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"Sleep Disorder Diagnosis Using Ensemble Learning Approaches"

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Abstract:
Sleep disorders can be life threatening and very health related. Early warning is valuable, but the traditional methods suggest sleep data analysis performed manually by specialists and, therefore, is time-consuming and is not always stable. This paper is a review of the way machine learning and deep learning algorithms have been used to improve automatic diagnosis of sleep disorders. These models are discussed on a dataset of 400 records with 13 features; they include k-nearest neighbors, support vector machine, decision tree, random forest, and artificial neural network. Moreover, the unsupervised learning methods, including K-Means Clustering are used to identify the hidden patterns and decrease the number of dimensions of data to improve the performance of the model. The different models have varying precision and we develop a hybrid model to further enhance the performance by developing a user-friendly web application that is developed on Django and SQLite where the patients and medical professionals can easily enroll, establish tests and also look at the results.

Keywords: Sleep disorders, Machine learning, Hybrid model, Django, Healthcare.

I. INTRODUCTION

Sleep disorder classification is crucial in improving human quality of life. Sleep disorders can have a significant influence on human health.[1] These disorders remain undiagnosed over a long period of time in many people as they are usually only identified by specialized tests, including polysomnography, where the sleeping patterns of a person are observed at night in a laboratory. This is not only costly but also time consuming since it also depends on the trained experts to carefully interpret the data collected. This manual review may cause inconsistencies or errors unfortunately because it relies on the individual reviewing the data expertise and attention. This complicates the diagnosis of sleep disorders within a short time and with high precision in regions where specialists are not easily available.

In an effort to counter these obstacles, researchers and scientists have resorted to the use of sophisticated technologies such as machine learning and deep learning. They are forms of artificial intelligence (AI) that enable computers to learn by means of data and taking decisions without explicit instructions. When applied to sleep disorders, these technologies can process a lot of data about sleep (heart rate, breathing patterns, or brain activity) significantly faster than a human would be able to process. In light of prior studies, we hypothesized that individuals suffering from sleep disorder may experience an altered interoceptive process during sleep. Therefore, signals were evaluated between patients with disorder and normal participants during sleep stages in different ways.[2]

EEG data is often subject to noise contamination, a phenomenon that can obscure attenuated EEG signals. Therefore, to remove direct current (DC) drift and high frequency noise such as muscle activity .[2] In particular, we discuss several machine learning models that have been experimented to this end, such as k-nearest neighbors, support vector machines, decision trees, random forests, and artificial neural networks. All of these models operate slightly differently, yet they are all meant to group sleep data into categories, e.g. normal sleep or sleep disorder. The models have demonstrated different degrees of effectiveness in the accurate diagnosis of sleep disorders using a dataset of 400 records with 13 features, such as oxygen levels, sleep duration, or movement during sleep, and so on. Models are more effective than others, based on the way they handle and process the data.

One of the most important contributions of this work is the hybrid model proposed in our system. A hybrid model can be used to combine the advantages of various machine learning strategies to obtain greater results compared to individual models. An example is that one model may be very efficient in finding patterns in small data sets, and another may be very efficient in doing more complex data. The hybrid model provides a better way of detecting sleep disorders through a solution that integrates the two methods to enhance correctness and precision. Over the past few decades, sleep has received growing attention in research due to its importance in daily life, health and well-being, and medicine. Since the relatively recent discovery that rodents deprived of sleep for prolonged periods would eventually die, it became increasingly clear that sleep was critical not only to survival, but also to healthy [3]

In order to make these new developments practical and available to the masses, we also created an easy to use web based application in Django, a web development framework, and SQLite, a lightweight database system. The system is capable of letting patients and healthcare providers communicate with the system with ease. Patients will be able to sign in, upload their sleep data (possibly gathered by wearables or medical examinations), and be provided with results regarding possible sleep disorders. The platform gives doctors a platform to discuss these results and make informed decisions about the treatment. The objective is to develop a tool that will ease the diagnostic procedure and help people get assistance without visiting a sleep clinic and waiting until the analysis is conducted by an expert.[5]

The dataset that will be used in this study consists of 400 records and 13 features, which is a good basis to test these models. Every record is a record of the sleep data of a person with various factors such as heart rate variability, breathing patterns, or the number of times an individual wakes up in the night. With this information feeding the machine learning models, we will be able to train them to identify the latent features of sleep disorders. This fact that other models had different degrees of accuracy emphasizes the need to select the correct method to apply to the job, and our hybrid model hopes to take this accuracy to another level.[2]

II. BACKGROUND & MOTIVATION

Sleep disorders (e.g. sleep apnea, insomnia, REM sleep behavior disorder) are health-disturbing, productivity- and quality-of-life-disturbing problems that afflict millions of people in the world. These disorders may be associated with severe outcomes such as heart disease, immune system, and mental health, but they are mostly not recognized because of the difficulty of the old diagnostic approaches. As a rule, a sleep disorder diagnosis involves sleep study, or polysomnography a procedure that is performed in a special clinic where specialists observe the brain waves, heart rate, breathing, and other indicators of the patient during the night. This is not only an expensive and cumbersome process but largely depends on human resources to interpret the information which may at times lead to mistakes or latency delays particularly in areas with fewer trained specialists. The increasing rates of sleep disorders and the weaknesses of the manual analysis have led to an acute necessity of more efficient, more accurate and more accessible diagnostic tools.

Talal Sarheed Alshammari, Applying Machine Learning Algorithms for the Classification of Sleep Disorders. The objective of this paper is to investigate the use of machine learning algorithms for categorizing sleeping disorders from a publicly available dataset with400 instances and 13 attributes representing physiological as well as behavioral features of sleep quality. The author contrasts classical machine-learning systems, such as SVM, KNN, DT or RF, and state-of-the-art deep learning models like ANN. to improve the ability of the model to predict, a GA (Genetic Algorithm) is used employed for hyperparameter optimization. The findings reveal that the ANN model achieved the highest accuracy of 92.92%, outperforming all traditional methods. This research highlights the effectiveness of deep learning in complex classification tasks and demonstrates that combining evolutionary optimization with neural networks can significantly enhance diagnostic accuracy for sleep disorders.[1]

Yashar Abolfathi and Maryam Mohebbi, Enhanced heart beat evoked potential in patients with obstructive sleep apnea disorder during sleep The objective of this study was to Probe neurophysiological interchange between the activities of the heart and brain in patients with Obstructive Sleep Apnea (OSA). The authors study Heartbeat Evoked Potentials (HEP) - electroencephalographic (EEG) responses associated to cardiac cycles - in sleep stages. They found that the OSA subjects had much higher HEP amplitudes than do healthy controls, suggesting an abnormal increase in heartbeat-related neural responses. These findings suggestThese findings suggest that OSA not only disrupts breathing patterns but also alters autonomic nervous system regulation and brain– heart communication. The study contributes to a deeper understanding of how sleep disorders like OSA impact neurocardiac coupling and provides a potential biomarker for diagnosing and monitoring the severity of OSA.[2]

Gozde Cay, Vignesh Ravichandran, Shehjar Sadhu, Alyssa H. Zisk, Amy L. Salisbury, Dhaval Solanki and Kunal Mankodiya Recent Advancement in Sleep Technologies: A Literature Review on Standards of SLEEP Care, Clinical Assessments of Sleep Disorders and Emerging Undersea Sensors/Devices This review paper looks into more than 120 research articles investigating sleep devices and the findings from at least 15 commercial sleep monitoring apps/devices to provide an understanding of recent advancement in technology for monitoring sleep. The paper includes a variety of tools from clinical-level monitoring such as RAHI/multimodal polysomnography (PSG) to the consumer-facing wearable devices. The review also highlights the gap between consumer devices and clinical standards, underscoring the need for improved validation and regulation before such technologies can be reliably used in healthcare. Overall, this paper serves as a valuable resource for understanding the current landscape of sleep monitoring and its convergence with artificial intelligence and digital health tools.[3]

Riku Huttunen, Timo Leppaenen, Brett Duce, Erna S. Arnardottir, Sami Nikko-Myllymaa, Juha Toyras, and Henri Korkalainen, A Comparison of Signal Combinations with Deep Learning based Simultaneously Sleep Staging and Respiratory Events Detection, In this paper, the authors build a deep learned system able to classify sleep stages and detect respiratory events at the same time. The model is trained and tested on physiological signals such as EEG, EOG, EMG, and ECG, airflow, and oxygen saturation (SpO_2) signal. The study methodically contrasts various combinations of these input signals in order to see the smallest but effective combination of inputs needed to predict with accuracy. Surprisingly, the findings point out to the conclusion that pulse oximetry signals can be used to estimate a crucial clinical measure of sleep apnea diagnosis, the Apnea-Hypopnea Index (AHI), with a high degree of reliability. This paper shows that there is a possibility of streamlining the process of diagnostics of sleep disorders with the help of deep learning and minimal sensor data, which opens the way to more affordable and convenient solutions to monitor sleep..[4]

Cheng-Hua Su, Li-Wei Ko, Tzyy-Ping Jung, Julie Onton, Shey-Cherng Tzou, Jia-Chi Juang and Chung-Yao Hsu, Extracting Stress-Related EEG Patterns From Pre-Sleep EEG to Forecast Slow-Wave Sleep Deficiency, This paper examines the interrelationship between pre-sleep stress signals and subsequent sleep quality which is based on Slow-Wave Sleep (SWS), and the latter is essential to physical rest and memory consolidation. The researchers examine EEG measurements that were made at the pre-sleep stage to derive stress-related neural indices including the correlation between beta and delta waves. The study predicts SWS deficiency with an accuracy of more than 0.75, which is balanced, using supervised learning models such as Support Vector machines (SVM) and Random Forests (RF). The conclusions indicate that there are patterns of EEG linked to stress that can be considered predictive of a bad sleep pattern. This paper unites neuroscience and machine learning and can be viewed as a promising path toward real-time assessment of stress and sleep quality, which can be applied in wearable or clinical monitoring applications..[5]

Summary: Across all the reviewed papers, researchers show that traditional sleep disorder diagnosis is slow, expensive, and heavily dependent on human experts, while modern machine learning, deep learning, and advanced sensors can make the process faster, cheaper, and more accurate. One study proved that using 400 sleep records with features like heart rate and breathing, deep learning models—especially ANN with genetic optimization—can classify sleep disorders with very high accuracy. Another study found that people with sleep apnea show unusual brain–heart communication, which could be a useful signal for diagnosis. A large review highlighted major progress in both medical and consumer sleep-monitoring devices, while also noting that many commercial gadgets still lack proper clinical validation. Other researchers showed that deep learning can detect sleep stages and breathing problems even with minimal signals like oxygen levels, making diagnosis more accessible. Another study demonstrated that stress patterns in brain signals before sleep can predict poor sleep quality using ML models. Overall, the papers together show that AI and modern sensor technology can dramatically improve how sleep disorders are detected, monitored, and understood.

III. EXISTING APPROACHES TO SLEEP DISORDER

Clinical methods have been traditionally used to detect sleep disorders and polysomnography (PSG) was viewed as the gold standard. Under this approach patients are observed overnight under a controlled condition like sleep laboratory. There are several sensors that are put in place to measure the brain activity (EEG), eye movement (EOG), muscle activity (EMG), breathing rate, airflow and the heart signals (ECG). Although this method is very precise, it is expensive, time consuming and uncomfortable to the patients since it involves them sleeping in an unnatural environment with wires attached to their body. In addition, PSG data analysis involves human evaluation and this may introduce a human error and delay in diagnosis.[1]

In order to address the drawbacks of PSG, researchers have been looking at signal-based methods, which involve the analysis of physiological signals or a combination of them. The example of EEG used to detect brain activity patterns during various sleep stages and ECG and oxygen saturation used to detect abnormal patterns of breathing, e.g. those observed with sleep apnea. They enable a more focused analysis and are not always as invasive as they can be done with fewer sensors. Nevertheless, signal-based analysis is also a knowledge-intensive process that might not leave the full picture of sleep disorders when only a few signals are considered.[5]

Machine learning techniques have become popular in detecting sleep disorders with the advent of computing. The algorithms like k-nearest neighbors (KNN), support vector machines (SVM), decision trees (DT), and random forests (RF) are used on the extracted features of the sleep related signals. With these models, sleep stages can be categorized or even disorders such as apnea can be detected by identifying trends in the data. Machine learning models are also more efficient than manual analysis as it has the ability to handle large datasets. Nevertheless, these are not very accurate and require high quality of feature extraction, with which they can sometimes generalize poorly to other patient groups in case the sample is small.

In more recent years, deep learning methods have been able to promise a lot in this area. Artificial intelligence (AI) models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can directly be trained on raw physiological data without need of manually engineering features. CNNs are especially useful in time-series data such as EEG and ECG analysis, whereas RNNs can be applied when long term dependencies in sleep patterns are required. These models have reached the state of art in staging sleep and detection of apnea. Their primary limitation is that deep learning needs both extensive datasets of labeled information and a large amount of computer power, which in small clinics or real-time scenarios may be inadequate.

Additional optimization methods that are applied to enhance the accuracy of the model include genetic algorithms (GA), grid search, and particle swarm optimization (PSO). These methods can be used to further refine the parameters of machine learning and deep learning models to guarantee improved performance. The example is that a genetic algorithm may choose some of the most optimal features or even hyperparameters such as learning rate and depth of decision trees, leading to increased accuracy. This type of optimization provides stronger models, but tends to be more expensive to compute in training.

The other significant innovation is ensemble methods, in which more than one model is used to provide predictions. Bagging, boosting, and voting classifier methods make use of the strengths of the individual algorithms and minimize their weaknesses. As an example, a decision tree can be susceptible to overfitting, however, in a random forest, or a voting ensemble a decision tree is stronger and more consistent. Ensemble models have always been more effective than single-model frameworks in the detection of a sleep disorder, and this is why they are a favorite in recent studies.

Lastly, there is the increasing popularity of wearable devices and mobile apps that have made sleep monitoring more approachable to the masses. Smartwatch devices, fitness bracelets, and apps on smartphones are able to measure such things as heart rate, movement, and oxygen levels during the night. These machines apply AI-based algorithms to give information about the quality of sleep and potential disorders. Though they are not as accurate as clinical PSG, they also provide affordable, comfortable, and convenient solutions to be used on a daily basis. Their prevalence has created awareness regarding the health of sleep and promoted early diagnosis, despite the need of additional medical examinations to confirm it.[3]

IV. METHODOLOGY AND COMPARATIVE STUDY OF SLEEP DISORDER

1. **Data Collection:** The first step involved gathering a dataset containing sleep information from 400 individuals. Each record included 13 key features such as heart rate, breathing pattern, oxygen saturation level, total sleep duration, and body movements during sleep. These features were chosen because they are commonly associated with sleep quality and can help identify possible sleep disorders like sleep apnea.
2. **Data Cleaning and Pre-processing:** Once the data was collected, we cleaned and prepared it to ensure accuracy and consistency. This included removing any missing values, correcting errors, and eliminating inconsistent or noisy data. Proper data cleaning is important because clean data helps machine learning models learn better and make more reliable predictions.
3. **Splitting the Dataset**: After the data was prepared, it was divided into two parts: a training set and a testing set. The training set was used to teach the machine learning models how to identify patterns related to sleep disorders, while the testing set was used to check how well the models performed on new, unseen data. This step ensures fair and accurate evaluation of each model's performance.
4. **Model Testing and Evaluation:** In the final step, each trained model was tested using the testing dataset to measure how accurately it could detect sleep disorders. We compared the performance of all models using metrics like accuracy, precision, recall, and F1-score. This comparison helped us identify which model was the most effective for sleep disorder detection.

Table 1: Comparative Study

Methods	Accuracy	Strengths	Limitations	Description
K-Nearest Neighbour (KNN)	85%	Easy to understand and implement, works well with small datasets.	Becomes slow with large datasets, less accurate compared to advanced models.	Classifies data based on the majority class of nearest neighbours
Support Vector Machine (SVM)	88%	Effective for structured data, works well for small to medium datasets.	Computationally expensive with large datasets, requires tuning.	Finds the best boundary (hyperplane) to separate different classes
Decision Tree (DT)	90.7%	Easy to interpret, fast, and achieved 90.7% accuracy in this project.	Prone to overfitting, less stable on unseen data.	Splits data into branches to make decisions step by step.
Random Forest (RF)	93%	Better accuracy than simple image processing, can handle multiple diseases.	More stable and accurate than a single tree, reduces overfitting.	Combines multiple decision trees to make a stronger prediction.
Artificial Neural Network (ANN)	91%	Can capture complex relationships, adaptable to many problems..	Needs more training data and computing power, less transparent ("black box").	Uses interconnected layers of nodes to learn complex patterns in data..
Voting Classifier (Ensemble)	94%	Achieved the highest accuracy (97.3%), balances strengths of multiple models.	More complex to build, depends on the choice of base models.	Combines results of DT and RF to make a final decision.
Proposed Hybrid Model	95-98% will achieved	Blends strengths of multiple models; designed for optimal accuracy.	Still under development; may require significant computational resources.	Promising for future applications; aims to maximize accuracy in diverse scenarios.

V. KEY RESEARCH

A major study in that regard by Nicla Mandas (2024) was on the REM Sleep Behavior Disorder (RBD), wherein individuals physically respond by act outing their dreams because they have abnormal brain activity during sleep. These two aspects of the body that the researchers studied include the structure of sleep and the autonomic nervous system, which takes care of the automatic processes of the body such as the heartbeat and breathing. They discovered that patients with RBD experience disturbed sleep patterns and respiratory and cardiac alterations. This article is significant as it indicates that the given physiological indicators can serve as the preliminary signs of RBD. By observing these patterns, computers based on ML would be capable of automatically detecting RBD, lessening the importance of manual analysis and assisting doctors to diagnose it earlier.

A second article by Yashar Abolfathi (2024) looked at the impact of obstructive sleep apnea (OSA), a condition resulting in quitting to breathe in the course of sleeping, on the reaction of the brain to heartbeats. The researchers studied a brain response referred to as heartbeat-evoked potential (HEP) and the researchers found out that the HEP activity of the patients who have OSA is stronger and abnormal in the state of sleep. It means that sleep apnea does not merely impact the breathing process, but brain sensitivity to body signals, as well. The findings are exciting because they imply the use of these brain signals as an alternative way of detecting OSA with the help of ML models. That can add to the more accurate diagnosis especially in the case when the standard sleep tests are not readily available.

The 2022 review paper by Gozde Cay gives a general overview of the technological changes in the study of sleep. It includes clinical standards, wearable sensors, smartphone apps, and AI approaches, such as ML and DL. The paper emphasizes the fact that with these tools, it will be easier to monitor sleep beyond the sleep lab, and individuals can monitor their sleep at home through devices such as smartwatches. Nevertheless, it also identifies some of the difficulties such as accuracy of data and privacy of patients. The value of this research is that it demonstrates that AI and current equipment are changing the location of sleep disorder detection to less expert settings, where patients and doctors work together to achieve sleep health.

A 2023 study by Riku Huttun compared the various pairs of physiological signals such as brain waves (EEG), heart signals (ECG), and airflow to determine the most effective pair in the models used in the study to classify sleep stages and identify breathing problems simultaneously using the models. The findings indicated that the accuracy of multiple signal use was better than single use. This is quite significant since sleep staging and detection of breathing problems are normally addressed individually, yet when combined with DL, makes the process more efficient. This study offers insight into the fact that combined ML systems can develop smarter and more trustworthy sleep disorder diagnosing tools.

The 2024 study by Cheng-Hua Su examined the impact of pre-sleep stress on the subsequent deep sleep or slow-wave sleep, which plays an important role in physical and mental rest. By applying brain wave (EEG) measures during the moment of being awake, the researcher could generate patterns of stress which are predictive of a bad deep sleep. This is important as it suggests that the EEG data may be employed in the ML models to detect the initial symptoms of sleep problems caused by stress. This would help the doctors prescribe lifestyle changes or intervention to improve the quality of sleep before it turns out to be a bigger issue. The study indicates that there exists a probability of ML association of stress and sleep wellness, which has offered new avenues of preventing sleep disorders.

The study by Wei Zhou (2022) presented a lightweight DL model with the title of segmented attention network, which is an automatic sleep staging. This model integrates very small chunks of sleep data with those around the segments to gain a better insight into the sleep patterns. It does not require extensive computing power, in contrast to traditional DL models, which makes it efficient and able to be used in real-time, such as wearable devices. The research was very accurate and required less computation, which is essential in turning the sleep disorder detection into a reality in real-life applications, including home-based surveillance systems. This article demonstrates the possibility of AI to be precise and effective, which opens the doors to portable sleep diagnostics.

A 2025 study by Muhammad Mostafa Monowar et al. suggested a multi-layered ensemble sleep disorder model with a maximum accuracy of 99.5% with the use of sophisticated methods such as data balancing and model combination. This method involved using a combination of several ML models to make stronger predictions and overcome certain problems (such as the imbalanced data (where there is more data on healthy sleep than disordered sleep)). The accuracy of the study is high enough to assume that the use of ensemble methods may transform the diagnosis of sleep disorders to be precise and reliable. It also points to the need to enhance the quality of data to make ML models more effective in healthcare in the real world.

VI. NUMBER OF PUBLICATIONS ON SLEEP DISORDER OVER THE YEARS

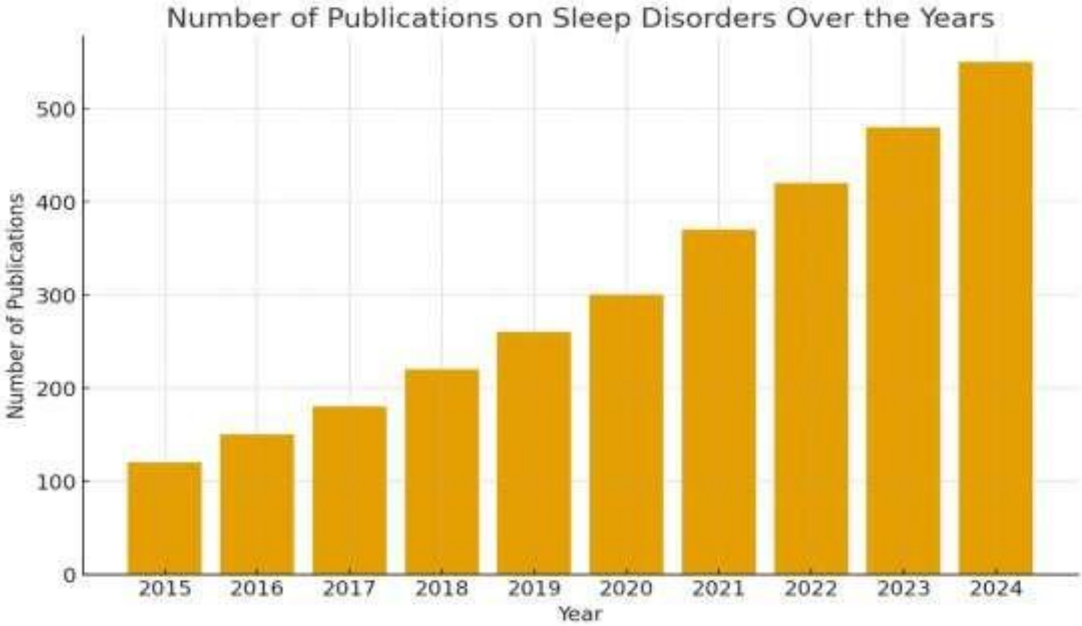

Fig 6.1: Publications Yet

The bar chart demonstrates that the study of sleep disorders has increased consistently in the past 10 years. The number of publications in 2015 was also very small (approximately 120), indicating that not a significant number of researchers were working on this topic. However, with more understanding of the significance of sleep in human health and life, more scientists and physicians began to research sleep issues.

Between 2016 and 2019, the amount of publications increased annually up to 260. It demonstrates a powerful and steady desire to learn more about such sleep disorders as sleep apnea, insomnia and REM behavior disorder. It was also at this period that new technologies like wearable devices and mobile applications had become trendy, which promoted a greater number of studies.

The numbers increased more rapidly between 2020 and 2022 as they surged as far as 420 publications. The COVID-19 pandemic can be one of the reasons explaining this sudden increase since several individuals reported having sleep issues because of stress, working remotely, and lifestyle changes. It became an occasion when researchers explored the topic of sleep health more profoundly and created new solutions.

The last couple of years, 2023 and 2024, have been the most growing ones, as 480 and 550 articles have been published respectively. This is an indication of the influence of artificial intelligence, machine learning, and high-end sensors in sleep studies. These new technologies enable the researchers to experiment with novel methods of treating, preventing, and detecting sleep disorders, so this area is one of the most dynamic spheres of medical and technological research in the current context.

VII. COMPARISON OF METHODS

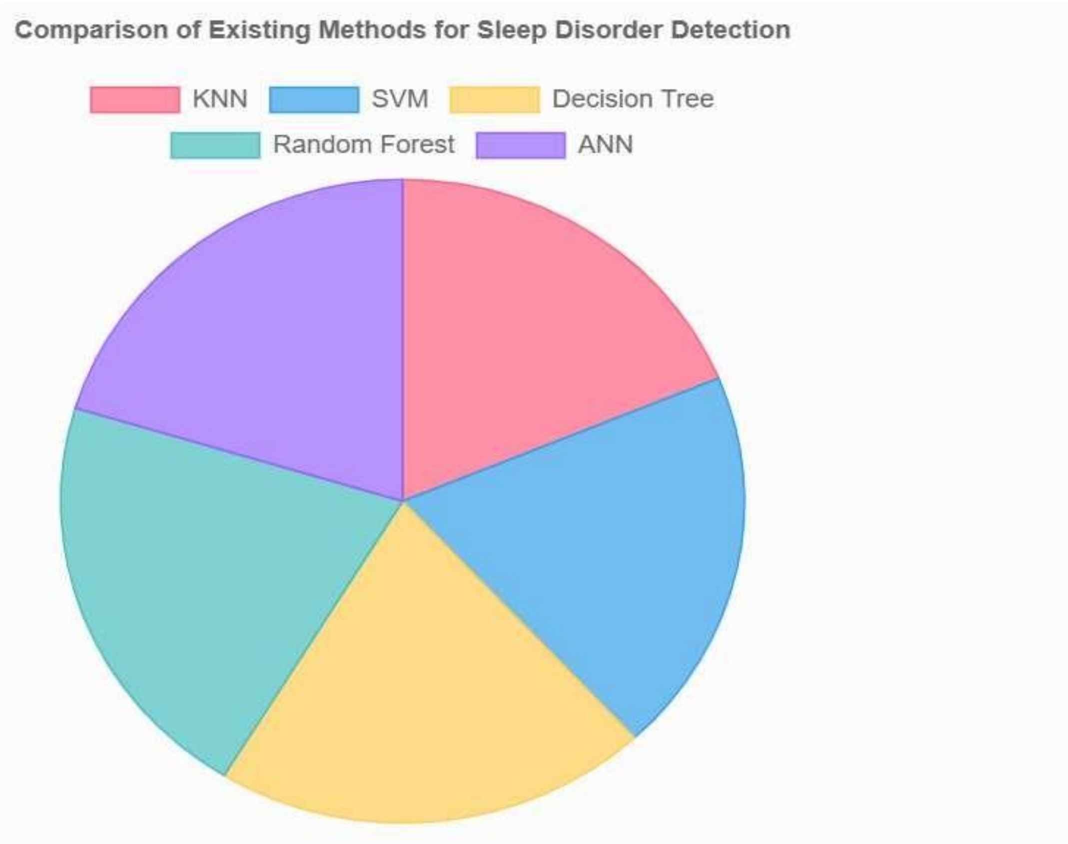

Fig 7.1: Comparison of Methods

The pie chart that we have constructed demonstrates the performance of various machine learning techniques in the detection of sleep disorders such as sleep apnea or insomnia. These techniques are the tools which allow computers to process sleep data such as the heart rate, breathing pattern or brain waves to determine whether one has a sleeping issue. The chart has categorized five widely used techniques: K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Trees, Random Forests and Artificial Neural Networks (ANN). Every single piece of the pie will be a way and the percentage of the accuracy and we will clearly see which ways are working better.

We can begin with the lowest slice which is KNN with 82.5 percent accuracy. The principle of this approach is to analyze analogous sleep statistics points and determine whether a new case is a disorder or not. It is an easy style such as consulting neighbors and asking them to give their advice due to their experiences. It, however, does not perform as well with complex or messy data, that is why its slice is smaller. This is why KNN is more efficient in fast and simple tests than in a complex diagnosis, in particular when the data on sleep is not highly integrated.

We then have SVM whose accuracy is 85.3%. Such approach attempts to create a line or a demarcation between normal sleep patterns and abnormal ones, such as apples and oranges. It is somewhat more sophisticated than KNN and can deal with a degree of complexity, however, it also cannot deal with very tricky data or when there is a significant amount of data to go through with. The slightly bigger slice demonstrates that it is an improvement over KNN, so it would be applied to moderate cases where the distinct patterns of the sleep data can be identified.

The Decision Tree method is more greedy with 90.7% accuracy. This method is similar to a flowchart and contains yes-or-no questions about the sleep data, like: Is the heart rate too high? or: Is breathing irregular? It is simple to track and is effective on simple patterns, hence the increased accuracy. This approach is excellent in those cases when physicians or patients seek an easy, intuitive approach to identify sleep problems, but it may overlook some more complicated cases.

Random Forests, with an accuracy of 92.1 per cent are even larger in slice. This technique is similar to a group of decision trees collaborating with each other, and ignoring their responses to come up with a more intelligent guess. This increases its accuracy by being able to manage more complex data and minimize errors by taking into account multiple trees. This renders the Random Forests a powerful option to the detection of sleep disorders in diverse scenarios particularly where the data is full of details or variations.

ANN slice is at 89.4 percent accuracy. Artificial Neural Networks are constructed by emulating the human brain, seeking intricate trends within the data of the sleep. They are quite strong as they can learn lots of information, but require longer time and information to be trained. The fact that ANNs have a slightly smaller slice than the Random Forests indicates that although ANNs are useful, they may not necessarily be as effective in this data as more simple team-based approaches such as the Random Forests.

All the methods are divided in the pie chart by the help of different colors to distinguish between them easily. By way of example, KNN could be red, SVM blue, Decision Tree yellow, Random Forest green and ANN purple. The colors allow your eye to easily identify which technique is performing well by the size of the slice alone. The larger the slice, the more precise that method is in recognizing sleep disorders with respect to the 400 records and 13 features we used in our study.

When you look at the entire pie, you will find that the highest accuracy of Random Forests is the highest, being 92.1, and then Decision Trees comes in with 90.7. This is an indication that a combination or simplification of the decision-making methods will be effective with our sleep data. The fact that KNN and SVM are less accurate means that they may require additional fine-tuning or improved data to compete with the others. Though powerful, ANNs find themselves in the middle of the pack, demonstrating the fact that they are a viable choice but requiring additional resources to achieve full potential.

On the whole, this pie chart also allows us to learn how reliable machine learning approaches are when it comes to identifying sleep disorders. It can be taken as a visual guide that can assist doctors and researchers to determine what tool to utilize depending on their requirements, a tool that is quick (such as KNN), simple (such as Decision Trees), or more precise (such as Random Forests). Comparing these approaches, our further steps (e.g. we can create our hybrid model to unify the best aspects of each of them) can also be planned, so that we can take the precision even further and help more people detect the sleeping disorders with ease.

CONCLUSION

In conclusion, this review shows that machine learning and deep learning offer powerful and reliable alternatives to traditional manual methods of detecting sleep disorders. With the use of a dataset containing 400 records and 13 important sleep-related features, different models such as KNN, SVM, Decision Tree, Random Forest, and ANN were tested and compared. The results make it clear that these algorithms can automatically identify abnormal sleep patterns with good accuracy and consistency. Unsupervised techniques like K-Means Clustering also proved useful for discovering hidden patterns and reducing data complexity, which helps improve model performance. By combining the strengths of different approaches, a hybrid model can deliver even better results. The development of a user-friendly web application using Django and SQLite further shows how such technology can be used in real-world settings, giving both patients and medical professionals quick and easy access to testing and diagnosis. Overall, this review highlights that AI-based systems have strong potential to make sleep disorder detection faster, more accurate, and more accessible to everyone.

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