HARNESSING REM SLEEP DYNAMICS FOR EARLY DETECTION OF PSYCHIATRIC DISORDERS

MAJOR PROJECT

Submitted to

Visvesvaraya Technological University
BELAGAVI - 590 018

by

Mr. Darshan B M	**4SU22AD009**
Mr. Deekshith	**4SU22AD010**
Mr. Jeevan	**4SU22AD018**
Mr. Prajwal	**4SU22AD035**

Under the guidance of

Mr. Rama Murali Krishna P.G

Assistant Professor

in partial fulfillment of the requirements for the award of the degree of

Bachelor of Engineering

Department of Artificial Intelligence & Data Science

SDM INSTITUTE OF TECHNOLOGY

UJIRE - 574 240

Abstract

Application of REM sleep dynamics to the early diagnosis of psychiatric disorders represents an innovative intersection of artificial intelligence (AI), machine learning (ML), and sleep science. Psychiatric disorders such as depression, anxiety, and schizophrenia are strongly associated with irregularities in REM sleep architecture and quality. The proposed system integrates objective REM sleep parameters with subjective PSQI scores to identify early indicators of psychiatric risk. The hybrid framework employs the XGBoost algorithm, a gradient boosting machine learning model known for its high accuracy and interpretability, to classify risk levels based on extracted temporal and spectral features from sleep data. Mathematical techniques, including Fourier-based transformations and statistical analysis, are applied to derive informative patterns. The system is implemented as a web-based application developed using Next.js (frontend) and FastAPI (backend), with Firebase providing authentication and secure data storage. Continuous Integration and Deployment (CI/CD) pipelines using GitHub, Vercel, and Render ensure automated version control and scalability. This AI-driven approach enables non-invasive, real-time, and data-supported psychiatric-risk assessment, offering clinicians and individuals an accessible tool for proactive mental health monitoring. The project demonstrates the potential of combining sleep analytics and machine learning to enhance early diagnosis, improve patient outcomes, and promote psychological well-being.

1. INTRODUCTION

This Chapter provides an overview of the project, highlighting the role of REM sleep in psychiatric disorder detection. It defines the problem, objectives, scope, and methodology, emphasizing the use of AI-driven models and wearable technology for real-time mental health monitoring.

Overview of the Project

This system will identify early signs of psychiatric risks by integrating REM sleep dynamics and PSQI questionnaire data through a hybrid, machine-learning-based framework. Unlike deep-learning methods, such as REM-U-Net, the developed model uses the XGBoost algorithm, which exhibits high interpretability and faster computation, along with reliable performance even in scenarios of limited and heterogeneous data. The application, which is web-based and supported by Next.js at the frontend and FastAPI in the backend, will take inputs from the users, process them through the trained XGBoost model, and then store those outcomes securely in Firebase Firestore. Complete CI/CD pipeline GitHub → Vercel → Render ensures smooth version control, automated deployment, and continuous integration.

2. Literature Survey

[1] Pittsburgh Sleep Quality Index Buysse et al. (1989) introduced the Pittsburgh Sleep Quality Index (PSQI), a gold-standard tool for assessing subjective sleep quality in clinical and research environments. The study validated PSQI across seven components, enabling comprehensive sleep evaluation. Its strong reliability and widespread adaptability made it essential for sleep-disorder screening. The PSQI remains one of the most widely used scales globally. This forms the subjective assessment backbone for modern sleep-health research.

[2] Anto et al. (2025) – Stress–Sleep Correlation in Nursing Students. This study examined the association between stress levels and sleep quality among nursing students. Anto et al. identified a strong inverse correlation—higher stress significantly reduced sleep quality. The findings underline the importance of monitoring sleep as an indicator of psychological strain. The work emphasizes young adult vulnerability to sleep-related health deterioration. It supports PSQI use in academic mental-health monitoring.

[3] Dan Zhang et al. (2024) – Eye Movement Biomarkers for Psychosis investigated how eye-movement abnormalities can predict transition to psychosis. Longitudinal findings showed that oculomotor patterns reflect cognitive and neural disruptions preceding psychotic onset. Metrics like fixation stability and saccadic response were strong predictors. This demonstrates REM-related biomarkers' value in identifying early psychiatric risk. The study reinforces eye movement as an objective screening tool.

[4] Yetton et al. (2017) – Automatic REM Detection proposed a machine-learning pipeline for automatic REM detection using EOG signals. Techniques like SVM and decision trees successfully differentiated REM vs. non-REM events. The approach reduced the need for manual annotation, improving efficiency and scalability. The system showed high accuracy and clinical applicability. This supports automated REM analysis in large-scale monitoring.

[5] Sharma & Verbeke (2020) – XGBoost for Depression Diagnosis to a large dataset of over 11,000 participants to detect depression. The model achieved high accuracy across clinical biomarkers such as lipids and inflammatory markers. Sampling techniques addressed dataset imbalance effectively. Results demonstrated XGBoost’s superiority over traditional ML models. This validates gradient boosting as a robust tool for psychiatric classification.

[6] Meyer et al. (2024) – Sleep–Circadian Interface & Mental Disorders mapped the relationship between circadian rhythms, sleep patterns, and psychiatric disorders. The study showed that circadian disruption contributes to depression, bipolar disorder, and schizophrenia risk. Neurobiological insights linked sleep timing with cognitive and emotional regulation. This work highlights circadian-informed mental-health diagnostics. It supports REM and sleep-continuity assessment for psychiatric prediction.

[7] Peever & Fuller (2017) – Biology of REM Sleep reviewed the neurophysiology of REM sleep, focusing on brainstem mechanisms controlling atonia and dreaming. They emphasized REM's role in emotional memory processing and neural restoration. Dysregulation was linked to disorders like RBD and PTSD. The review provides foundational understanding of REM functions. It supports using REM abnormalities as psychiatric biomarkers.

[8] Mollayeva et al. (2018) – Dimensionality of PSQI systematically reviewed PSQI's factor structure, emphasizing variability across populations. Findings showed PSQI can present one-, two-, or three-factor scoring depending on demographic and clinical conditions. The paper reinforced PSQI's usefulness but highlighted interpretation challenges. Their review validated PSQI's global importance. This supports adapting PSQI scoring to diverse user groups.

[9] Mollayeva et al. (2016) – PSQI as Screening Tool. This meta-analysis confirmed PSQI's effectiveness for screening sleep dysfunction in clinical and non-clinical samples. High sensitivity and specificity were observed across multiple studies. Authors highlighted PSQI's role in early detection of sleep problems linked to mental disorders. The study emphasized the need for complementary objective measures. It supports combining PSQI with physiological REM features.

[10] Zanini et al. (2015) – Sleep Abnormalities in Psychosis & Bipolar Risk assessed sleep parameters in individuals at risk of psychosis and bipolar disorder. Results showed altered REM latency, decreased sleep efficiency, and irregular sleep patterns in high-risk groups. These abnormalities were strongly correlated with psychiatric vulnerability. The study highlighted sleep traits as early diagnostic indicators. It reinforces REM-based psychiatric screening.

[11] Jeong et al. (2024) – EEG ML Models for RBD Phenoconversion developed EEG-based ML models to predict phenoconversion in REM Sleep Behavior Disorder (RBD). Their models accurately forecasted progression to neurodegenerative conditions like Parkinson's disease. Key EEG features served as biomarkers for conversion timing. This represents a major advancement in

early disease prediction. It strengthens the use of physiological signals in forecasting psychiatric decline.

[12] Yuan et al. (2023) – Predictors of Phenoconversion in Idiopathic RBD investigated clinical predictors for phenoconversion in idiopathic RBD. Loss of REM atonia, cognitive decline markers, and autonomic changes were key indicators. Their findings reinforced REM physiology's role in neurodegenerative pathways. The prospective design added high credibility. This paper supports REM-based risk stratification.

[13] Della Monica et al. (2018) – REM Sleep & Cognition Across Lifespan examined how REM sleep, slow-wave sleep, and sleep continuity affect cognition, mood, and subjective sleep quality across ages 20–84. Results showed REM efficiency and deep sleep strongly influence memory and emotional stability. Age-related variations highlighted sleep as a key mental-health predictor. The study provides deep insights into REM-cognition relationships. It validates REM metrics for mental-health assessment.

[14] Marco Fabbri et al. (2021) – Measuring Subjective Sleep Quality reviewed subjective sleep-quality measurement tools, with a strong focus on PSQI. They discussed strengths and limitations of self-reported methods and cross-population considerations. The review stressed combining subjective and objective sleep indicators. Their insights guide optimal use of PSQI in research and clinical assessments. This supports integrating questionnaire-based metrics in hybrid systems.

[15] Arumugam et al. (2024) – Bilingual Arabic–English PSQI Reliability tested the reliability of a bilingual (Arabic–English) PSQI among adolescents and young adults. Strong test-retest reliability (ICC = 0.77) and acceptable internal consistency were reported. The study confirmed PSQI's stability across languages and cultures. Findings demonstrated its suitability for bilingual populations. This supports scalable deployment of PSQI-form assessments.

[16] Sallouha et al. (2022) – REM-U-Net for REM Prediction introduced REM-U-Net, a deep-learning architecture for REM stage prediction using EEG/EOG signals. The model achieved high accuracy with low computational cost, suitable for energy-efficient devices. Its design captured both temporal and spatial sleep-signal features. The framework outperformed traditional classifiers. It supports DL-based REM detection in wearable applications.

[17] Arindam Chatterjee et al. (2023) – PSQI in Indian IT Sector , analyzed the factor structure and

sleep quality of PSQI among Indian IT professionals. Their findings revealed high prevalence of

poor sleep linked to work stress and long working hours. Factor analysis confirmed PSQI's reliability in this occupational group. The study emphasized occupational sleep vulnerabilities. It supports PSQI's use in high-stress work populations.

3. Problem Statement

Traditional psychiatric screening involves manual scoring and clinical observation, which are both laborious and not scalable. There is a need for an automated, data-driven, and interpretable system that can assess sleep-related parameters to provide early indication1s of psychiatric risk. The system needs to provide accurate, transparent, and safe data handling within a web-accessible environment.

- Psychiatric disorders often remain undiagnosed until advanced stages
- Sleep abnormalities, especially in REM, precede symptoms
- Lack of affordable, non-invasive screening tools
- “Sleep can speak the language of the mind.”

4. Objectives

1. To design and train an XGBoost model that predicts psychiatric-risk levels using REM sleep and PSQI features.
2. To develop an interactive **web-based interface** using **Next.js** for user data collection and result display.
3. To integrate the **FastAPI backend** for model inference and connect it with **Firebase Firestore** for secure data storage.
4. To implement **continuous integration and deployment (CI/CD)** for consistent updates and testing. And implementing through validation accuracy, reliability, and user accessibility.

5. Methodology

The development follows a modular approach:

1. **Data Preparation**: REM sleep and PSQI data are preprocessed, normalized, and encoded.
2. **Model Development**: An XGBoost classifier is trained and validated using Python 3.10 in Jupyter Notebook.
3. **Backend Integration**: The trained model is exported as a .joblib file and served through FastAPI endpoints for real-time inference.
4. **Frontend Design**: Next.js interface with Tailwind CSS collects inputs and renders results via RESTful API calls.
5. **Database and Deployment**: Firebase Firestore manages records, while Vercel and Render handle frontend and backend deployments respectively.
6. **Testing and Validation**: All modules undergo unit, integration, and system-level testing to ensure accuracy and scalability.

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