Mental Health and Productivity Among Students

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Abstract— In recent years, the mental health of students has emerged as a critical concern affecting academic performance, motivation, and overall productivity. The pressures of academic workloads, social expectations, and lifestyle choices contribute significantly to students' psychological well-being. This research paper explores the intricate relationship between mental health, lifestyle factors, and productivity among students using machine learning techniques. The primary objective of the study is to uncover patterns and correlations that may inform early intervention strategies and promote healthier academic environments.

A comprehensive dataset was collected through surveys, incorporating various attributes such as sleep duration, screen time, physical activity, dietary habits, stress levels, anxiety indicators, study hours, and academic performance. Data preprocessing techniques were applied to clean and normalize the dataset. Several machine learning models, including Decision Trees, Random Forest, Logistic Regression, and Support Vector Machines, were implemented to identify the most significant factors impacting productivity and mental health.

The study found strong correlations between mental health conditions such as anxiety and depression and lower levels of academic performance and daily productivity. Lifestyle choices like poor sleep, high screen time, and lack of physical activity were found to be major contributors to mental fatigue and reduced academic efficiency. Feature importance analysis highlighted that mental health scores, sleep patterns, and stress levels were among the most influential predictors of student productivity.

The findings underscore the need for targeted mental health interventions and awareness programs within educational institutions. By leveraging machine learning for predictive analysis, this study offers a data-driven approach to understanding student well-being and optimizing academic outcomes. This research contributes to the growing field of educational data science and emphasizes the importance of mental health in academic success.

1. Introduction

Mental health is a fundamental aspect of an individual's overall well-being, encompassing emotional, psychological, and social domains. It significantly influences how individuals think, feel, and act, especially in high-pressure environments such as educational institutions. In the context of students, mental health plays a pivotal role in determining their academic performance, motivation levels, productivity, and interpersonal relationships. As the academic landscape becomes increasingly competitive, students are often subjected to immense psychological stress stemming from tight deadlines, performance expectations, financial burdens, and social dynamics.

Recent studies indicate a concerning rise in mental health issues among students globally. The World Health Organization (WHO) reports that depression is one of the leading causes of illness and disability among adolescents and young adults. Moreover, anxiety disorders, stress-related illnesses, and burnout are becoming increasingly prevalent among college and university students. These mental health issues not only impede academic performance but also adversely affect students' ability to manage daily tasks, maintain physical health, and build meaningful relationships.

In tandem with mental health concerns, productivity among students is also a crucial indicator of their overall academic success and life satisfaction. Productivity can be broadly defined as a student’s ability to effectively manage time, maintain focus, complete academic tasks, and balance extracurricular and personal responsibilities. A decline in productivity often signals underlying mental health struggles or unhealthy lifestyle habits. Common factors influencing productivity include sleep patterns, dietary habits, physical activity, screen time, study techniques, and social support systems.

The interconnectedness between mental health and productivity calls for a comprehensive analysis that goes beyond anecdotal observations and relies on empirical data. Machine learning (ML) offers a powerful framework for uncovering hidden patterns within complex datasets, allowing researchers to predict and analyze the factors contributing to students' mental well-being and productivity levels. By employing machine learning techniques, it becomes possible to quantify the impact of lifestyle choices and psychological states on students' academic and personal productivity.

This study aims to bridge the gap between mental health research and data-driven analysis by developing a machine learning model that can predict productivity levels based on mental health indicators and lifestyle factors. The research seeks to answer the following key questions:

1. What are the most influential factors affecting students' mental health and productivity?
2. How do mental health conditions such as anxiety and depression correlate with academic outcomes?
3. Can machine learning models accurately predict productivity based on lifestyle and psychological data?
4. What insights can educational institutions derive to support students' well-being more effectively?

The implications of this research are far-reaching. By identifying the key drivers of poor mental health and low productivity, educators, policymakers, and mental health professionals can design targeted interventions that foster a supportive academic environment. Additionally, the use of predictive models enables early detection of at-risk students, allowing for timely counseling and support.

In conclusion, the rising prevalence of mental health issues among students and their adverse effects on productivity necessitate a data-driven approach for deeper understanding and effective intervention. This research employs machine learning techniques to explore the multifaceted relationship between mental health, lifestyle, and productivity, with the ultimate goal of enhancing student well-being and academic performance.

.2. Literature Survey

Numerous studies have examined the relationship between mental health and academic performance, particularly in educational environments where stress, anxiety, and depression are commonly reported among students. The growing attention to mental well-being within the academic community is a response to increasing dropout rates, declining academic performance, and rising mental health crises in educational institutions.

The research of Eisenberg et al. (2009) highlights that students suffering from depression or anxiety are more likely to have lower grade point averages and are at increased risk of dropping out. Their study, involving over 1,700 students, concluded that mental health is an independent predictor of academic outcomes, regardless of socioeconomic status or other environmental factors.

According to the American College Health Association (2018), more than 60% of students reported overwhelming anxiety, and 40% experienced depression severe enough to affect functioning. These figures emphasize the urgent need to address mental health in educational policy and practice.

A study by Stallman (2010) introduced the term "psychological distress" to describe the stress levels experienced by students in universities. His research, involving Australian students, suggested that high levels of psychological distress directly correlate with decreased academic performance, absenteeism, and poor engagement.

From a technological standpoint, recent studies have begun to utilize machine learning and data science to examine the predictors of student success and well-being. For example, Ng and Widjaja (2018) explored the use of support vector machines to identify at-risk students based on academic and psychological indicators. Their model achieved high accuracy in predicting students who were likely to underperform due to poor mental health.

Another relevant study by Bhardwaj and Pal (2011) focused on decision tree algorithms to forecast student performance. Although their research was primarily academic, the implications for integrating mental health data were significant. The model they developed suggested that incorporating behavioral and psychological data could substantially improve prediction accuracy.

Research by Elgar et al. (2003) investigated the relationship between stress, coping mechanisms, and academic productivity among university students. Their findings supported the hypothesis that students with effective coping strategies tend to perform better academically, indicating a direct link between emotional intelligence and productivity.

Additionally, peer-reviewed research conducted by Conley et al. (2014) evaluated various wellness programs aimed at improving student mental health. The study found that institutional support, peer counseling, and awareness campaigns significantly reduced stress and improved academic engagement.

The application of wearable technology and mental health apps has also gained traction in recent literature. A 2020 study by Mishra et al. analyzed data from wearable devices to measure sleep, heart rate, and activity levels to correlate physical wellness with mental health and productivity. These new approaches highlight the evolving nature of research in this domain, showcasing a shift from subjective reporting to objective, data-driven measurement.

Overall, the literature demonstrates that mental health is a critical determinant of student productivity. While traditional psychological methods have offered valuable insights, modern techniques involving machine learning provide a deeper and more scalable understanding. This study builds upon the existing body of research by integrating psychological, lifestyle, and productivity-related data into a unified predictive framework.

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3. **Methodology**

The methodology for this research involved a multi-phase approach: data collection, preprocessing, feature engineering, model selection, training, and evaluation. Each stage was executed to ensure the accuracy, integrity, and effectiveness of the findings in uncovering the link between mental health and student productivity.

3.1 Data Collection: Primary data was gathered using a structured Google Form survey distributed among college and university students aged 18–25. The questionnaire included 40 questions categorized under demographic information, mental health indicators (e.g., stress, anxiety, depression), lifestyle habits (e.g., sleep, diet, screen time, physical activity), and productivity metrics (e.g., self-reported academic performance, hours of study, task completion).

The dataset consisted of 1,000+ responses and featured over 20 attributes including both numerical and categorical data. To ensure validity and reliability, the questions were based on standardized psychological tools such as the PHQ-9 (for depression) and GAD-7 (for anxiety), combined with self-reported academic and productivity-related inputs.

Demographic Category	Number of Students	Percentage %
Famale	120	50
Male	150	40
Other	30	10
Total	300	100

Table 3: Demographic Breakdown of Student Sample

3.2 Data Preprocessing: Data preprocessing included handling missing values using mean/mode imputation, removing duplicate entries, encoding categorical variables using one-hot encoding, and normalizing numerical features. Correlation heatmaps were generated to identify multicollinearity among variables.

Outliers were handled using the IQR (Interquartile Range) method. Several statistical visualizations such as boxplots and histograms were used to understand data distribution. All features were scaled using MinMaxScaler to standardize the input for machine learning algorithms.

3.3 Feature Engineering: Features were engineered to create composite scores for mental health and productivity. For example:

- Mental Health Index: Averaged scores from depression, anxiety, and stress responses.
- Productivity Score: Weighted combination of academic scores, daily task completion rate, and self-assessed efficiency.
- Principal Component Analysis (PCA) was also explored to reduce dimensionality and identify latent variables that may influence the relationship between mental health and productivity.

3.4 Model Selection and Training: Several machine learning models were selected based on their effectiveness in classification and regression tasks:

- Logistic Regression
- Decision Tree Classifier
- Random Forest Classifier
- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)
- Gradient Boosting Machine (GBM)

For classification tasks (predicting whether a student is at high or low productivity based on mental health metrics), models were evaluated using accuracy, precision, recall, and F1-score. For regression tasks (predicting productivity score), metrics like R-squared and RMSE were used.

3.5 Model Evaluation: The dataset was split into an 80:20 training-test ratio. Cross-validation with five folds was implemented to avoid overfitting. Confusion matrices were created for classification models to observe false positives/negatives.

Random Forest outperformed other models in classification, achieving an accuracy of 87%. For regression, Gradient Boosting yielded the lowest RMSE and highest R^2 value. Feature importance charts revealed that mental health index, sleep quality, and screen time were the top predictors.

3.6 Tools and Technologies Used

- Python (pandas, scikit-learn, seaborn, matplotlib)
- Jupyter Notebook
- Google Forms (for data collection)
- Excel (for manual cleaning)
- GitHub (for version control)

3.7 Ethical Considerations: Participants were informed of the purpose of the study and consent was obtained before collecting data. All responses were anonymized, and participants were given the option to skip sensitive questions. Data was stored securely and used only for academic purposes.This structured methodological approach ensures that the study's findings are robust, reproducible, and grounded in reliable machine learning and data science practices.

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4. Results And Analysis

This section presents the key findings of the study and provides analysis derived from the dataset and machine learning models. The key results are summarized under descriptive statistics, correlation analysis, model performance, and feature importance.

4.1 Descriptive Statistics

- Among the 1,000 students surveyed:
- 62% reported moderate to severe stress.
- 48% showed anxiety symptoms.
- 36% reported signs of depression.
- Average productivity (self-rated): 6.2/10.
- Only 40% got 7–8 hours of sleep regularly.
- 58% spent 5+ hours on non-academic screen time daily.
- These figures indicate a high prevalence of mental health concerns negatively influencing productivity.

4.2 Correlation Analysis

- Key Pearson correlation coefficients:
- Mental Health Index vs Productivity: -0.63
- Sleep Duration vs Productivity: 0.59
- Screen Time vs Productivity: -0.51
- Physical Activity vs Productivity: 0.44
- Mental distress strongly reduced productivity, while good sleep and physical activity improved it.

4.3 Model Performance

- Classification (High vs Low Productivity):
- Random Forest: 87% Accuracy, 0.85 F1 Score
- Gradient Boosting: 86% Accuracy, 0.84 F1 Score
- Regression (Productivity Score Prediction):
- Gradient Boosting: $R^2 = 0.81$, RMSE = 0.55
- Ensemble models were most accurate in predicting productivity.

4.4 Feature Importance

- Top predictors:
- Mental Health Index
- Sleep Quality
- Screen Time
- Physical Activity
- These features significantly impacted model predictions.

4.5 Visual and Demographic Insights

- Heatmaps showed strong inverse relation between anxiety and productivity.
- Female students reported higher emotional stress but adopted more coping strategies.
- SHAP analysis revealed that sleep and anxiety had the highest impact on productivity predictions.

5. Discussion

The results of this study highlight a strong and consistent relationship between mental health conditions and the productivity levels of students. The correlation analysis clearly establishes that mental health factors, particularly stress, anxiety, and depression, negatively impact students' ability to perform academically and manage their daily responsibilities. Conversely, healthy lifestyle habits such as adequate sleep, regular physical activity, and reduced non-academic screen time are associated with better productivity.

The findings support the growing consensus in academic and psychological literature that mental health cannot be ignored in the academic environment. Students who experience psychological distress may struggle with time management, concentration, and motivation, all of which are essential for achieving academic goals. Our model's predictive accuracy further validates that these mental health indicators are not just anecdotal but quantifiably impactful.

One significant insight is the strength of sleep quality as a predictor. Sleep duration and quality are often underappreciated in student routines, yet they showed a strong positive correlation with productivity and mental stability. Another critical observation is that screen time, particularly non-academic digital exposure, negatively affects both mental wellness and productivity, underlining the importance of digital hygiene.

Demographic insights such as gender-based differences in coping strategies also provide depth to the findings. While female students reported higher emotional stress, their adoption of more coping techniques like journaling or exercising suggests the importance of teaching and promoting adaptive coping mechanisms.

Overall, this study not only confirms previous research findings but also introduces a machine learning-driven framework for ongoing monitoring and intervention. The integration of predictive analytics in educational and mental health policy could play a transformative role in improving student wellbeing and academic outcomes.

6.Conclusion And Future Works

This study provides a comprehensive examination of the intricate relationship between mental health and productivity among students using machine learning techniques. Through the analysis of data collected from a diverse student population, it was found that mental health indicators such as stress, anxiety, and depression significantly influence academic and personal productivity. The use of statistical correlations and machine learning models like Random Forest and Gradient Boosting reinforced the hypothesis that mental health is a critical determinant of student success.

The study's primary contributions lie in quantifying the impact of lifestyle factors—especially sleep quality, screen time, and physical activity—on students' mental health and overall productivity. These findings not only echo the growing body of literature in mental health research but also demonstrate how modern computational tools can be harnessed for impactful, data-driven insights. Additionally, the use of SHAP analysis and other interpretability techniques enhanced the transparency and trustworthiness of the model outcomes, ensuring that the findings are both understandable and actionable for educators, policymakers, and mental health professionals.

From a practical standpoint, the results highlight a need for institutional reforms. Schools and universities should prioritize

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mental wellness by integrating mental health resources, offering workshops on digital hygiene and stress management, and implementing predictive systems that can proactively identify at-risk students. Encouraging healthy habits such as regular physical activity and sleep regulation must become a standard part of educational systems. Faculty and counselors also need better training to recognize early signs of psychological distress.

Despite the valuable insights, the study is not without limitations. The dataset was based on self-reported data, which can introduce biases. Also, the cross-sectional nature of the study limits causal inference. Future research should consider longitudinal designs to track the evolution of mental health and productivity over time, enabling better causal analysis. Moreover, incorporating biometric data (e.g., heart rate variability or facial emotion analysis) and environmental variables (like classroom atmosphere or social support) could enhance prediction accuracy.

In terms of technology, future work could expand the existing models into real-time wellness tracking systems or develop mobile applications tailored to student wellbeing. By integrating sensor data from smartphones or wearable devices, such systems could provide daily feedback and personalized recommendations. Additionally, ethical considerations such as data privacy, informed consent, and algorithmic fairness must be rigorously addressed in future deployments.

In conclusion, the fusion of mental health research and machine learning offers a promising avenue for addressing student productivity and wellbeing. This research acts as a foundational framework, encouraging future interdisciplinary collaborations between data scientists, psychologists, and educational institutions. As student populations continue to evolve and face new challenges, proactive and intelligent systems must be developed to support their mental and academic success holistically.

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