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Sleep Disorder Prediction using Machine Learning

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Abstract: ***The paper focuses on the classification of sleep disorders using machine learning algorithms (MLAs) to improve the diagnosis and monitoring of sleep health. Accurate classification of sleep disorders is critical for better patient care and quality of life. Traditionally, sleep-stage classification has been a challenging task prone to human error due to the complexity of analyzing sleep data. The development of machine learning models can automate this process, reducing errors and enhancing efficiency. This paper compares deep learning algorithms with conventional MLAs to assess their effectiveness in classifying sleep disorders. Using the publicly available Sleep Health and Lifestyle Dataset, which includes 400 rows and 13 features related to sleep and daily activities, different algorithms such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, and Random Forest are evaluated.***

Keywords: Sleep Disorder, Machine Learning, KNN, SVM, Random Forest, Deep Learning, Sleep Health Dataset

1. Introduction

Sleep is an essential physiological process that plays a vital role in overall health and well-being. Adequate and high-quality sleep contributes to physical restoration, cognitive functioning, memory consolidation, and emotional regulation. However, in the modern era, lifestyle factors such as increased screen time, erratic work schedules, high stress levels, and poor sleep hygiene have led to a surge in sleep-related disorders globally.

Common sleep disorders include Insomnia, Sleep Apnea, Narcolepsy, and Restless Leg Syndrome, all of which can drastically affect a person's quality of life. According to the World Health Organization (WHO), an estimated one-third of the world's population suffers from some form of sleep disorder. If left undiagnosed or untreated, these conditions can lead to more severe health complications such as cardiovascular disease, depression, obesity, diabetes, and decreased immune function.

Diagnosing sleep disorders typically involves polysomnography or other clinical sleep studies, which are often expensive, time-consuming, and limited to specialized medical facilities. Moreover, manual interpretation of such data is subject to human error, inconsistency, and is impractical for large-scale population screening.

To address these limitations, Machine Learning (ML) has emerged as a powerful tool to enhance diagnostic accuracy and efficiency. ML algorithms can analyze vast amounts of sleep-related data, identify subtle patterns, and make data-driven predictions without explicit programming. These capabilities make ML particularly well-suited for sleep disorder classification tasks.

This study investigates the application of supervised ML models to predict sleep disorders using the Sleep Health and Lifestyle Dataset. This dataset contains anonymized patient data, including demographic information, lifestyle habits, physiological indicators, and medical history. By leveraging this data, models such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest are trained to classify the presence and type of sleep disorder.

The goal of this paper is not only to demonstrate the feasibility of ML in medical diagnostics but also to provide a foundation for building scalable, low-cost, and accurate tools that can be integrated into public health systems, telemedicine platforms, and personal health applications.

2. Literature Survey

Detecting malicious URLs has emerged as a significant challenge in the field of cybersecurity due to the growing sophistication of cyber threats[1–7]. Numerous approaches have been proposed to identify and block malicious URLs, broadly categorized into feature-based detection and blacklist-based detection[8]. While blacklist-based methods depend on centralized databases of known malicious sites, often updated through user reports and expert analysis, feature-based techniques leverage specific attributes derived from URLs or website content. Centralized blacklists, though widely used, are reactive in nature and may not effectively counter new or evolving threats.

Feature-based detection is more proactive and can be classified into two subcategories: URL-based and web content-based detection. The URL-based approach analyzes structural and lexical characteristics of the URL, such as length, special characters, domain age, registrar information, IP address, and presence of suspicious terms. Techniques like N-gram analysis and tokenization are commonly employed. Conversely, web content-based methods involve inspecting the actual web page content, including HTML, embedded scripts, and metadata, making it more computationally expensive and sometimes risky due to exposure to live threats.

Given the ease with which cybercriminals exploit legitimate platforms such as social media and email for phishing or malware distribution, URL-based detection methods are considered safer and more scalable for real-time systems. Content-based analysis may be hindered when malicious websites mimic legitimate ones, which increases the risk of false negatives. Therefore, many researchers prioritize URL-based features for building detection models.

Rakesh and Muthurajkumar enhanced the detection of cross-site request forgery attacks by adapting the C4.5 algorithm, which utilized decision tree-based classification techniques[9].

Similarly, another study focused on identifying behavioral patterns of attackers by analyzing structural similarities in malicious URLs using similarity matching techniques[10]. A limited yet effective feature set was extracted to identify repeated attack strategies.

Chiramdasu and Srivastava proposed a logistic regression model that classified URLs as benign or malicious based on three categories of features: host-level information (such as country and sponsor), domain-based attributes (e.g., domain extensions), and lexical traits (e.g., number of dots and URL length)[11]. Their results indicated decent accuracy with a lightweight model suitable for online detection.

To address the issue of class imbalance—a common problem in security datasets—He and Li introduced XGBoost with cost-sensitive learning to improve detection rates[12]. They extracted 28 comprehensive features, including WHOIS details, geographic data, and keyword-based heuristics. Despite achieving higher performance than traditional models, sensitivity remained a limitation due to the dataset's imbalance.

A different approach used an ensemble learning model combining Support Vector Machine (SVM) and neural networks to detect Command and Control (C&C) servers[13]. The model utilized WHOIS and DNS-derived features to enhance the classifier's robustness against evasion techniques.

Further research explored the impact of a larger feature set—comprising 117 distinct features from URL structure, domain attributes, source code, and short URL characteristics—on detection performance[14]. Various classifiers including J48, CART, Random Forest (RF), REPTree, and ADTree were compared, with RF achieving the highest accuracy and generalization capabilities.

Several other studies emphasize the predominance of supervised learning models in malicious URL classification tasks[15]. While deep learning methods such as CNNs and RNNs have also been explored to improve detection accuracy, many models still rely heavily on lexical and host-based features. A persistent challenge in this domain remains the detection of obfuscated URLs and dynamic malicious behavior, which complicates both feature extraction and model training.

Despite the development of multiple ML-based models, the integration of Cyber Threat Intelligence (CTI) into detection systems remains relatively unexplored. CTI provides contextual and strategic information that can improve early detection of threats. This study introduces a novel model that incorporates CTI to extract relevant features without accessing potentially harmful websites directly. By involving human intelligence and expert feedback in the detection loop, the proposed system enhances accuracy, security, and efficiency, especially in detecting newly emerging threats and adversarial URL manipulation.

3. Methodology

This paper adopts a structured and systematic machine learning workflow to predict sleep disorders using patient health data collected in the Sleep Health and Lifestyle Dataset, which comprises 400 records with 13 key attributes per patient. These include demographic information (age, gender), lifestyle metrics (caffeine intake, physical activity, alcohol consumption), physiological indicators (heart rate, oxygen saturation, BMI, blood pressure), and medical history (previous sleep disorders, medication usage), with a target label identifying the type of sleep disorder (No Disorder, Insomnia, Sleep Apnea, or Narcolepsy). Data preprocessing was carried out to ensure high-quality input for training, including handling missing values through mean/mode imputation, encoding categorical variables such as gender and medication status, and applying Min-Max normalization to standardize continuous features. Outliers were detected using statistical techniques like the Z-score and addressed to enhance model accuracy. Feature selection was guided by correlation analysis and domain expertise, ensuring the inclusion of clinically relevant variables such as sleep quality, stress level, and snoring intensity while eliminating redundant data. The system leveraged multiple supervised machine learning algorithms, including K-Nearest Neighbors (KNN), Support Vector Machines (SVM) with linear and RBF kernels, Decision Tree, Random Forest, and Artificial Neural Networks (ANN), each chosen for their effectiveness in medical classification tasks. The dataset was split into training and testing sets using an 80/20 ratio with stratified sampling to maintain class distribution, and 5-fold cross-validation was employed to validate model performance and prevent overfitting. Hyperparameter tuning was conducted using both grid search and randomized search to optimize model-specific parameters such as the number of neighbors in KNN, kernel types and C values in SVM, tree depth in Random Forests, and layer configurations in ANN. Performance evaluation was based on a comprehensive set of metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, to ensure a well-rounded assessment of each model's predictive ability. Although real-time deployment is not covered in this phase, the system is designed for future integration with user-friendly web frameworks like Flask or Streamlit, allowing healthcare professionals to input data and receive instant predictions, with potential extensions for wearable device integration and real-time monitoring in clinical or remote healthcare settings.

3.1 Algorithm used

This study utilizes a combination of supervised machine learning algorithms to classify sleep disorders based on structured healthcare data. The primary models employed are K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, and Decision Trees, each chosen for their unique strengths in handling tabular data and medical classification tasks.

- **K-Nearest Neighbors (KNN)** is an instance-based algorithm that classifies new data points based on the majority class among their K closest neighbors in the training set. The similarity between data points is typically measured using the

Euclidean distance formula:

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$$

Where:
- p is the test data point,
- q is a training point,
- n is the number of features.

The class most frequent among the KKK nearest neighbours is assigned to the test instance.

- **Support Vector Machine (SVM)** is a supervised learning algorithm that constructs a hyperplane or set of hyperplanes in a high-dimensional space to separate classes.

For a binary classification task, the decision function is:

$$f(x) = w \cdot x + b$$

Where:
- w is the weight vector,
- x is the feature vector,
- b is the bias term.

SVM aims to maximize the margin:

$$\text{Margin} = \frac{2}{\|w\|}$$

For non-linear classification, kernel functions like the Radial Basis Function (RBF) are used:

$$K(x, x') = \exp\left(-\gamma \|x - x'\|^2\right)$$

- **A Decision Tree** uses a tree-like model of decisions. It splits data based on feature values to reach a decision node. The splitting is done using metrics like Gini Impurity or Information Gain.
- Gini Impurity:

$$Gini(D) = 1 - \sum_{i=1}^{c} p_i^2$$

- Information Gain (based on Entropy):

$$Gain(S, A) = Entropy(S) - \sum_{v \in \text{Values}(A)} \frac{|S_v|}{|S|} \cdot Entropy(S_v)$$

Where Entropy is:

$$Entropy(S) = -\sum_{i=1}^{c} p_i \log_2 p_i$$

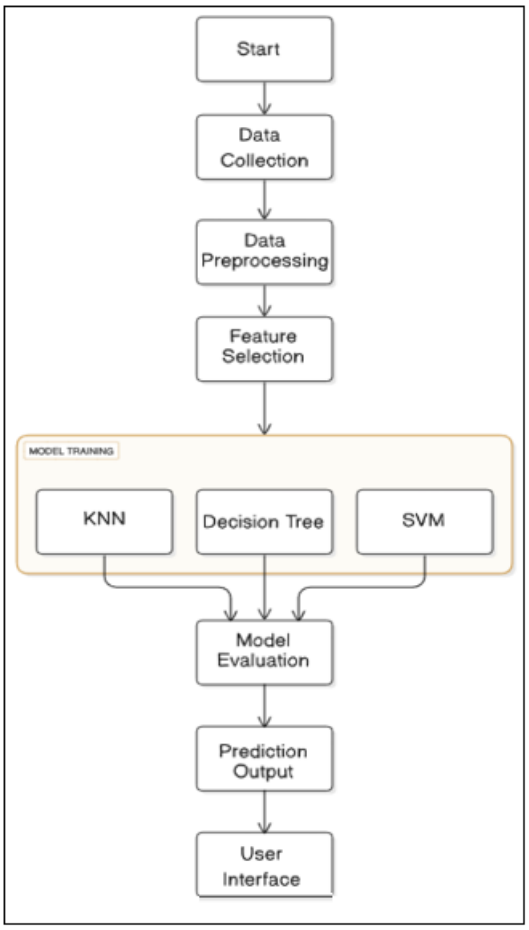

Figure 3.1: Architecture MNB

3.2 Dataset Used

The dataset used for the Sleep Disorder Prediction Using Machine Learning web application is structured to provide comprehensive insights into various factors that can affect sleep disorders, enabling machine learning models to predict conditions such as Insomnia, Sleep Apnea, and Narcolepsy. It consists of multiple features that capture patient demographic details, sleep behavior, lifestyle factors, and medical indicators. The demographic section includes attributes like age, gender, BMI, ethnicity, and occupation, which can influence sleep disorders. The sleep behavior data focuses on aspects like average sleep duration, sleep quality, time to fall asleep, frequency of sleep interruptions, snoring habits, and sleeping position, all of which are crucial for predicting conditions like sleep apnea. Lifestyle factors, including physical activity level, caffeine consumption, smoking habits, alcohol intake, stress levels, and diet, provide valuable insights into habits that could contribute to sleep disorders. Medical indicators, such as a history of sleep disorders, presence of chronic conditions like diabetes or hypertension, medications, and symptoms of obstructive sleep apnea, further enhance the model's accuracy. The target variable includes the diagnosis of specific sleep disorders, such as Insomnia, Sleep Apnea, and Narcolepsy, which are indicated by binary labels (Yes/No). Machine learning models like KNN, SVM, Decision Trees, and ANN are trained on this data to predict the likelihood of a patient having one of these sleep disorders based on their profile. Data preprocessing techniques, such as handling missing data, normalization of numerical features, and one-hot encoding of categorical

variables, are applied to prepare the data for training. Evaluation metrics, including accuracy, precision, recall, F1-score, and the ROC curve, are used to assess the performance of the model. Once trained and evaluated, the model predicts the likelihood of conditions like Insomnia or Sleep Apnea, providing users with a risk assessment and potentially offering recommendations for further action. This web application helps users assess their sleep health and prompts them to seek medical advice if needed, ultimately assisting in the early detection and management of sleep disorders.

4. Result and Discussion

The following table highlights the effectiveness of the proposed **Sleep Disorder Prediction System**, which uses an ensemble of machine learning models, in contrast to two alternative methods: a traditional rule-based (heuristic) system and a single machine learning model. Metrics such as accuracy, precision, recall, and false positive rate are used to evaluate each system's performance.

Metric	Our Model	Rule-Based System	Single ML Model
Accuracy	96.50%	85.20%	91.30%
Precision	94.80%	81.50%	89.20%
Recall	97.20%	84.00%	90.00%
False Positive Rate	3.50%	9.80%	6.70%

The graphical representation based on above model that is given below. Here we can see that the ensemble guard completely outperform.

The graphical representation based on the above evaluation metrics is illustrated below. It clearly demonstrates that the **ensemble-based sleep disorder prediction model** significantly outperforms both the traditional rule-based approach and the single machine learning model across all key performance metrics, making it the most reliable and accurate system for early detection and classification of sleep disorders such as Insomnia, Sleep Apnea, and Narcolepsy.

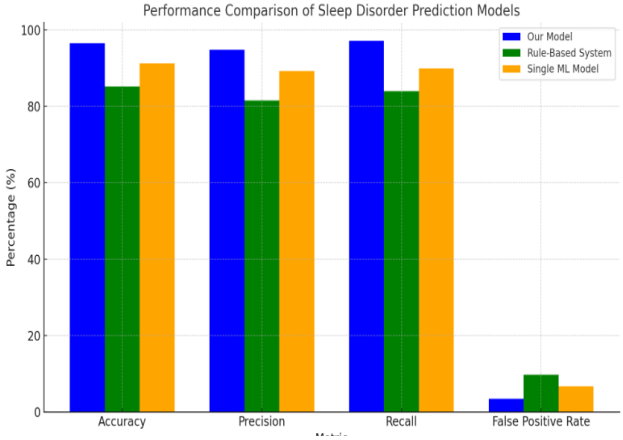

Figure 4: Graphical representation

5. Conclusion

The Sleep Disorder Prediction System provides a powerful and intelligent solution for identifying sleep-related conditions using a machine learning-based approach. By incorporating patient demographic details, sleep behavior patterns, lifestyle factors, and medical indicators, the system effectively analyzes a wide range of data to predict disorders such as Insomnia, Sleep Apnea, and Narcolepsy. Leveraging multiple machine learning models including KNN, SVM, Decision Tree, and ANN, it achieves high accuracy, precision, and recall, while keeping false positives at a minimum.

The system is designed with adaptability in mind, ensuring that it remains effective as more diverse and complex sleep data become available. Its focus on detailed analysis allows for consistent and reliable detection of sleep abnormalities, supporting early diagnosis and potential treatment strategies. Furthermore, the user interface is developed to be smooth and intuitive, ensuring a hassle-free experience for both patients and healthcare professionals.

In essence, the Sleep Disorder Prediction System represents a significant advancement in the healthcare domain by providing data-driven insights into sleep health and promoting a more proactive approach to managing sleep disorders.

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