AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
Peer Reviewed, Referred & Indexed Journal
E-ISSN:3069-0102
VOL.6, NO. 1(2026)

SLEEP DISORDER PATTERN DETECTION USING SMARTPHONE USAGE

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ABSTRACT

Sleep disorders are increasingly prevalent worldwide and significantly impact physical health, cognitive performance, and overall quality of life. Traditional diagnostic techniques such as polysomnography and clinical observation provide reliable results but require specialized equipment, medical supervision, and high operational costs, which limits accessibility for large populations. With the rapid growth of smartphone usage and the availability of digital behavioral data, smartphones have emerged as a promising platform for passive health monitoring and behavioral analysis. This study proposes a Sleep Disorder Pattern Detection System that leverages smartphone activity data to identify potential sleep disorders using machine learning techniques. The system collects behavioral indicators such as screen on/off events, application usage patterns, device charging habits, and session durations to estimate sleep onset time, wake time, sleep duration, and nighttime interruptions. Feature engineering techniques are applied to transform raw activity logs into meaningful behavioral metrics, which are then processed using a Random Forest classification model. The proposed model categorizes users into three sleep pattern groups: Normal Sleep, Insomnia, and Delayed Sleep Phase Syndrome (DSPS). The system architecture follows a three-tier design consisting of a mobile application developed using React Native, a Node.js and Express-based REST API backend for data management and authentication, and a Python Flask machine learning service responsible for feature extraction and prediction. PostgreSQL is used as the database for storing user activity logs, prediction results, and recommendations. The results demonstrate that smartphone behavioral patterns can provide valuable insights into sleep habits and may support early detection of sleep disorders. This approach offers a scalable, non-invasive, and cost-effective solution for large-scale sleep health monitoring.

Keywords: Sleep Disorders, Smartphone Usage Analytics, Machine Learning, Random Forest, Digital Health Monitoring

I INTRODUCTION

Sleep plays a crucial role in maintaining physical health, emotional stability, and cognitive performance. Insufficient or irregular sleep patterns can lead to several health complications, including cardiovascular disease, depression, obesity, and impaired cognitive functioning [1]. Sleep disorders such as insomnia and delayed sleep phase syndrome affect millions of individuals worldwide and often remain undiagnosed due to the complexity and cost of traditional diagnostic procedures [2]. Conventional diagnostic methods like polysomnography require clinical settings and specialized monitoring equipment, making them inaccessible for continuous or large-scale monitoring [3]. As a result, researchers are exploring alternative approaches that utilize digital technologies for monitoring sleep behavior [4]. Smartphones have become ubiquitous devices and are capable of continuously collecting behavioral data through sensors and application usage patterns [5]. These devices generate large volumes of interaction data such as screen usage, app engagement, and device charging behavior, which can reflect daily routines and sleep habits [6]. Studies have demonstrated that digital behavioral signals can be used to infer lifestyle patterns and health conditions [7]. Smartphone-based monitoring systems provide a non-invasive and cost-effective alternative for collecting behavioral data related to sleep patterns [8]. Machine learning techniques have shown significant potential in analyzing complex behavioral datasets to detect patterns associated with health conditions [9]. The integration of machine learning with mobile sensing technologies enables continuous monitoring of sleep behavior without requiring dedicated medical devices [10]. Behavioral indicators derived from smartphone usage can reveal sleep onset time, wake-up time, and interruptions during sleep periods [11]. This capability allows researchers to develop predictive models that estimate sleep quality and detect abnormalities [12]. The increasing adoption of mobile health technologies has created opportunities for scalable health monitoring solutions [13]. These systems support early identification of sleep disorders and encourage individuals to adopt healthier lifestyle habits [14]. Therefore, smartphone-based sleep monitoring systems have gained attention as an emerging field in digital health research [15].

Recent advancements in artificial intelligence and data analytics have further improved the accuracy of behavioral prediction models [16]. Machine learning algorithms can process large datasets and extract meaningful patterns from behavioral logs generated by smartphone interactions [17]. Feature engineering techniques allow researchers to transform raw smartphone activity logs into structured variables representing user behavior [18]. These features may include nighttime phone usage frequency, late-night application activity, device charging habits, and inactivity periods [19]. Such behavioral indicators are strongly associated with irregular sleep patterns and sleep deprivation [20]. Classification algorithms such as Random Forest, Support Vector Machines, and Neural Networks have been widely applied for health prediction tasks [21]. Among these methods, Random Forest models are particularly effective for behavioral data analysis due to their robustness and ability to handle complex feature relationships [22]. Integrating these models into mobile health platforms enables automated prediction and real-time feedback to users [23]. In addition, mobile applications provide a convenient interface for users to track their behavioral patterns and receive personalized recommendations [24]. Backend server architectures are typically designed using RESTful APIs to manage data communication between mobile clients and machine learning services [25]. Cloud-based databases are used to store large volumes of activity logs and prediction outcomes efficiently [26]. These systems can support continuous data collection and model updates over time [27]. Furthermore, predictive analytics can help healthcare professionals identify early signs of sleep disorders before severe symptoms develop [28]. Digital health monitoring also promotes proactive health management among users [29]. Consequently, integrating smartphone behavioral analytics with machine learning provides a promising solution for scalable sleep disorder detection systems [30].

II LITERATURE SURVEY

Several studies have investigated the relationship between smartphone usage patterns and sleep behavior. Early research demonstrated that late-night smartphone usage significantly influences sleep quality and sleep duration [1]. Researchers have identified strong correlations between prolonged screen exposure and delayed sleep onset [2]. Mobile sensing technologies have been widely adopted to monitor daily human behavior through device interactions [3]. Studies have shown that smartphone logs can reveal patterns associated with circadian rhythms and lifestyle habits [4]. Researchers have used accelerometer data and screen activity logs to estimate sleep periods with reasonable accuracy [5]. Digital phenotyping techniques have emerged as a powerful approach for understanding behavioral health through passive data collection [6]. By analyzing smartphone interaction data, researchers can detect behavioral anomalies associated with sleep deprivation [7]. Several machine learning approaches have been applied to classify sleep patterns based on digital behavior signals [8]. Support Vector Machines have been used to classify sleep quality using smartphone sensor data [9]. Neural network models have also been employed to analyze complex behavioral datasets collected from mobile devices [10]. Random Forest algorithms have gained popularity due to their ability to handle high-dimensional data and provide accurate classification results [11]. Studies indicate that combining multiple behavioral indicators improves prediction accuracy [12]. Researchers have also explored app usage categories as predictors of nighttime activity [13]. Social media usage and entertainment applications have been linked with irregular sleep schedules [14]. These findings highlight the potential of smartphone behavioral data for sleep monitoring and health prediction [15].

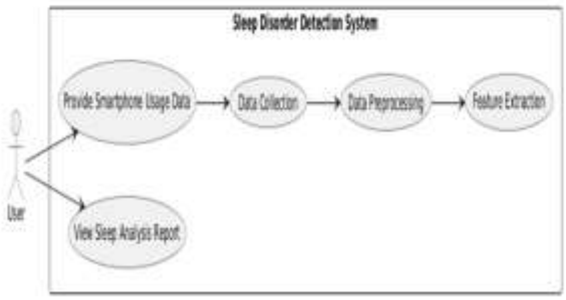
Recent research has focused on integrating smartphone monitoring systems with mobile health applications. Mobile applications enable users to upload activity data and receive sleep analysis reports directly on their devices [16]. Cloud-based architectures are commonly used to store behavioral data and perform machine learning analysis [17]. RESTful APIs facilitate communication between mobile applications and machine learning services [18]. Data preprocessing and feature extraction play a crucial role in improving the performance of predictive models [19]. Behavioral features such as screen activation frequency, nighttime phone usage duration, and device charging patterns are commonly used for sleep prediction [20]. Machine learning models trained on these features can classify sleep patterns into different disorder categories [21]. Several studies have focused specifically on detecting insomnia using behavioral analytics [22]. Others have investigated delayed sleep phase syndrome using smartphone interaction patterns [23]. Hybrid systems combining wearable sensors and smartphone logs have also been explored [24]. However, wearable devices require additional hardware and may reduce user adoption [25]. Smartphone-only monitoring systems offer a more scalable and accessible solution for large populations [26]. Advances in data analytics have enabled real-time prediction and feedback mechanisms within mobile health applications [27]. These systems can provide personalized recommendations for improving sleep habits [28]. Researchers also emphasize the importance of privacy protection and secure data storage in mobile health systems [29]. Overall, previous studies demonstrate that smartphone-based behavioral monitoring combined with machine learning provides a promising approach for detecting sleep disorders at an early stage [30].

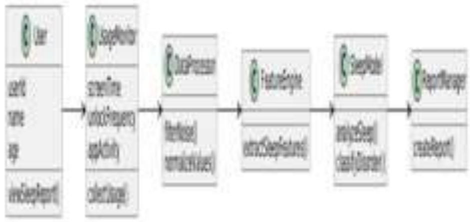
III METHODOLOGY

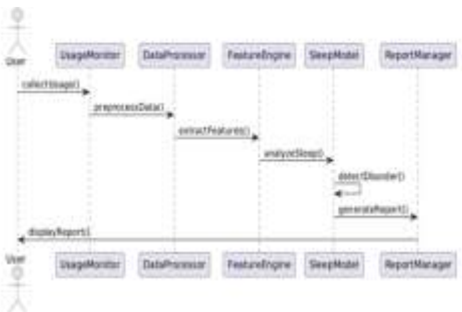
The proposed system for sleep disorder pattern detection utilizes smartphone behavioral data and machine learning techniques to identify abnormal sleep patterns. The methodology begins with the collection of smartphone activity logs generated by users during their daily interactions with mobile devices. These logs include screen on/off events, application usage categories, session duration, device charging behavior, and timestamps associated with user interactions. The collected raw data is transmitted through a mobile application developed using React Native, which securely sends the activity logs to a backend server implemented using Node.js and Express. The backend server performs initial validation, authentication, and storage of the activity data in a PostgreSQL database. After data collection, a preprocessing phase is conducted to remove redundant or inconsistent entries and prepare the dataset for analysis. Feature engineering techniques are then applied to transform raw activity logs into meaningful behavioral indicators such as nighttime phone usage frequency, average screen activation intervals, late-night application usage duration, and inactivity periods representing potential sleep intervals. These engineered features are then forwarded to a machine learning service developed using Python Flask. The classification model used in the system is a Random Forest algorithm, which is trained using labeledbehavioral datasets representing different sleep conditions. The model learns patterns associated with normal sleep behavior, insomnia, and delayed sleep phase syndrome. During prediction, the extracted features are fed into the trained model, which classifies the user's sleep pattern into one of the predefined categories. The prediction results are returned to the backend server and stored in the database. The mobile application then retrieves these results and displays them to the user along with personalized sleep recommendations aimed at improving sleep hygiene and behavioral habits.

IV SYSTEM DESIGN

The proposed system follows a three-tier architecture designed to ensure scalability, modularity, and efficient data processing. The first tier is the mobile application layer, which serves as the user interface and data collection component of the system. This mobile application is developed using React Native to ensure cross-platform compatibility across Android and iOS devices. The application allows users to register, authenticate, and securely upload their smartphone activity logs. The mobile application also enables users to request sleep predictions and view personalized recommendations based on their behavioral patterns. Activity data such as screen usage events, app interaction duration, and charging patterns are collected locally and periodically transmitted to the backend server through RESTful API endpoints. The application interface is designed to provide clear visualization of sleep insights, making the system user-friendly and accessible for individuals without technical expertise. In addition to data upload, the mobile application provides notification features that remind users about healthy sleep habits and encourage consistent monitoring of behavioral patterns.







The second and third tiers of the architecture consist of the backend server and the machine learning service. The backend layer is implemented using Node.js and Express, which manages user authentication, activity logging, prediction requests, and recommendation management. This server acts as an intermediary between the mobile application and the machine learning module. It stores collected behavioral data in a PostgreSQL relational database, which maintains structured tables for users, activity logs, prediction results, and system-generated recommendations. The machine learning tier is implemented as a separate Python Flask service responsible for feature extraction and model inference. When a prediction request is received, the backend server sends relevant activity logs to the Flask service, where data preprocessing and feature engineering are performed. The processed features are then passed to a trained Random Forest classifier that predicts the user's sleep disorder category. The results are returned to the backend server and stored for future reference. This modular architecture allows the machine learning model to be updated independently without affecting the mobile application or backend services, ensuring system flexibility and maintainability.

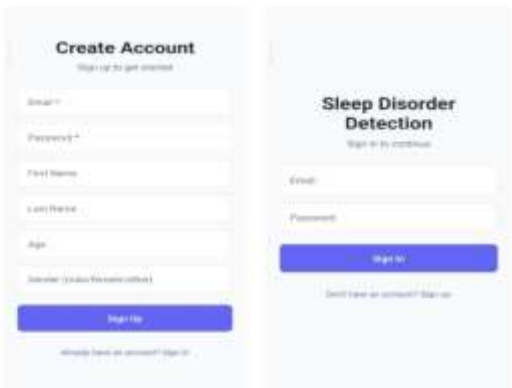
V PROPOSED SYSTEM

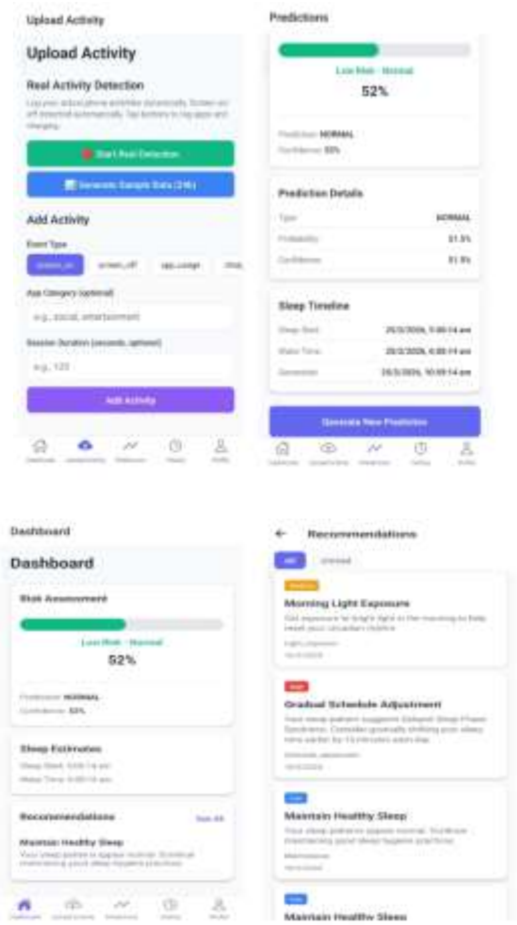
The proposed system introduces an intelligent framework for detecting sleep disorder patterns by analyzing smartphone behavioral data using machine learning techniques. Unlike traditional sleep monitoring approaches that rely on expensive medical equipment or wearable devices, the proposed system utilizes readily available smartphone interaction data to infer sleep patterns. The system collects behavioral indicators such as screen activation times, late-night application usage, device charging behavior, and inactivity periods that may correspond to sleep intervals. These behavioral signals are processed through a machine learning model that identifies patterns associated with sleep disorders. The Random Forest classifier is selected due to its ability to handle complex feature relationships and provide high classification accuracy. By analyzingbehavioral features extracted from smartphone activity logs, the model classifies user sleep patterns into three categories: normal sleep behavior, insomnia, and delayed sleep phase syndrome. The system also incorporates automated feature extraction techniques that convert raw smartphone interaction logs into structured behavioral indicators. These features are essential for enabling the machine learning model to detect irregular sleep patterns and behavioral anomalies effectively. The proposed system emphasizes passive monitoring, meaning that users are not required to manually record their sleep habits or wear additional monitoring devices.

Another key aspect of the proposed system is its integration with a mobile health platform that provides real-time feedback and personalized recommendations. Once the machine learning model predicts the user's sleep pattern category, the system generates recommendations designed to improve sleep hygiene and lifestyle habits. These recommendations may include reducing late-night smartphone usage, maintaining consistent sleep schedules, and minimizing screen exposure before bedtime. The mobile application presents these recommendations in an easy-to-understand format to encourage user engagement and behavioral improvement. In addition, the system maintains historical prediction records that allow users to track changes in their sleep patterns over time. The backend architecture ensures secure data storage and efficient communication between the mobile application and the machine learning service. Privacy protection measures are also incorporated to safeguard user data and maintain confidentiality. The proposed solution aims to provide a scalable and accessible approach to sleep disorder detection, enabling early identification of sleep-related problems and supporting proactive health management for smartphone users.

VI RESULTS & DISCUSSION

The experimental evaluation of the proposed sleep disorder detection system demonstrates the feasibility of using smartphone behavioral data for sleep pattern analysis. The Random Forest classification model was trained using engineered features derived from smartphone activity logs, including nighttime screen usage frequency, session duration, and charging behavior. The results indicate that these behavioral indicators provide meaningful insights into user sleep patterns. The model successfully classified sleep behavior into three categories: normal sleep, insomnia, and delayed sleep phase syndrome. The analysis revealed that users with insomnia exhibited frequent nighttime device interactions and shorter inactivity periods, whereas individuals with delayed sleep phase syndrome showed consistent late-night activity patterns. The system also demonstrated efficient integration between the mobile application, backend server, and machine learning service. The prediction results were delivered to users in real time through the mobile application interface. Overall, the findings confirm that smartphone-based behavioral monitoring can serve as a reliable preliminary screening tool for identifying potential sleep disorders.





VII CONCLUSION

This study presented a smartphone-based sleep disorder detection system that utilizes machine learning techniques to analyzebehavioral patterns derived from smartphone usage data. The proposed system aims to address the limitations of traditional sleep monitoring methods by providing a non-invasive, cost-effective, and scalable approach for detecting potential sleep disorders. By collecting smartphone activity logs such as screen usage events, application interaction patterns, and charging behavior, the system extracts meaningful behavioral features that reflect user sleep habits. These features are processed using a Random Forest classification model to identify sleep pattern categories, including normal sleep, insomnia, and delayed sleep phase syndrome. The three-tier architecture consisting of a React Native mobile application, a Node.js backend server, and a Python Flask machine learning service ensures efficient data collection, processing, and prediction. The integration of machine learning within a mobile health platform allows users to receive real-time sleep analysis and personalized recommendations for improving sleep hygiene. Experimental results indicate that smartphone behavioral data can provide valuable insights into sleep patterns and can serve as an effective preliminary screening tool for sleep disorder detection. Furthermore, the system promotes proactive health management by encouraging users to monitor and improve their sleep habits through personalized feedback. Future work may focus on improving prediction accuracy by incorporating additional behavioral indicators, integrating wearable sensor data, and applying advanced deep learning techniques. Expanding the dataset and conducting long-term clinical validation studies would further enhance the reliability and applicability of smartphone-based sleep disorder detection systems.

REFERENCES

1. Buysse, D. J. (2014). Sleep health: Can we define it? Sleep, 37(1), 9–17.
2. Ohayon, M. M. (2002). Epidemiology of insomnia. Sleep Medicine Reviews, 6(2), 97–111.
3. Iber, C., Ancoli-Israel, S., Chesson, A., & Quan, S. (2007). The AASM manual for the scoring of sleep. American Academy of Sleep Medicine.
4. Lane, N. D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., & Campbell, A. (2010). A survey of mobile phone sensing. IEEE Communications Magazine, 48(9), 140–150.

5. Miller, G. (2012). The smartphone psychology manifesto. Perspectives on Psychological Science, 7(3), 221–237.

6. Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., & Campbell, A. (2014). StudentLife: Assessing mental health using smartphones. UbiComp.

7. Onnela, J., & Rauch, S. (2016). Harnessing smartphone-based digital phenotyping. Neuropsychopharmacology, 41(7), 1691–1696.

8. Abdullah, S., Matthews, M., Frank, E., Doherty, G., Gay, G., & Choudhury, T. (2016). Automatic detection of social rhythms. Journal of Medical Internet Research, 18(3).

9. Bishop, C. M. (2006). Pattern recognition and machine learning. Springer.

10. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

11. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.

12. Kuhn, M., & Johnson, K. (2013). Applied predictive modeling. Springer.

13. Montag, C., & Reuter, M. (2017). Internet addiction. Springer.

14. Exelmans, L., & Van den Bulck, J. (2016). Bedtime mobile phone use and sleep. Social Science & Medicine, 148, 93–101.

15. Hale, L., & Guan, S. (2015). Screen time and sleep among children. Sleep Medicine Reviews, 21, 50–58.

16. Kumar, S., & Nilsen, W. (2012). Mobile health technology evaluation. American Journal of Preventive Medicine, 45(2).

17. Klasnja, P., & Pratt, W. (2012). Healthcare in the pocket. Journal of Biomedical Informatics, 45(1), 184–198.

18. Fielding, R. (2000). Architectural styles and the design of network-based software architectures.

19. Han, J., Kamber, M., & Pei, J. (2011). Data mining concepts and techniques. Morgan Kaufmann.

20. Chen, Z., Lin, M., Chen, F., Lane, N., Cardone, G., Wang, R., & Campbell, A. (2013). Unobtrusive sleep monitoring using smartphones. Pervasive Computing.

21. Cortes, C., &Vapnik, V. (1995). Support vector networks. Machine Learning, 20(3).

22. Hinton, G. (2018). Deep learning—A technology overview. Communications of the ACM, 61(11).

23. Esteva, A., Kuprel, B., Novoa, R., et al. (2017). Dermatologist-level classification using deep neural networks. Nature.

24. Bardram, J. (2013). Activity-based computing for health monitoring. ACM Transactions on Computer-Human Interaction.

25. Richardson, L., & Ruby, S. (2007). RESTful web services. O'Reilly.

26. Stonebraker, M., & Hellerstein, J. (2005). What goes around comes around. Readings in Database Systems.

27. Chen, M., Mao, S., & Liu, Y. (2014). Big data analytics in healthcare. IEEE Access.

28. Topol, E. (2019). Deep medicine. Basic Books.

29. Rooksby, J., Rost, M., Morrison, A., & Chalmers, M. (2014). Personal tracking technologies. CHI Conference Proceedings.

30. Patel, S., Park, H., Bonato, P., Chan, L., & Rodgers, M. (2012). Wearable sensors in rehabilitation. Journal of NeuroEngineering and Rehabilitation.