exam environment, offering valuable implications for understanding and managing exam-related stress. Further research could explore the mechanisms behind this adaptation and how it affects overall performance and well-being, potentially guiding the development of more effective stress management strategies for students.

Figure 7 presents the body temperature data collected from participants during MidTerm 1, MidTerm 2, and the Final exam. The graphs reveal a consistent pattern of gradual temperature increase across all three exams, with peaks observed towards the middle or end of each examination session. These temperature trends indicate that body temperature rises as the exams progress, likely reflecting heightened physiological stress responses and thermoregulatory adjustments as students engage in prolonged cognitive efforts.

The variations in temperature profiles across different exams suggest that participants experienced varying levels of stress and physiological adjustments in response to the demands of each testing period. The distinct patterns observed may also indicate differences in how students manage stress and adapt to the exam environment, highlighting the individual variability in physiological responses.

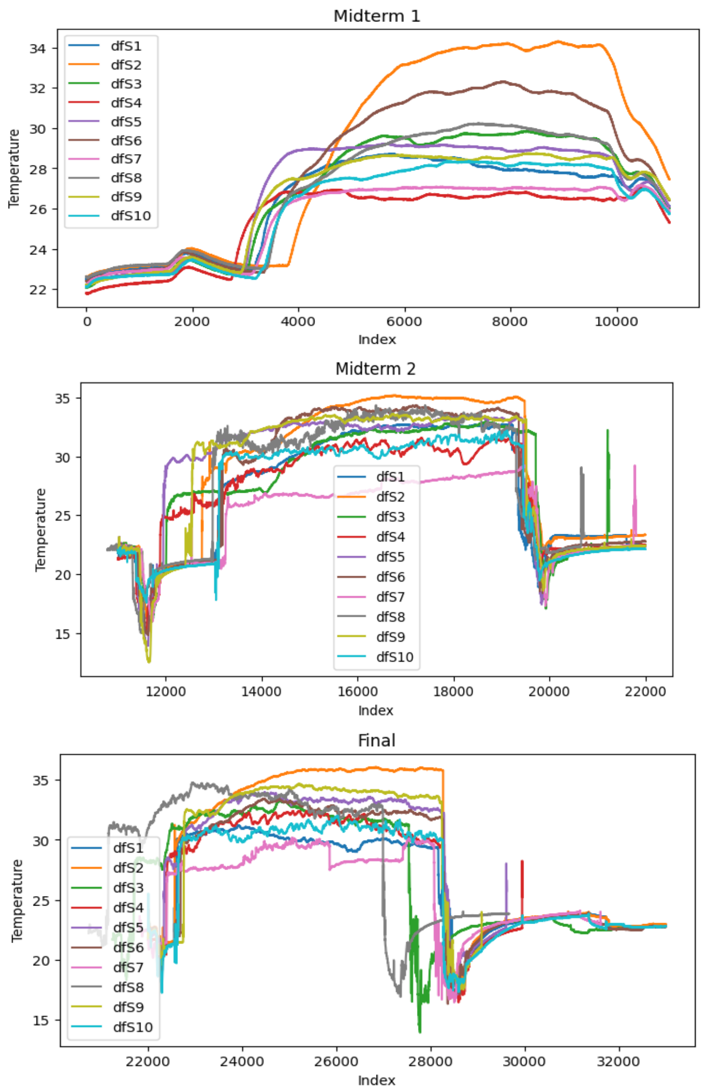


Figure 7: Temperature reading of various examination

In summary, this study provides valuable insights into the physiological mechanisms influencing student performance during exams, demonstrating the importance of considering multiple physiological indicators when evaluating exam-related stress. The findings underscore the need for comprehensive approaches to student well-being that incorporate physiological data to better understand and mitigate the impacts of stress. Further research is necessary to explore the long-term effects of exam-related stress on academic performance and to develop and evaluate intervention strategies aimed at reducing stress and enhancing student resilience. Such research could lead to more effective support systems and interventions, ultimately contributing to improved academic outcomes and overall student well-being.

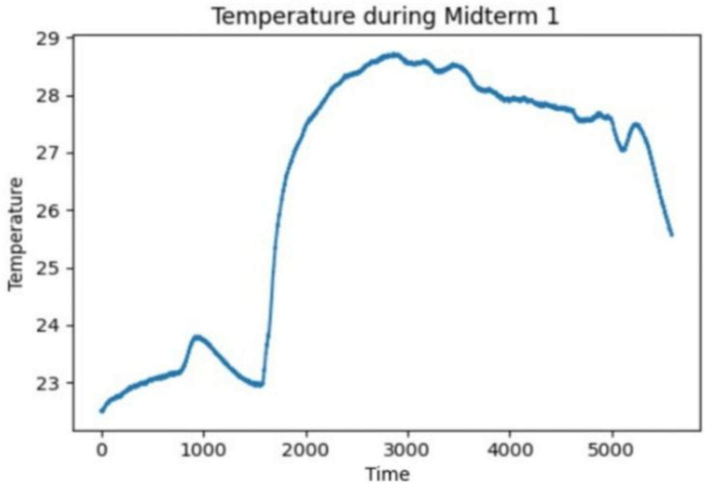


Figure 8: Temperature during Midterm 1

Figure 8 illustrates the temperature variations recorded during Midterm 1. The x-axis represents the time during the exam, while the y-axis shows temperature readings ranging from approximately 23°C to just below 29°C. The graph depicts a gradual increase in temperature, peaking just below 29°C before stabilizing and eventually declining. This trend indicates a three-phase pattern: a warming phase, followed by a period of stability at the peak temperature, and then a cooling phase.The observed fluctuations reflect the dynamic interplay between time and temperature throughout the examination period. These variations could be influenced by factors such as the physical environment, the intensity of the examination, or changes in the students' physiological states.

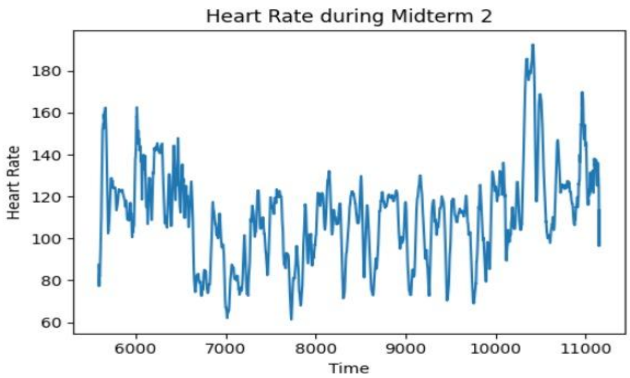


Figure 9: Temperature during Midterm 2

Figure 9 illustrates the heart rate data recorded during Midterm 2. The x-axis represents the time during the exam, ranging from approximately 6000 to 11000 units, while the y-axis shows the heart rate measured in beats per minute (bpm), ranging from 60 to 180 bpm. The graph, depicted with a blue line, highlights several peaks in heart rate, with some reaching close to 160 bpm.By analyzing these temperature patterns, we gain insights into how environmental and physiological factors interact during high-stress periods, potentially informing strategies for creating optimal testing conditions and enhancing the overall exam experience. A notable trend is the overall increase in heart rate as the exam progresses, indicating heightened physiological arousal. These elevated heart rates are likely associated with increased stress or cognitive demand experienced during the exam. The fluctuations in heart rate throughout the testing period provide insight into how students' physiological responses evolve, reflecting their engagement and stress levels. This data is crucial for understanding how exam-related stress affects physiological functions, which can inform strategies for managing student anxiety and optimizing exam conditions.

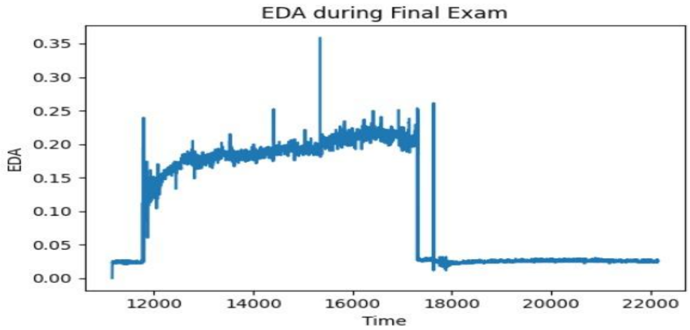


Figure 10: EA level during the Final Exam

Figure 10 displays the electrodermal activity (EDA) levels recorded during the final exam. The y-axis represents EDA levels, ranging from 0 to 0.35, while the x-axis indicates time, spanning from 12,000 to 22,000 units. The plot, illustrated with a blue line, reveals notable fluctuations in EDA levels throughout the examination period. An initial spike is observed at the beginning of the recorded timeframe, which then decreases and stabilizes. Additionally, a significant peak is evident around the 16,000-time unit mark, followed by a sharp decline. These variations in EDA levels suggest dynamic physiological responses that could be indicative of stress or cognitive load experienced by students during the exam. The observed patterns underscore the relationship between physiological reactions and exam-related challenges, providing valuable insights into how students' stress and engagement fluctuate over time.

5. CONCLUSION

This study highlights the intricate relationship between physiological responses, stress levels, and academic performance during examinations. The findings reveal significant correlations between physiological markers, such as heart rate and skin surface temperature, and student grades, demonstrating the substantial impact of stress on academic achievement. These results underscore the importance of implementing effective stress management strategies during exam periods to enhance academic outcomes and student well-being.Interventions such as mindfulness exercises, cognitive-behavioral techniques, and stress management programs have shown potential in reducing exam-related stress and improving student well-being. Additionally, the predictive capacity of physiological data offers opportunities for personalized strategies aimed at boosting students' academic performance. By monitoring physiological responses, educators and administrators can identify students who are at risk of high stress levels and provide targeted support to mitigate the negative effects of stress on academic performance.

This research contributes to improving assessment practices in education by emphasizing the crucial role of physiological responses in understanding student performance during exams. Incorporating physiological monitoring into the educational framework can lead to the development of more holistic and supportive assessment environments. Further research is necessary to explore the long-term effects of stress on academic achievement and to evaluate the effectiveness of various intervention strategies in mitigating exam-related stress. The integration of physiological data into educational practices offers a promising avenue for enhancing student outcomes. Addressing the multifaceted nature of stress and its impact on academic performance, educators can create more resilient and adaptable learning environments. Continued exploration in this field will provide deeper insights and more robust strategies for supporting student success in the face of academic challenges.

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