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Predictability: Advancing Mental Health Modeling for Students

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Abstract
This study explores the development of a machine learning-based approach to proactively manage student mental health in higher education. Through these advanced analytical techniques, key mental health determinants were identified, integrating demographic, academic, socioeconomic, and behavioral factors. A Random Forest model, optimised via hyperparameter tuning, demonstrated superior predictive performance with an accuracy of 91% effectively classifying at-risk students. The determinants translate these findings into actionable insights, offering educators a comprehensive tool for timely interventions. By bridging technology and mental health management, this research underscores the transformative potential of predictive frameworks in fostering inclusive, supportive academic environments. This work advances the discourse on student mental health, emphasising data-driven strategies for early detection and intervention to improve educational outcomes.

Keywords: *human-environment-interaction; student health service; machine learning models; behavioural healthcare; predictive analytics; student metal health.*

1. Introduction

Human-Environment Interaction (HEI) plays a crucial role in shaping societal progress, cultural dynamics, and ecosystem transformations. In higher education (HE), this interplay is particularly significant, as global challenges - notably the mental health crisis - demand urgent and innovative responses. The COVID-19 pandemic exacerbated these challenges, intensifying stressors such as academic pressure, financial insecurity, and social isolation. These disruptions have significantly impacted students' academic performance, personal development, and career trajectories, underscoring the pressing need for targeted, data-driven interventions.

Mental health, encompassing emotional, psychological, and social well-being, is fundamental to student success (Skrividya, 2018). However, mental health disorders - including anxiety, depression, and stress - remain pervasive and often go unreported. A 2015 National Union of

Students (NUS) survey found that 78% of UK university students experienced mental health challenges in the past year, with 33% reporting suicidal thoughts (Gil, *The Guardian*, 2015). Alarmingly, 54% of those affected did not seek support. The pandemic further heightened these risks, with over 50% of Northern England students exhibiting clinical levels of anxiety and depression, disproportionately affecting females due to financial instability and strained relationships (Chen & Lucock, 2022). This research explores how machine learning (ML) can transform mental health interventions in HE by identifying, classifying and predicting at-risk students. ML's ability to process complex datasets enables early identification, allowing for timely, personalised interventions. By analysing academic performance, behavioural trends, and socioeconomic factors, this study aims to foster proactive support mechanisms, enhance inclusivity, and normalise mental health disclosure within HE institutions

1.1. Significance of Machine Learning in Addressing Mental Health in Higher Education

Mental health challenges in higher education (HE) remain significantly underreported due to stigma and concerns over data privacy. UCAS (2021) indicates that nearly 70,000 UK students enter university annually with a mental health condition, yet 49% of first-year students choose not to disclose it. This reluctance exacerbates academic attrition rates and limits long-term career prospects. Globally, anxiety disorders affect 18.1% of adults and 25.1% of adolescents, yet only 36.9% seek treatment, largely due to cultural barriers and fear of discrimination (Anxiety and Depression Association of America, 2019). Addressing these challenges requires proactive, data-driven interventions that encourage disclosure and facilitate timely support. Machine learning (ML) presents a transformative solution to the mental health crisis in HE by identifying at-risk students early and enabling targeted interventions. Unlike traditional statistical models, ML excels at processing complex datasets, detecting subtle risk patterns, and providing personalised predictions. Supervised learning techniques, such as Decision Trees (DT) and their ensemble variant, Random Forests (RF), enhance prediction accuracy (Rahma et al., 2022). Support Vector Machines (SVMs) optimise decision boundaries, as demonstrated in predicting suicidal behaviours among French students (Macalli et al., 2021). Meanwhile, Artificial Neural Networks (ANNs) model intricate patterns but require higher computational resources, whereas Logistic Regression (LR) remains effective for binary classifications, such as assessing suicide risk (Navarro et al., 2021). This study integrates diverse ML models to identify mental health risks among UK university students, assessing their predictive accuracy and practical applications. Additionally, it introduces a real-time interactive assessment tool, bridging the gap between predictive insights and institutional action. By leveraging ML, this research not only advances early detection and intervention strategies but also informs policy development, fosters inclusivity, and strengthens institutional support systems, ultimately improving student well-being and resilience.

2. Methods: Predictive Modelling of Student Mental Health in UK Universities

This section outlines our mental health modelling approach, detailing its core components and operational processes. Central to the framework is the integration of data collected through web- and mobile-based questionnaires, which capture diverse indicators of student well-being. These data streams are systematically fed into a machine learning (ML) model, which processes and structures the information into actionable datasets. The outputs are then visualised through a real-time dashboard, providing institutions with dynamic, data-driven insights into emerging mental health trends. This end-to-end system enables timely identification of at-risk individuals, facilitating proactive interventions and fostering a more responsive, preventative approach to mental health management within higher education settings.

2.1. Data Collection, Cleaning, and Preprocessing

Effective machine learning solutions rely on a robust data pipeline tailored to the research problem (Rahman et al., 2023). This study collected data from 1,875 university students across the UK (54.1%), Nigeria (27.5%), Germany (9.9%), and other regions (8.6%) via an electronic questionnaire. The survey, developed from insights gained through five focus groups (n = 24) and document analysis, comprised 70 questions covering internal (e.g., lectures, course structure, timetables) and external (e.g., family background, demographics, personality) factors influencing student mental health. The dataset, exported as a CSV file, contained 70 labelled features for supervised learning classification. Python libraries - including NumPy, Pandas, Matplotlib, and Scikit-learn - were used for data exploration, manipulation, visualization, and machine learning tasks. The cleaning and preprocessing pipeline is structured as follows:

1. **Renaming Features:** All 70 question columns were renamed to concise feature phrases for streamlined processing using Pandas rename method.
2. **Standardising Categorical Data:** Variations in spellings across five categorical records (e.g., "UK" vs. "United Kingdom") were harmonised.
3. **Streamlining Verbose Text:** Ten features with verbose text entries were replaced with concise equivalents for easier handling.
4. **Dropping Irrelevant Columns:** Features deemed non-contributory to predictive modelling (e.g., ‘Consent,’ ‘Referrer Name,’ ‘Timetable preference reasons’) were removed, resulting in 26 dropped columns.
5. **Handling Missing Values:** Features with null values were excluded, leaving the dataset with no apparent missing data (confirmed using Pandas’ *isna* method).

The cleaned data was exported as a CSV file for subsequent preprocessing. This structured process ensured the dataset’s readiness for feature engineering, model training, and evaluation.

2.2. Data Transformation and Encoding

Data transformation and encoding are crucial for ensuring consistency, comparability, and compatibility in machine learning workflows. These processes enhance model performance by standardising numerical features, encoding categorical variables, and managing dimensionality. In this study, numerical features were normalized using the Min-Max Scaling technique, which rescales values to a range of 0 to 1, mitigating dominance of features with larger ranges, ensuring fair comparisons. Categorical variables were systematically encoded to facilitate seamless integration into the machine learning pipeline. Binary variables, such as *mental health issues declaration*, were mapped as 1 ("Yes") and 0 ("No"), while ordinal variables like *year of study*, *quality of life*, *family earning*, and *diet* were encoded based on hierarchical relationships. High-cardinality features, such as *home country* and *course of study*, were processed using binary encoding to preserve information while managing dimensionality. One-hot encoding was applied to variables like *ethnic_group* and *personality_type*, expanding them into binary indicator columns without inflating feature space. Following data transformation, the dataset comprised 54 features, optimised for predictive modelling. These preprocessing steps not only improved model accuracy and robustness but also provided deeper insights into key predictors influencing mental health outcomes.

2.3. Feature Engineering and Selection

Feature selection plays a pivotal role in enhancing the predictive performance thus, by refining features, we can reduce noise, improve interpretability, and optimise computational efficiency.

2.3.1. Consolidation of Features

To streamline analysis, related columns such as *hours spent on Facebook*, *hours spent on Twitter*, and *hours spent on Instagram* were merged into a single feature: *total hours spent on social media.* Similarly*, hours spent on desktop*, *laptop* and *smartphone* were merged as a single feature *Total_device_hours_per_day* to reduce redundancy and maintain information integrity.

2.3.2. Feature Selection Techniques

To identify the most impactful predictors, we applied three complementary feature selection methods: Chi-Square Test, Mutual Information Classification, and Random Forest Classifier to enhance model performance by uncovering key relationships and refining feature priority. Chi-Square Test assesses independence between categorical predictors and the target variable, highlighting relevant features without measuring the strength of association (Singhal et al., 2015). Mutual Information Classification captures both linear and non-linear dependencies, quantifying relationship intensity of between variables (Xu et al., 2007). The Random Forest Classifier ranks feature importance based on predictive contribution, offering a base for feature selection. By integrating these methods, we identified significant predictors while eliminating less impactful features - below 25th percentile in the RF rankings. This refinement resulted in streamlined dataset enhancing model accuracy, reducing overfitting, and greater generalization.

2.4. Machine Learning Models

The modelling approach was guided by the dataset's characteristics and research objectives. Given the nature of the target variable, *Mental Health State*, the task was framed as a supervised, classification problem. Three ML models - neural networks, random forests, and support vector machines - were evaluated for modelling suitability. Using the *scikit-learn* library, a structured pipeline ensured computational efficiency and reliable outcomes. The dataset was split into training (75%) and testing (25%) sets, with classifiers trained on the former and validated on the latter. Performance was assessed through classification reports and ROC curves, confirming each model's predictive accuracy and interpretability. To enhance model's accuracy and reliability, in predicting mental health risks in HE, hyperparameter tuning was conducted using *GridSearch* (Zoller, 2019). *GridSearchCV* from *scikit-learn* iterated multiple hyper-parameter combinations to identify optimal configuration for RF model (Hutter et al., 2019).

3. Results

By combining advanced analytical methods, this study identified core mental health determinants with significant impact on student wellbeing. These determinants were then used to model a machine learning-based dashboard application, equipping educators with a powerful tool to support student mental health effectively. This approach bridges technology and education, fostering a more responsive and inclusive learning environment.

3.1. Key Mental Health Determinants in Higher Education

Using the three different techniques: Chi-Square test, mutual information classification and random forest classifier, twenty-seven features with significant parameters and weight associated with target variable (mental_health_issues_declaration) were identified (Table 1).

For this work, Chi-square and Mutual Information classification resulted in the identification of eighteen features and Random Forest classifier resulted in the identification of twenty-one feature having the best performance. All three techniques had nine common features.

3.2. Model Evaluation

While a high accuracy score may initially suggest strong model performance, accuracy alone fails to reveal insights into class-specific misclassifications. In this study, the models were evaluated using multiple classification metrics. The ROC Curve for the three models with AUC were computed via the scikit-learn package: 85%, 87% and 91% for SVM, neural network and random forest, respectively as shown in Figure 1.

Table 1. Predictive determinants for Mental Health in HE

No	Predictive Lifestyle Factors	Chi Square	Mutual Information Classification	Random Forest Classifier
1	alcohol_consumption	X	X	X
2	cost_of_study			X
3	course_of_study	X		X
4	diet	X	X	X
5	ethnic_group	X	X	X
6	exercise_per_week	X	X	X
7	family_earning_class		X	X
8	feel_afraid			X
9	financial_support	X	X	
10	form_of_employment	X	X	
11	home_country	X	X	
12	hours_between_lectures	X	X	X
13	hours_per_week_lectures	X		X
14	hours_per_week_university_work	X		X
15	hours_socialising	X	X	X
16	institution_country	X	X	
17	known_disabilities	X		
18	personality_type		X	X
19	quality_of_life	X	X	X
20	social_media_use		X	X
21	stress_before_exams			X
22	stress_in_general		X	X
23	total_device_hours	X	X	X
24	total_social_media_hours	X	X	X
25	well_hydrated		X	X
26	work_hours_per_week	X		
27	year_of_study			X

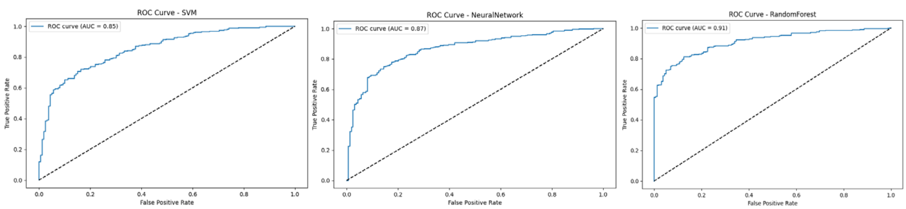

Figure 1. ROC Curve and AUC score for SVM, Neural Network and Random Forest models

Following hyperparameter optimisation performed via GridSearchCV, the random forest model presents the best modelling configuration amongst the three evaluated models. Therefore, the random forest model was adopted for the dashboard application development. By integrating academic performance, attendance, and self-reported surveys into computational models, the dashboard provides educators with actionable insights to foster a supportive learning. Features like filterable views and real-time updates enhance its utility, enabling institutions to address specific needs. By transforming raw data into accessible intelligence, the tool streamlines risk assessment and facilitates timely, targeted mental health interventions, exemplifying the power of machine learning in education.

4. Discussion

This study examined the effectiveness of machine learning models in predicting and classifying student mental health conditions, as well as identifying key risk factors influencing students' emotional well-being. While the number of respondents (1875) was lower than anticipated given the UK student population of 100,000, the dataset was sufficient for effective machine learning analysis. Employing a Random Forest classifier with hyperparameter tuning, the model achieved an accuracy of 91%, demonstrating robust predictive capability. Notably, the model's recall score indicated it correctly identified 75% of students with mental health conditions, while a precision score of 86% confirmed the reliability of positive predictions. The ROC curve further validated the classification strength, underscoring its potential for practical application.

4.1. Risk Factors Influencing Student Mental Health

This study reaffirms the complex interplay of financial, academic, and lifestyle pressures in shaping student mental health. Key predictors include lifestyle habits (diet, exercise, hydration), social engagement (social media use, socialisation hours), demographic attributes (ethnicity, economic class, student type), and situational stressors (anxiety, workload, employment hours). Structural factors, such as tuition costs and field of study, further influence mental well-being, underscoring the interconnected nature of these determinants. Consistent with prior research, these findings highlight the urgent need for universities to adopt systematic mental health interventions. Students facing mental health challenges experience lower retention rates, diminished academic performance, and limited career progression (UCAS, 2021). By integrating machine learning into predictive mental health frameworks, institutions can proactively identify at-risk students and connect them with targeted support. Embedding mental health considerations into university policies, and student services fosters a culture of inclusivity and proactive care. This data-driven approach enhances early intervention, strengthens student retention, and ensures equitable access to support systems. Ultimately, universities that bridge technological innovation with holistic well-being strategies will be better equipped to safeguard student success and create a resilient learning environment.

5. Conclusion, Limitations, and Recommendations for Future Research

The growing prevalence of mental health challenges among students highlights the urgent need for data-driven, predictive solutions. Machine learning models offer transformative potential by analysing diverse risk factors to identify at-risk individuals and enable timely interventions. This study advances predictive mental health modelling by pinpointing key risk indicators, yet several limitations reveal opportunities for refinement. First, the model's reliance on university-centric factors narrows its predictive scope. Excluding external influences such as family history and upbringing which are central determinants of mental health could reduce model's effectiveness. Expanding predictor variables in future research could enhance the model's comprehensiveness. Second, the binary classification system oversimplifies mental health conditions, failing to capture varying levels of severity. A more nuanced, spectrum-based approach distinguishing low, moderate, and high-risk cases would support tailored interventions and improve predictive accuracy. Finally, the study's relatively small dataset (1,875 observations) constrains its generalizability. Larger datasets would not only strengthen the model's reliability but enable more sophisticated machine learning techniques, enhancing predictive precision and scalability. Future research should prioritise broader risk factors, refined classification methods, and larger datasets. These advancements could transform predictive modelling into a powerful tool for proactive mental health interventions, ultimately improving student well-being and institutional support systems.

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