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# Predictive Mental Health Risk Assessment in Undergraduate Students Using Personalized Adaptive Machine Learning

**Saai Jaswant[1], Ahamed Saif[2], Aishwarya Balaji[3], Sree Mouthika[4], Neelam Sanjeev Kumar[5]**

Student, Department of CSE (E.Tech),SRM Institute of Science and Technology, Vadapalani Campus, Chennai, India.[1,2,3,4]

Assistant Professor (SG), Department of CSE (E.Tech), SRM Institute of Science and Technology, Vadapalani Campus, Chennai, India[5]

**Abstract:** Mental health challenges among college students have reached epidemic proportions, with approximately 40% of students experiencing significant psychological distress during their university years. Traditional reactive approaches to student mental health support have proven inadequate in addressing the scale and complexity of this crisis affecting millions of students globally. This study presents an Enhanced Adaptive K-Nearest Neighbor (EAKNN) algorithm for early detection of psychological issues in college students through intelligent analysis of behavioral patterns and temporal changes. The proposed system learns individual baseline behaviors, adapts to personal patterns, and identifies concerning deviations that may indicate developing mental health concerns before they escalate. Experimental validation with 200 college students over six months demonstrated that EAKNN achieved 92.5% overall accuracy, 92.7% sensitivity, and 91.1% precision in identifying at-risk students an average of 3.7 weeks before traditional screening methods. The algorithm incorporates temporal weighting, adaptive feature importance, and explicit uncertainty quantification to provide personalized, interpretable assessments tailored to individual circumstances. Statistical analysis confirmed significant improvements over baseline methods including Random Forest ($p < 0.001$, Cohen's $d = 0.82$). This research demonstrates that personalized, adaptive machine learning approaches can transform mental health support from reactive crisis management to proactive early intervention, potentially improving outcomes for thousands of students while optimizing limited counseling resources.

Keywords: Mental Health Detection, Machine Learning, EAKNN Algorithm, College Students, Early Detection, Behavioral Analysis, Predictive Analytics, Student Wellbeing.

## I. INTRODUCTION

In the contemporary landscape of higher education, mental health challenges among college students have emerged as a critical concern demanding immediate attention and innovative solutions. The traditional college experience, once characterized primarily by academic rigor and social development, now encompasses an increasingly complex array of psychological stressors that impact student wellbeing, academic performance, and overall quality of life. Mental health issues among college students have reached epidemic proportions, with approximately 40% of students experiencing significant psychological distress during their university years. This alarming statistic represents not merely numbers but individual lives affected by conditions such as anxiety, depression, stress disorders, and other mental health challenges that can profoundly impact academic success and personal development.

The college years represent a unique developmental period characterized by significant life transitions and challenges. Students navigate the difficulties of leaving home for the first time, managing substantially increased academic pressures and competitive environments, developing new social relationships and support networks, establishing personal identity through diverse experiences, and making critical decisions about their future careers and life directions. These simultaneous pressures create a perfect storm of stressors that can overwhelm even the most resilient individuals. Traditional approaches to student mental health have proven fundamentally inadequate in addressing the scale and complexity of this ongoing crisis affecting campus communities nationwide. Most universities rely on reactive models that depend on students self-identifying their struggles and actively seeking help from counseling services. By the time students reach out for support, they have often been suffering for extended periods, their academic performance has significantly declined, and their conditions have become more severe and increasingly difficult to treat effectively.

The emergence of artificial intelligence and machine learning technologies presents unprecedented opportunities to transform mental health support in educational settings and beyond. Universities already collect vast amounts of digital

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data about student behavior through learning management systems, card access systems, campus WiFi networks, and other administrative platforms. This data, when analyzed thoughtfully and ethically, can reveal patterns that indicate emerging mental health concerns long before they become crises requiring intensive intervention. Our research explores the application of advanced machine learning algorithms to create an early warning system for student mental health. By developing the Enhanced Adaptive K-Nearest Neighbor (EAKNN) algorithm, we aim to identify students who may be beginning to struggle with psychological issues, enabling timely intervention and support that can prevent more serious problems from developing and escalating.

This research represents a paradigm shift from reactive to proactive mental health support strategies. Rather than waiting for students to experience crisis situations, our system aims to identify subtle changes in behavior patterns that may indicate developing mental health issues. This approach respects individual differences in baseline behavior while flagging concerning deviations from personal norms and patterns. The potential impact of this work extends beyond the immediate application to college mental health, with principles and methods that could be adapted to support mental health monitoring in secondary schools, workplace environments, healthcare settings, and other contexts where early intervention could make a meaningful difference in people's lives.

## II. RELATED WORK

The intersection of mental health assessment, machine learning technology, and higher education represents a rapidly evolving field with significant implications for student wellbeing and institutional support systems. Existing approaches to student mental health screening typically rely on self-report questionnaires, clinical interviews, or standardized assessments administered periodically. While these traditional methods provide valuable information, they suffer from significant limitations including reporting bias where students may underreport symptoms, low participation rates with many students never seeking screening, and inability to detect gradual changes in functioning over time.

Machine learning applications in mental health assessment have demonstrated promising results across various populations and settings. Previous research has shown that algorithms analyzing speech patterns, text communications, and behavioral data can identify individuals with depression, anxiety, and other mental health conditions with reasonable accuracy. However, most existing work treats populations as homogeneous, using one-size-fits-all models without accounting for individual differences in baseline functioning and normal behavioral variation. This approach often produces high false positive rates, incorrectly flagging healthy individuals and leading to unnecessary alarm or unnecessary treatment.

The EAKNN approach represents an advancement over traditional K-Nearest Neighbor classification through several innovations specifically designed for mental health screening. Our method emphasizes personalization through learning individual baselines, adaptability through weighting features based on personal variability, temporal sensitivity through incorporating time-decay functions recognizing that recent behavior is more relevant than historical patterns, and uncertainty quantification providing confidence estimates for predictions. This personalized approach aligns with contemporary understanding that mental health must be assessed in individual context rather than through universal criteria.

## III. DATASET DESCRIPTION AND PREPROCESSING

Our study involved 200 college students across all four undergraduate years from diverse academic programs including engineering, sciences, humanities, social sciences, and business, with 60% female and 40% male participants, ages ranging from 18-24 years with modal age of 20 years. We collected three main categories of data over a six-month study period: Academic engagement data including class attendance records, assignment submission patterns, learning management system usage frequency, and grade trends across all courses. Mental health screening assessments using standardized instruments PHQ-9 for depression, GAD-7 for anxiety, and DASS-21 for broader psychological distress administered at baseline, monthly throughout study duration, and upon completion. Optional lifestyle and behavioral data including sleep patterns, physical activity levels, campus engagement metrics, and digital behavior collected from approximately 50% of participants who consented to share additional data sources.

Data preprocessing transformed disparate data sources into clean, standardized formats suitable for machine learning. Missing data required careful handling distinguishing between Missing Completely at Random from technical failures, Missing at Random with systematic patterns, and Missing Not at Random representing meaningful absences. Our approach used interpolation for random missing data, regression-based imputation for systematic patterns, and creation of missingness indicators for meaningful absences. Outlier identification employed multiple complementary methods including Z-scores, interquartile ranges, isolation forests, and domain knowledge rules with verification against original sources.

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## IV. SYSTEM ARCHITECTURE

Creating meaningful features from raw data significantly impacts model performance. Temporal features captured changes over time through rolling averages, trend analysis, variability measures, and change indicators. Academic features included assignment submission timing relative to deadlines, consistency of attendance patterns, learning management system engagement per course credit hour, and grade trajectories. Behavioral pattern features captured sleep regularity through consistency metrics, social engagement indices, digital behavior patterns, and physical activity levels. Interaction features proved most informative, such as declining grades combined with increased study time suggesting difficulty coping, reduced social engagement combined with irregular sleep indicating withdrawal, and academic struggle combined with reduced support service usage.

Dimensionality reduction focused on most informative patterns through Principal Component Analysis and feature selection methods including statistical tests, recursive elimination, regularization, and Random Forest importance scores. This process reduced feature space while maintaining predictive capacity.

## V. METHODOLOGY

The Enhanced Adaptive K-Nearest Neighbor algorithm extends traditional K-Nearest Neighbor classification with features specifically designed for mental health screening. The algorithm operates through four phases: baseline learning of individual patterns, adaptive comparison incorporating personal weightings, prediction with uncertainty quantification providing confidence estimates, and continuous updating as new data arrives.

Rather than using standard Euclidean distance, EAKNN employs weighted, time-aware distance metrics:

$$ d(x_i, x_j) = \sqrt{\sum_{f=1}^F w_f^{(i)} \cdot \tau(t_i, t_j) \cdot (x_{i,f} - x_{j,f})^2} $$

Recent observations receive higher importance through exponential decay temporal weighting:

$$ \tau(t_i, t_j) = \exp(-\lambda \cdot |t_i - t_j|) $$

Feature importance adapts for each individual based on baseline variability:

$$ w_f^{(i)} = \frac{1}{\sigma_f^{(i)} + \epsilon} $$

Features with low personal variability receive higher weight when changes occur, enabling personalized detection.

## VI. RESULTS AND ANALYSIS

Experimental validation demonstrated EAKNN achieved 92.5% overall accuracy, 92.7% sensitivity, and 91.1% precision in identifying at-risk students. Early detection occurred an average of 3.7 weeks before traditional screening methods, providing critical time for intervention. Statistical analysis confirmed significant improvements over Random Forest ($p < 0.001$, Cohen's $d = 0.82$) and other baseline methods. Performance remained consistent across demographic groups without significant bias.

## VII. ADVANTAGES AND LIMITATIONS

The personalized approach reduces false positives compared to population-level models through individual baseline learning. Early detection enables proactive intervention. Interpretability through identifiable feature contributions aids human decision-making. Limitations include dependence on data quality, requiring sufficient baseline data before effective detection, and potential privacy concerns requiring careful institutional implementation with appropriate ethical oversight and informed consent protocols.

## VIII. CONCLUSION AND FUTURE WORK

This research demonstrates that personalized adaptive machine learning can transform mental health support from reactive crisis management to proactive early intervention. EAKNN's personalized approach, temporal sensitivity, and uncertainty quantification provide a promising framework for identifying at-risk college students. Future work extends toward real-time integration into campus systems, incorporation of contextual factors like academic calendars and major life events, and development of accompanying support resources. This research shows potential to improve mental health outcomes while optimizing limited institutional resources for supporting student wellbeing.

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