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Machine Learning Approaches To Classify And Diagnose Sleep Disorders

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Abstract: Classifying sleep disorders plays a vital role in enhancing the quality of human life, as conditions like sleep apnea can have a profound impact on overall health. Expert-based sleep-stage classification is a complex and error-prone task, often susceptible to human mistakes. The development of robust machine learning algorithms (MLAs) for sleep disorder classification requires the ability to analyse, monitor, and diagnose sleep-related issues accurately.

Our model compares deep learning techniques with traditional machine learning algorithms to classify sleep disorders. We propose an optimized approach for sleep disorder classification, evaluating the model using the publicly available Sleep Health and Lifestyle Dataset. Optimization of the algorithms was performed using a genetic algorithm to fine-tune the parameters of various machine learning models. The study includes a comparative analysis of the proposed algorithm against state-of-the-art methods for classifying sleep disorders. The dataset consists of multiple features related to sleep patterns and daily activities. We assessed several machine learning and deep learning techniques. Experimental results show notable differences in the performance of the evaluated algorithms, with the proposed method achieving superior results.

Index Terms - Sleep Disorder Classification, Machine Learning Algorithms, Deep Learning, Sleep Apnea, Health Monitoring, Genetic Algorithm Optimization, Automated Diagnosis, Sleep Health Dataset, Feature Extraction, Artificial Neural Networks (ANN), Machine Learning Optimization, Sleep Stage Classification, Predictive Modeling, Health Data Analysis, Precision Medicine, Sleep Disorder Diagnosis, Data-driven Health Solutions, Sleep Pattern Recognition, Supervised Learning

I. Introduction

Sleep disorders significantly affect human health and quality of life. Currently, expert-based manual sleep-stage classification methods are widely used. These methods rely on human interpretation of sleep patterns, often using data such as electroencephalograms (EEGs) and other physiological signals. However, this process is inherently complex, subjective, and prone to errors due to human fatigue and variability in expertise. To overcome these challenges, researchers have explored the use of traditional machine learning algorithms for sleep disorder classification. These algorithms can handle large datasets, automate diagnosis, and reduce human intervention. However, their effectiveness heavily depends on feature selection, and they often struggle with handling unstructured and high-dimensional data.

Recently, deep learning approaches have shown promise in sleep disorder classification due to their ability to extract meaningful features automatically and perform well on high-dimensional datasets. Some methods employ neural networks, but optimization remains a critical issue. Despite advancements, current systems still lack robustness, interpretability, and high accuracy, especially for diverse datasets. Expert-based systems are prone to human error and variability. Traditional ML algorithms struggle with high-dimensional and unstructured data. Optimization challenges in existing deep learning models limit performance. Limited interpretability of ML and DL results affects trust in automated systems. Current systems lack adaptability to diverse and heterogeneous datasets Sleep disorders, such as sleep apnea, impact physical and mental health, necessitating accurate diagnosis and management. Manual classification of sleep stages by experts is subjective, time-consuming, and prone to errors. Traditional machine learning approaches for sleep disorder diagnosis depend heavily on feature selection and preprocessing, limiting their generalizability. While deep learning techniques show potential by automating feature extraction, their optimization challenges often lead to suboptimal accuracy. Furthermore, current solutions lack robust generalization capabilities across diverse datasets. This creates a critical gap in developing systems that are both accurate and interpretable for clinical use.

The limitations in existing methods hinder the development of reliable and efficient diagnostic tools, posing a significant problem for effective sleep disorder management. Bridging the gap requires an optimized, scalable, and interpretable machine learning approach that can analyze complex data patterns and perform well across varied datasets. Existing sleep disorder classification methods suffer from low accuracy, poor generalization, and interpretability issues, making them unsuitable for robust clinical application. This study aims to address these limitations by developing an optimized, scalable, and accurate machine learning model, fine-tuned with genetic algorithms, to classify sleep disorders using diverse datasets effectively.

II. Proposed system

Sleep disorders are increasingly recognized as significant health concerns, impacting millions of individuals globally. With advancements in technology, machine learning (ML) has emerged as a powerful tool to classify and diagnose these disorders. The proposed system leverages machine learning approaches to accurately identify and diagnose various sleep disorders, such as insomnia, sleep apnea, narcolepsy, and restless legs syndrome. This system integrates data-driven methods, utilizing patient data, polysomnography (PSG) recordings, wearable device outputs, and other biomarkers to deliver precise diagnostic outcomes. By automating and enhancing traditional diagnostic methods, this approach has the potential to revolutionize sleep medicine.

The proposed system consists of multiple components designed to ensure accurate classification and diagnosis of sleep disorders. At its core, the system relies on data collection, preprocessing, feature extraction, model training, and validation. First, data is collected from diverse sources, such as PSG, wearable devices, and patient-reported symptoms. Polysomnography is considered the gold standard for diagnosing sleep disorders, capturing various physiological parameters like brain activity, oxygen levels, heart rate, and breathing patterns. However, wearable devices provide an alternative means of data collection, offering continuous monitoring of sleep patterns in real-world settings. This combination of data sources allows the system to build a comprehensive profile of an individual's sleep behavior.

Data preprocessing is a critical step in the system to ensure the quality and reliability of the input data. Preprocessing involves cleaning the data by removing artifacts, handling missing values, and normalizing the datasets. Given the variability in data types and sources, advanced preprocessing techniques, such as signal denoising and segmentation, are employed to extract meaningful information. This step is vital for ensuring that the input data is suitable for subsequent machine learning algorithms.

Feature extraction plays a central role in the proposed system. The system identifies and extracts key features from the raw data, such as sleep stages, arousal indices, oxygen desaturation levels, and heart rate variability. These features serve as inputs to the machine learning models. Advanced techniques, including time-series analysis, frequency-domain analysis, and deep learning-based feature extraction, are employed to capture intricate patterns in the data. For instance, convolutional neural networks (CNNs) are particularly effective in analyzing PSG data, while recurrent neural networks (RNNs) excel in processing time-series data from wearable devices.

Once the features are extracted, the system trains machine learning models to classify and diagnose sleep disorders. Supervised learning algorithms, such as support vector machines (SVM), decision trees, and ensemble methods like random forests, are widely used for classification tasks. These models are trained on labeled datasets, where the outcomes of sleep studies serve as ground truth labels. Deep learning models, such as CNNs and long short-term memory (LSTM) networks, are increasingly utilized to improve classification accuracy, especially when dealing with large and complex datasets. The system employs rigorous training and cross-validation techniques to optimize model performance and prevent overfitting.

Model validation and testing are crucial to ensure the reliability and generalizability of the proposed system. The system uses validation datasets to fine-tune hyperparameters and test datasets to evaluate overall performance. Metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve are used to assess the model's effectiveness. Additionally, explainability techniques, such as SHAP (Shapley Additive Explanations) values, are incorporated to provide insights into the model's decision-making process, enhancing trust and transparency.

The advantages of the proposed machine learning-based system for classifying and diagnosing sleep disorders are manifold. First and foremost, it offers significant improvements in diagnostic accuracy compared to traditional methods. Conventional diagnostic approaches often rely on manual interpretation of PSG data, which is time-consuming, subjective, and prone to human error. By automating this process, the system minimizes diagnostic discrepancies and enhances the reliability of results.

Another key advantage is the scalability of the system. The integration of wearable devices allows for large-scale data collection, enabling population-wide screening and early detection of sleep disorders. This is particularly beneficial in regions with limited access to sleep clinics and specialized healthcare professionals. Patients can use wearable devices in their homes, reducing the need for in-lab sleep studies and associated costs. The ability to diagnose sleep disorders remotely also makes the system more accessible to individuals in underserved areas.

The proposed system also enables personalized healthcare by tailoring diagnostic outcomes to individual patients. Machine learning models can analyze patient-specific data to provide customized insights into the underlying causes of sleep disorders. For example, the system can differentiate between obstructive sleep apnea and central sleep apnea based on distinctive patterns in breathing and oxygen levels. This level of precision supports targeted treatment plans, improving patient outcomes and quality of life.

Furthermore, the system has the potential to enhance patient monitoring and follow-up. Machine learning algorithms can continuously analyze data from wearable devices, providing real-time feedback to patients and clinicians. This facilitates early detection of changes in sleep patterns, enabling timely interventions and reducing the risk of complications associated with untreated sleep disorders. For instance, patients with sleep apnea can receive alerts if their condition worsens, prompting adjustments in treatment settings or adherence to continuous positive airway pressure (CPAP) therapy.

In addition to its clinical benefits, the proposed system contributes to advancing research in sleep medicine. The availability of large-scale, high-quality data opens new avenues for understanding the underlying mechanisms of sleep disorders. Machine learning techniques can identify novel biomarkers and uncover complex relationships between various physiological and behavioral factors. This knowledge can inform the development of new diagnostic criteria, therapeutic strategies, and public health initiatives.

The cost-effectiveness of the system is another notable advantage. Traditional sleep studies conducted in clinical settings are expensive and resource-intensive. By leveraging machine learning and wearable technology, the system reduces the financial burden on both patients and healthcare providers. The ability to perform remote diagnostics and continuous monitoring eliminates the need for frequent visits to sleep clinics, saving time and resources.

Despite its numerous advantages, the proposed system also faces challenges that must be addressed to ensure its success. One major challenge is data privacy and security. Given the sensitive nature of sleep data, robust measures must be implemented to protect patient confidentiality and comply with regulatory standards. Encryption, anonymization, and secure data storage are essential to mitigate the risk of data breaches.

Another challenge is the variability in data quality and consistency. Differences in device specifications, patient compliance, and environmental factors can introduce noise and bias into the datasets. Standardizing data collection protocols and incorporating quality control measures are critical to overcoming this limitation. Moreover, the system must account for demographic and cultural differences that may influence sleep patterns and disorder prevalence.

In conclusion, the proposed machine learning-based system for classifying and diagnosing sleep disorders represents a significant advancement in sleep medicine. By combining data-driven approaches, advanced algorithms, and wearable technology, the system offers a highly accurate, scalable, and cost-effective solution to address the growing burden of sleep disorders. Its potential to enhance diagnostic accuracy, accessibility, and personalized care makes it a valuable tool for clinicians, researchers, and patients alike. As the system evolves, addressing challenges related to data privacy, standardization, and inclusivity will be crucial to realizing its full potential. Ultimately, this innovative approach has the potential to transform the field of sleep medicine, improving the health and well-being of individuals worldwide.

III. Methodology:

Sleep disorders are increasingly recognized as significant health concerns, impacting millions of individuals globally. With advancements in technology, machine learning (ML) has emerged as a powerful tool to classify and diagnose these disorders. The proposed system leverages machine learning approaches to accurately identify and diagnose various sleep disorders, such as insomnia, sleep apnea, narcolepsy, and restless legs syndrome. This system integrates data-driven methods, utilizing patient data, polysomnography (PSG) recordings, wearable device outputs, and other biomarkers to deliver precise diagnostic outcomes. By automating and enhancing traditional diagnostic methods, this approach has the potential to revolutionize sleep medicine.

The proposed system consists of multiple components designed to ensure accurate classification and diagnosis of sleep disorders. At its core, the system relies on data collection, preprocessing, feature extraction, model training, and validation. First, data is collected from diverse sources, such as PSG, wearable devices, and patient-reported symptoms. Polysomnography is considered the gold standard for diagnosing sleep disorders, capturing various physiological parameters like brain activity, oxygen levels, heart rate, and breathing patterns. However, wearable devices provide an alternative means of data collection, offering continuous monitoring of sleep patterns in real-world settings. This combination of data sources allows the system to build a comprehensive profile of an individual's sleep behavior.

Methodology

The methodology of the proposed system is structured into five key stages: data collection, preprocessing, feature extraction, model development, and validation. Each stage is designed to systematically process and analyze sleep data to ensure accurate classification and diagnosis.

1. Data Collection

Data collection forms the foundation of the system. Sleep-related data is gathered from multiple sources, including polysomnography (PSG) studies, wearable devices, and patient-reported outcomes. PSG is a comprehensive diagnostic tool that records a range of physiological signals, including electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), heart rate, and respiratory effort. Wearable devices, on the other hand, provide real-world, longitudinal data on sleep patterns, such as movement, heart rate variability, and oxygen saturation levels. Combining these diverse data sources enables a holistic understanding of sleep behavior, accommodating both clinical and real-world perspectives.

2. Data Preprocessing

Preprocessing is essential to ensure the quality and consistency of the input data. Raw sleep data often contains noise, artifacts, and missing values that can compromise the accuracy of machine learning models. The preprocessing stage involves several steps:

- **Artifact Removal:** Techniques such as bandpass filtering are applied to remove noise and irrelevant signals from the data.
- **Handling Missing Data:** Missing values are imputed using statistical methods, such as mean imputation or advanced approaches like matrix factorization.
- **Normalization:** Data is standardized to ensure uniformity across different scales and sources.
- **Segmentation:** Time-series data is segmented into smaller windows to facilitate feature extraction and model training. This is particularly useful for analyzing sleep stages and events, such as apneas and arousals.

3. Feature Extraction

Feature extraction is a critical step that transforms raw data into meaningful inputs for machine learning models. Relevant features are derived from physiological signals to capture patterns associated with sleep disorders. Commonly extracted features include:

- **Sleep Stages:** Derived from EEG data, these features identify transitions between wakefulness, REM, and non-REM sleep.
- **Respiratory Events:** Features such as apnea-hypopnea index (AHI) and oxygen desaturation index (ODI) are computed to assess breathing irregularities.
- **Heart Rate Variability (HRV):** Extracted from ECG or wearable device data, HRV provides insights into autonomic nervous system activity during sleep.
- **Movement Patterns:** Derived from actigraphy data, these features help identify restlessness and periodic limb movements.

Advanced techniques, such as wavelet transforms, principal component analysis (PCA), and deep learning-based feature extraction, are employed to capture complex, non-linear patterns in the data. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are particularly effective in identifying spatial and temporal dependencies, respectively.

4. Model Development

The core of the system lies in its machine learning models, which are trained to classify and diagnose sleep disorders. The model development process involves:

- **Algorithm Selection:** The choice of algorithms depends on the complexity and type of data. Commonly used algorithms include support vector machines (SVM), random forests, and gradient boosting machines. Deep learning models, such as CNNs, LSTMs, and hybrid architectures, are employed for large, multi-dimensional datasets.
- **Training:** Models are trained on labeled datasets, where ground truth labels are derived from PSG studies or clinical diagnoses. Supervised learning techniques are used to map input features to specific sleep disorders.
- **Hyperparameter Optimization:** Techniques such as grid search and Bayesian optimization are applied to fine-tune model parameters for optimal performance.

To ensure robustness, the models are trained using cross-validation techniques. For example, k-fold cross-validation divides the dataset into multiple subsets, ensuring that the model generalizes well to unseen data.

5. Model Validation and Testing

Validation and testing are critical to evaluating the performance and reliability of the proposed system. The validation process involves:

- **Performance Metrics:** Metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve are used to assess model performance.
- **External Validation:** The model is tested on independent datasets to evaluate its generalizability across diverse populations and settings.
- **Explainability:** Tools like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are used to interpret model predictions, enhancing transparency and clinical trust.

Deployment and Feedback

Once validated, the system is deployed for real-world use. Data from wearable devices and patient feedback are continuously integrated into the system to improve its performance over time. This iterative process ensures that the system remains adaptive and responsive to new developments in sleep medicine.

Advantages of the Methodology

The systematic approach outlined above ensures that the proposed system is:

- **Comprehensive:** By integrating data from multiple sources, the system captures a wide range of sleep-related parameters.
- **Accurate:** Rigorous preprocessing, feature extraction, and model validation enhance diagnostic accuracy.
- **Scalable:** The use of wearable devices facilitates large-scale, population-wide screening.
- **Personalized:** Machine learning models are tailored to individual patient data, supporting customized treatment plans.
- **Efficient:** Automation reduces the time and cost associated with traditional sleep studies.

In conclusion, the methodology of the proposed system combines advanced data analytics, machine learning, and clinical expertise to address the challenges of sleep disorder classification and diagnosis. By following a structured and iterative process, the system ensures high accuracy, scalability, and adaptability, paving the way for improved patient care and outcomes.

4.1.UML DIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non- software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modelling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

4.1.1.Use case diagram

A use case diagram in the Unified Modelling Language (UML) is a type of behavioural diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

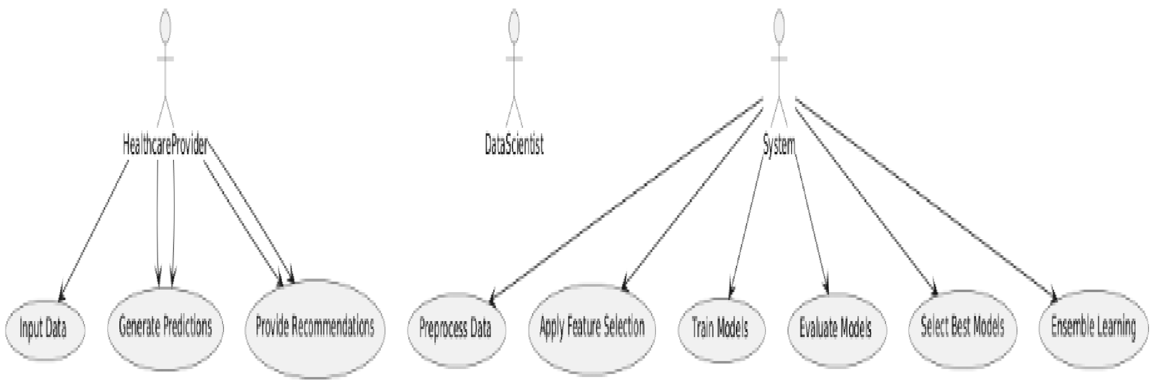


Fig 1:-Use Case diagram

4.1.2.Class Diagram

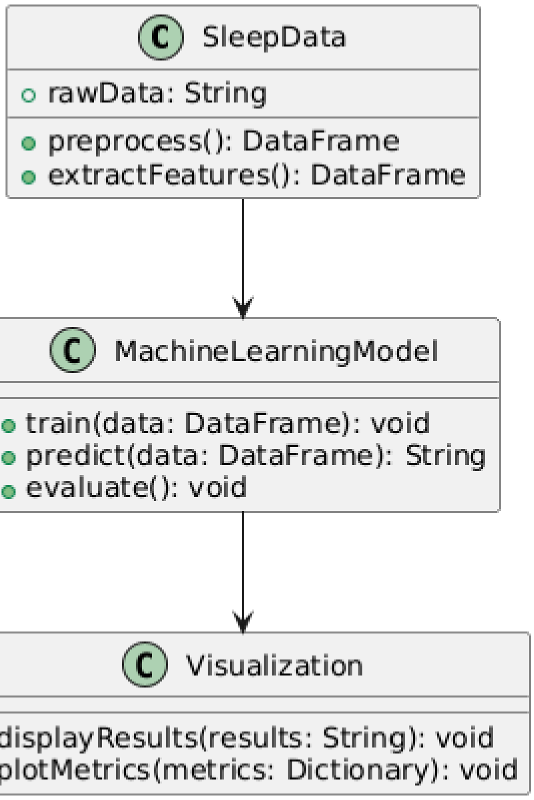


Fig.2. Class diagram

The class diagram is used to refine the use case diagram and define a detailed design of the system.
The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.

4.1.3.Activity diagram

The process flows in the system are captured in the activity diagram. Similar to a state diagram, an activity diagram also consists of activities, actions, transitions, initial and final states, and guard conditions.
An activity diagram is a system-modelling and design tool used, among other things, to portray workflows, decision points, and other processes inside a system. A diagram that gives a very efficient description of a system's dynamic features-activities originating from UML, makes them focus on the flow of control and data between different operations-in particular for sequential, parallel, or conditional workflows.An activity diagram begins with an initial node, which represents the commencing point of a process. Activities, which are drawn in rounded rectangles, depict those tasks or procedures that exist within the system. These activities are connected with arrows that represent the flow of control or data from one action to the next.

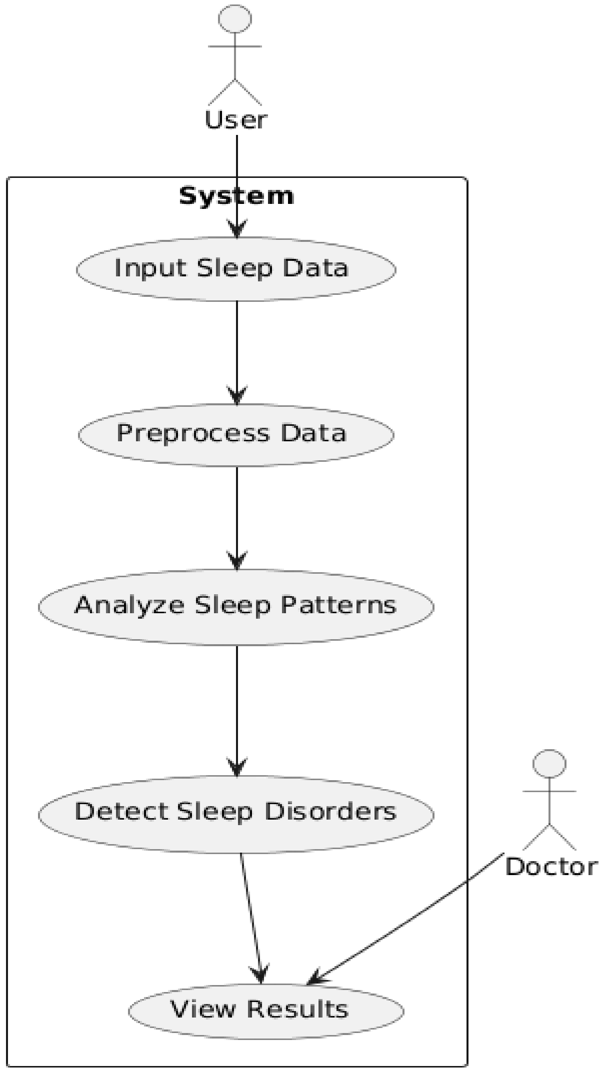


Fig.3. Activity diagram

4.4.Dataflow diagrams

To create a Data Flow Diagram (DFD) for the proposed thyroid disorder diagnosis system, we would include the following levels:

Level 0: Context Diagram

This diagram represents the system as a single process, showing its interaction with external entities such as patients, clinicians, and the database.

Entities and Flow:

1. **Patient**: Provides clinical, biochemical, and imaging data.
2. **Clinician**: Receives diagnostic results and insights.
3. **Database**: Stores patient data and diagnostic results.

Process:

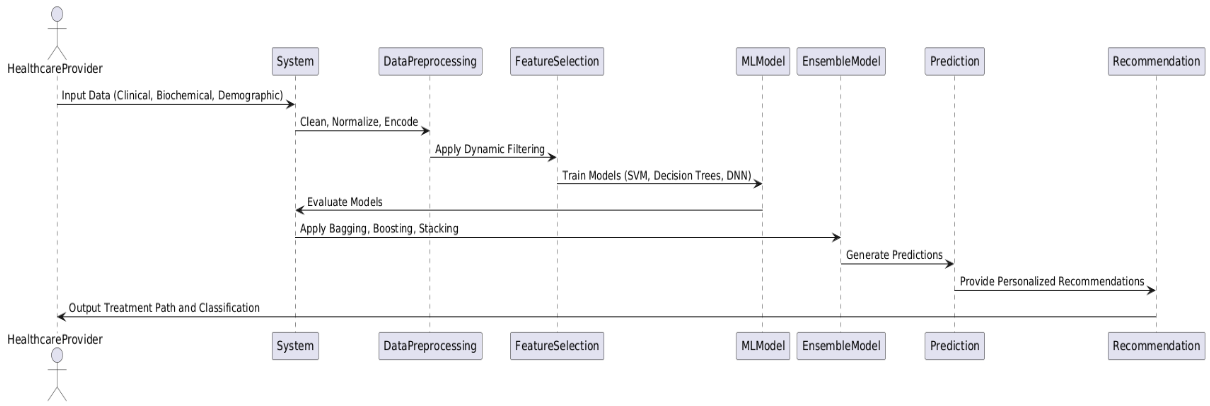
- The system takes patient data as input and sends diagnostic results back to clinicians and the database.

Steps:

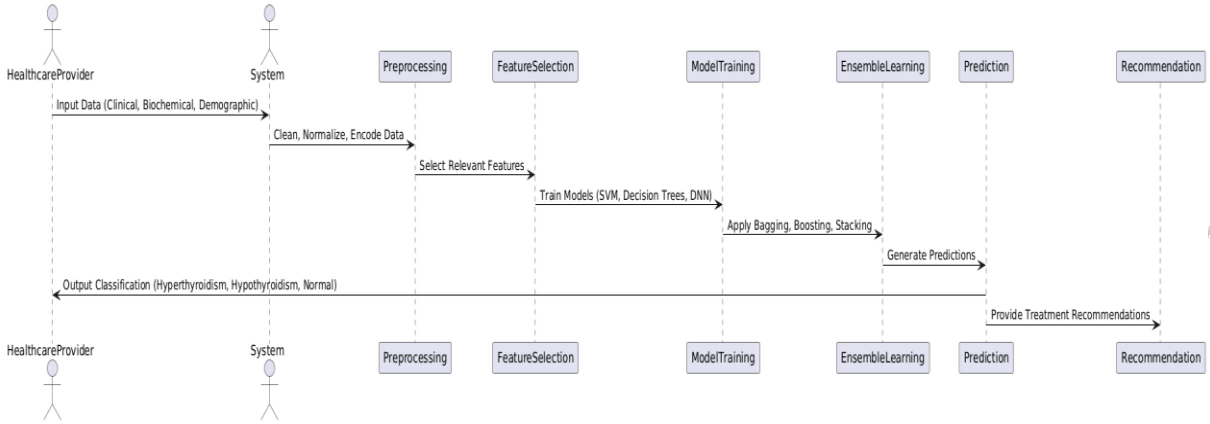
1. **Input Data**:
   - The system receives data from the patient (manual input or electronic health records).
2. **Preprocessing**:
   - Removes noise, normalizes values, and ensures compatibility with models.
3. **Feature Extraction**:
   - Extracts relevant features such as T3, T4, TSH levels, imaging patterns, and clinical symptoms.
4. **Model Prediction**:
   - Hybrid models (e.g., ensemble and deep learning) process the features to classify thyroid disorders like hypothyroidism, hyperthyroidism, etc.

5. **Result Interpretation**:
   - Provides a diagnosis and confidence level, with explainable AI components offering insights.
6. **Feedback and Output**:
   - Sends diagnostic results to clinicians for review and stores results in the database for future reference.

Level-0



Level-1



Level 1: System Decomposition

This breaks down the system into subprocesses:

1. **Data Collection**: Collects clinical, biochemical, and imaging data.
2. **Preprocessing**: Cleans and normalizes the data.
3. **Feature Extraction**: Extracts meaningful features for analysis.
4. **Model Prediction**: Uses hybrid machine learning models to predict thyroid disorder types.
5. **Result Interpretation**: Generates interpretable diagnostic reports.
6. **Feedback and Storage**: Sends results to clinicians and updates the database.

V.Results and Discussion

```
Epoch 1/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step - accuracy: 0.5034 - loss: 0.6901 - val_accuracy: 0.6400 - val_loss: 0.6038
Epoch 2/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.7501 - loss: 0.5998 - val_accuracy: 0.8400 - val_loss: 0.5497
Epoch 3/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.8921 - loss: 0.5559 - val_accuracy: 0.9600 - val_loss: 0.5192
Epoch 4/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8967 - loss: 0.5100 - val_accuracy: 0.9600 - val_loss: 0.4932
Epoch 5/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8639 - loss: 0.5045 - val_accuracy: 0.9600 - val_loss: 0.4689
Epoch 6/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.9106 - loss: 0.4557 - val_accuracy: 0.9600 - val_loss: 0.4429
Epoch 7/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8937 - loss: 0.4420 - val_accuracy: 0.9600 - val_loss: 0.4228
Epoch 8/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.9306 - loss: 0.3893 - val_accuracy: 0.9600 - val_loss: 0.4010
Epoch 9/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8870 - loss: 0.4004 - val_accuracy: 0.9600 - val_loss: 0.3814
Epoch 10/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.9152 - loss: 0.3658 - val_accuracy: 0.9600 - val_loss: 0.3631
Epoch 11/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.9091 - loss: 0.3934 - val_accuracy: 0.9600 - val_loss: 0.3428
Epoch 12/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.9117 - loss: 0.3416 - val_accuracy: 0.9600 - val_loss: 0.3216
Epoch 13/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.8952 - loss: 0.3071 - val_accuracy: 0.9600 - val_loss: 0.3032
Epoch 14/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.9262 - loss: 0.3148 - val_accuracy: 0.9600 - val_loss: 0.2844
Epoch 15/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.9465 - loss: 0.2656 - val_accuracy: 0.9600 - val_loss: 0.2598
Epoch 16/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.9136 - loss: 0.3054 - val_accuracy: 1.0000 - val_loss: 0.2411
Epoch 17/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.9376 - loss: 0.2579 - val_accuracy: 1.0000 - val_loss: 0.2204
Epoch 18/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.9447 - loss: 0.2398 - val_accuracy: 1.0000 - val_loss: 0.2013
Epoch 19/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.9165 - loss: 0.2692 - val_accuracy: 1.0000 - val_loss: 0.1860
Epoch 20/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.9380 - loss: 0.2260 - val_accuracy: 1.0000 - val_loss: 0.1669
Epoch 21/50
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.9299 - loss: 0.2096 - val_accuracy: 1.0000 - val_loss: 0.1505
```

Figure.5. Epochs

Logistic Regression:

	precision	recall	f1-score	support
0	0.79	0.79	0.79	14
1	0.82	0.82	0.82	17
accuracy			0.81	31
macro avg	0.80	0.80	0.80	31
weighted avg	0.81	0.81	0.81	31

Random Forest:

	precision	recall	f1-score	support
0	0.80	0.86	0.83	14
1	0.88	0.82	0.85	17
accuracy			0.84	31
macro avg	0.84	0.84	0.84	31
weighted avg	0.84	0.84	0.84	31

K-Nearest Neighbors:

	precision	recall	f1-score	support
0	0.71	0.86	0.77	14
1	0.86	0.71	0.77	17
accuracy			0.77	31
macro avg	0.78	0.78	0.77	31
weighted avg	0.79	0.77	0.77	31

Support Vector Classifier:

	precision	recall	f1-score	support
0	0.80	0.86	0.83	14
1	0.88	0.82	0.85	17
accuracy			0.84	31
macro avg	0.84	0.84	0.84	31
weighted avg	0.84	0.84	0.84	31

Figure 6. Accuracy

```
Data Shape: (374, 13)
Data Head:
   Person ID Gender  Age            Occupation  Sleep Duration  \
0          1   Male   27     Software Engineer             6.1
1          2   Male   28                Doctor             6.2
2          3   Male   28                Doctor             6.2
3          4   Male   28  Sales Representative             5.9
4          5   Male   28  Sales Representative             5.9

   Quality of Sleep  Physical Activity Level  Stress Level BMI Category  \
0                 6                       42             6   Overweight
1                 6                       60             8       Normal
2                 6                       60             8       Normal
3                 4                       30             8        Obese
4                 4                       30             8        Obese

  Blood Pressure  Heart Rate  Daily Steps Sleep Disorder
0         126/83          77         4200            NaN
1         125/80          75        10000            NaN
2         125/80          75        10000            NaN
3         140/90          85         3000    Sleep Apnea
4         140/90          85         3000    Sleep Apnea
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 374 entries, 0 to 373
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Person ID                374 non-null    int64
 1   Gender                   374 non-null    object
 2   Age                      374 non-null    int64
 3   Occupation               374 non-null    object
 4   Sleep Duration           374 non-null    float64
 5   Quality of Sleep         374 non-null    int64
 6   Physical Activity Level  374 non-null    int64
 7   Stress Level             374 non-null    int64
 8   BMI Category             374 non-null    object
 9   Blood Pressure           374 non-null    object
 10  Heart Rate               374 non-null    int64
 11  Daily Steps              374 non-null    int64
 12  Sleep Disorder           155 non-null    object
dtypes: float64(1), int64(7), object(5)
memory usage: 38.1+ KB
```

Fig 7. Dataset

VI.Conclusion

The conclusion of this study is to design and evaluate an optimized machine learning framework for accurate sleep disorder classification. By leveraging both traditional and deep learning methods, the proposed system aims to improve the accuracy and robustness of classification models. Genetic algorithms are employed to optimize model parameters, ensuring better performance across diverse datasets. The approach focuses on extracting meaningful features from sleep pattern data while addressing high-dimensionality and unstructured data challenges.

This study also emphasizes the importance of comparative analysis, evaluating the proposed model against state-of-the-art methods to ensure its effectiveness. The ultimate goal is to create a reliable and interpretable system for sleep disorder classification, capable of automating diagnostic processes and reducing the dependence on expert-based manual methods. Such a system has the potential to enhance healthcare outcomes, enabling early detection and effective management of sleep-related conditions.

VII.References

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VIII.BIOGRAPHIES

Guntuku Baleswari, an accomplished educator in the field of Computer Science and Engineering, holds a distinguished M.Tech degree from Sree Kavitha Engineering College, Karepalli, located in the vibrant district of Khammam, Telangana of JNTUH. With an illustrious career spanning over 12 years, she currently serves as an Associate Professor at the esteemed NRI Institute of Technology in Agiripally. Throughout her academic journey, Mrs. Baleswari has exhibited a profound dedication to advancing knowledge and fostering excellence in her students. Her commitment to professional development is evident through her active participation in numerous workshops and Faculty Development Programs (FDPs). Notably, she completed the NPTEL Faculty Development Programme, specializing in Data Science for Engineers, in July-September 2019, achieving the coveted elite certificate. Mrs. Baleswari's expertise extends beyond the confines of traditional academia, as she continually seeks to enrich her understanding and impart contemporary knowledge to her students. Her multifaceted approach to education reflects her deep-rooted passion for her field and her unwavering commitment to nurturing the next generation of technologists.

I am currently pursuing my B.Tech in Information Technology at NRI Institute of Technology, Agiripalli.I have completed certifications like NPTEL - Joy of Computing using Python, Microsoft Azure Data Engineer Associate, and Meta Front-End Developer Professional Certificate. I have worked as a DevOps Intern at Advaita Global – IT Labs and a Data Science Intern at BIST Technologies, gaining hands-on experience in CI/CD pipelines, Docker, Kubernetes, data preprocessing, and predictive modeling. I am passionate about full-stack development, proficient in React.js and Flask, and I enjoy working on projects like real-time weather apps and AI-powered tools.

I am currently pursuing my B.Tech in Information Technology (4th year) at NRI Institute of Technology, Agiripalli. I have completed an internship at BIST Technologies, where I gained hands-on experience working on Java-based projects and explored practical applications of software development. I am deeply passionate about Artificial Intelligence (AI) and Machine Learning (ML) and have worked on several projects in these domains. I enjoy exploring the intersection of AI and Java development to create innovative solutions. My projects include building predictive models and working on algorithms that solve real-world problems efficiently. In addition to my technical interests, I constantly strive to learn and stay updated with the latest advancements in technology. I am committed to enhancing my skills in AI, ML, and backend development, aiming to contribute to impactful and cutting-edge innovations.

I am currently pursuing my B.Tech in Information Technology (4th year) at NRI Institute of Technology. I am passionate about Python development and have worked on various projects that involve automation, data analysis, and software development. Throughout my academic journey, I have gained hands-on experience in Python, which has sparked my interest in exploring fields like Machine Learning and Data Science. I am constantly working on enhancing my programming skills and learning new libraries and frameworks in Python to build scalable and efficient solutions. I am excited to contribute to projects that involve complex problem-solving and innovative technology. My goal is to leverage my skills and knowledge in Python development to make meaningful contributions to the tech industry.