

Obstructive Sleep Apnea Detection Using Machine Learning Techniques

Submitted in partial fulfillment of the
requirements for the award of

Bachelor of Technology Degree in Information Technology

By

**TUFFIN SANDO J (40120100)
VELAN S (40120103)**



DEPARTMENT OF INFORMATION TECHNOLOGY

SCHOOL OF COMPUTING

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Category-1 University by UGC

**Accredited with Grade “A++” by NAAC | 12B Status by UGC |
Approved by AICTE**

**JEPPIAAR NAGAR, RAJIV GANDHI SALAI,
CHENNAI – 600119.**

APRIL - 2024



SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

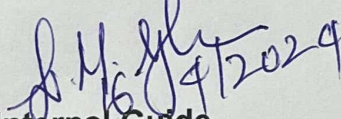
Accredited "A++" Grade by NAAC | 12B Status by UGC | Approved by AICTE

www.sathyabama.ac.in

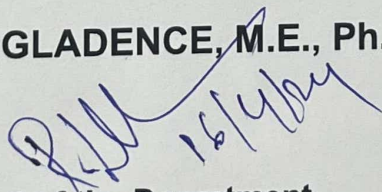
DEPARTMENT OF INFORMATION TECHNOLOGY

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **TUFFIN SANDO J (40120100)** and **VELAN S (40120103)** who carried out the Project entitled "**Obstructive Sleep Apnea Detection Using Machine Learning Techniques**" under my supervision from January 2024 to April 2024.


Internal Guide

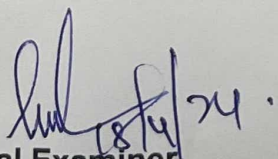
Dr. L. MARY GLADENCE, M.E., Ph.D.,

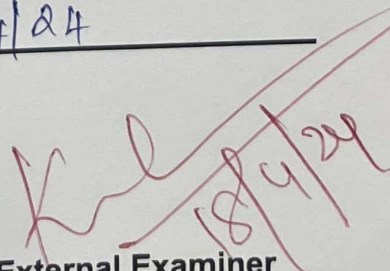

Head of the Department

Dr. R. SUBHASHINI, M.E., Ph.D.,

Submitted for Viva voce Examination held on

18/04/24


Internal Examiner


External Examiner

DECLARATION

I, **VELAN S (40120103)** hereby declare that the Report entitled **"Obstructive Sleep Apnea Detection Using Machine Learning Techniques"** done by me under the guidance of **Dr. L. MARY GLADENCE, M.E., Ph.D.,** is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in **Information Technology.**

DATE: 16/04/2024

PLACE: Chennai

Velan . S
SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management of SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr.T. Sasikala M.E., Ph. D**, Dean, School of Computing **Dr. R. SUBHASHINI M.E., Ph.D.**, Head of the Department of Information technology for providing me necessary support and details at the right time during the progressive

I would like to express my sincere and deep sense of gratitude to my Project Guide **Dr. L. MARY GLADENCE, M.E., Ph.D.**, for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my phase-2 project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Information Technology** who were helpful in many ways for the completion of the project.

ABSTRACT

Obstructive Sleep Apnea is a respiratory disorder that impairs sleep quality by causing respiratory arrest. An irregular breath delay or decrease of airflow during sleep is the hallmark of the apnea syndrome. According to the literature, approximately 2% of middle-aged women and 4% of middle-aged men are affected. The disease is diagnosed by the physician in two steps. In the first stage, the physician reviews the medical records obtained using the polysomnography system. The disease is diagnosed in two stages by the physician, who examines the patient records taken with the polysomnography system in the first stage. New diagnostic processes and equipment are required as a result of the negative aspects of this procedure. Sleep is a period of rest that is essential for functional learning ability, mental health, and even the performance of normal activities. Insomnia, sleep apnea, and restless legs are all examples of sleep-related issues that are growing more widespread. Obstructive Sleep Apnea is a respiratory disorder that impairs sleep quality by causing respiratory arrest. An irregular breath delay or decrease of airflow during sleep is the hallmark of the apnea syndrome. Sleep apnea is a sleep disorder that affects a large population. This disorder can cause or augment the exposure to cardiovascular dysfunction, stroke, diabetes, and poor productivity. Here, we use the machine learning algorithm are random forest and SVM as well as to create the web application of Django framework to predict the sleep apnea disease of the patient. Experimental results had shown the better performance of the system.

TABLE OF CONTENTS

CHAPTER NO	TITLE	PAGE NO
	ABSTRACT	v
	LIST OF FIGURES	viii
	LIST OF ABBREVIATIONS	ix
1	INTRODUCTION	1
	1.1 SLEEP APNEA	3
	1.2 SLEEP AND ITS TYPES	4
	1.3 TYPES OF SLEEP DISORDERS	5
	1.4 IMPACT OF SLEEP APNEA	7
	1.5 RISK FACTORS	9
	1.6 OBJECTIVE	12
	1.7 OUTLINE OF THE PROJECT	12
2	AIM AND SCOPE OF PROJECT	13
	2.1 AIM OF THE PROJECT	13
	2.2 SCOPE OF THE PROJECT	13
3	LITERATURE SURVEY OF PROJECT	14
	3.1 LITERATURE SURVEY	14
4	PROPOSED METHODOLOGY	20
	4.1 SOFTWARE REQUIREMENTS	20
	4.2 HARDWARE REQUIREMENTS	20
	4.3 PYTHON	20
	4.4 APPLICATION OF PYTHON	21
	4.5 MACHINE LEARNING	21
	4.6 DJANGO FRAMEWORK	22
	4.7 ALGORITHM STEPS	23
	4.7.1 WORKING OF RANDOM FOREST ALGORITHM	23
	4.7.2 WORKING OF SUPPORT VECTOR MACHINE ALGORITHM	25

5	PROJECT DESIGN AND IMPLEMENTATION	26
	5.1 EXISTING SYSTEM	26
	5.2 EXISTING SYSTEM DISADVANTAGES	26
	5.3 OBJECTIVE OF THE PROJECT	26
	5.4 FLOWCHART	27
	5.5 IMPLEMENTATION OF PROPOSED WORK	27
	5.6 MODULES	29
	5.6.1 DATA COLLECTION	29
	5.6.2 PRE-PROCESSING	29
	5.6.3 MODEL IMPLEMENTATION	30
	5.6.4 WEB APPLICATION	30
	5.7 PREDICTION	30
	5.8 ADVANTAGES OF PROPOSED WORK	30
6	RESULTS AND DISCUSSION	31
	6.1 RESULTS	31
7	CONCLUSIONS AND FUTURE ENHANCEMENTS	38
	7.1 CONCLUSIONS	38
	7.2 FUTURE ENHANCEMENTS	38
	REFERENCES	39
	APPENDIX	40
	A. SOURCE CODE	40
	B. SCREENSHOTS	44
	C. PUBLICATION	49

LIST OF FIGURES

FIGURE NO	NAME	PAGE NO
1.1	Obstructive Sleep Apnea	4
1.3	Types of Sleep Disorders	6
1.4	Impact of Sleep Apnea	7
1.5	Risk Factors for OSA	10
4.5.1	Working of Machine Learning Algorithm	22
4.7.1.1	Working of Random Forest Algorithm	23
4.7.1.2	Difference of Bagging & Boosting	24
4.7.2	Working of Support Vector Machine Algorithm	25
5.4	Flowchart Representing the Initial Steps of the Model	27
5.5	System Architecture of The Sleep Apnea Disease And Prediction	28
6.1.1	User Login Page	31
6.1.2	User Registration Page	32
6.1.3	Prediction Form Page Presence of Healthy patient Data	33
6.1.4	Output of Normal patient page	34
6.1.5	Prediction Form Page Presence of Sleep Apnea in Our Data	35
6.1.6	Output of sleep Apnea Present Page	36

LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
OSA	Obstructive Sleep Apnea
REM	Rapid Eye Movement
NREM	Non-Rapid Eye Movement
CVD	Cardiovascular Disorders
SQL	Structured Query Language
RDBMS	Relational Database Management System
SVM	Support Vector Machine
PSG	Polysomnography
NFC	Near Field Communication
ML	Machine Learning

CHAPTER 1

INTRODUCTION

Obstructive sleep apnea (OSA) is major type of sleep related breathing disorders. Poor sleep has a major impact on social and personal activities. Due to obstructions in the airway, it affects a person's ability to sleep well, causing loud snoring, choking, and gasping for breath while sleeping, as well as daytime sleepiness and headache. If not addressed, this could lead to health complications including hypertension, heart attacks, diabetes, depression, and early death. Obstructive sleep apnea (OSA) is a common chronic medical disease with an estimated prevalence rate of 5–14%. A recent study has suggested that the actual prevalence of OSA could be much higher, with estimates ranging from 24% to as high as 50% in the mean which would make it the most prevalent chronic medical condition. Besides high prevalence, OSA has a wide-ranging impact on health and has been shown to be associated with an increased risk of hypertension, cardiovascular disease, cerebrovascular disease, atrial fibrillation, impaired glycemic control, erectile dysfunction, and gastroesophageal reflux, as among other conditions.

Moreover, sleep disruption caused by sleep apnea leads to significant daytime sleepiness with implications for risk for motor vehicle accidents, especially in high-risk employees such as truck drivers or those heavy operating machinery. It can also lead to significant changes in mood, including depression, and cause attention deficit and loss of memory. Traditionally the diagnosis of sleep apnea has been made by overnight polysomnography, which is done in a sleep laboratory. However, this requires significant investment in infrastructure, including hiring certified personnel, and hence became an impractical solution to diagnose sleep apnea efficiently. With the advent of home sleep testing, it became easier to screen more people for sleep apnea. Still, given the high disease prevalence, and relatively small numbers of home sleep testing equipment in use, especially among certified sleep providers, this approach is associated with significant barriers and diagnosis delays.

Healthcare is one of the critical concerns for global nations. Irrespective of whether it's a developing nation or the super economic nations, in common one of the key areas of focus is the quality healthcare to the public. Alongside the increasing amenities and developments in the healthcare solutions, even the complexities too are on rise. For instance, some of the challenges that are impact the quality health for the individuals are the stress related health

problems, obesity related and the contemporary issues like the sleep apnea conditions that are adding up the complexities of quality health for public of the system.

Due to different sleep disorders, the death rate is increasing day by day. Not only India but the whole world is facing the wide spread of the infectious sleep disorders. The major reason for death is unawareness among people related to sleep disorders. Also, people are very careless regarding their lifestyle and eating habits which causes a sleep disorder to grow at a fast rate in their body and finally leads to the end of a human life. Computer science is growing at a surprising rate, giving new arenas and progress interfaces to tackle the disastrous situations that can be a great source of assistance for an ordinary human being to diagnose and further get to know about the deadly sleep disorders with which they are suffering. As per the survey, 93% population in India is suffering from sleep-related issues, however just 2% Indians talk about their sleep-related issues with physicians. Further, sleep loss and sleep disorders have critical commercial effects. Along with this, sleep disorders have also a significant economic impact.

These economic, socio and personal consequences which the people with sleep disorders face are much higher than the cost involved in the treatment. An enormous amount of money for every year is spent on direct medical cost related to doctor's visits, service charges, medicinal cost etc. In comparison to healthy people, who experience the effects of sleep loss, sleep disorders, or both are less productive and are more inclined to accidents. Out of the total population, 20% of severe car crash accidents are related with driver's sleepiness rather than the consumption of alcohol. There are many short and long-term effects of sleep disorders. The short living impacts tend to less consideration, affect personal satisfaction, loss of potential and sometimes lead to mishappening.

The long-term impacts of sleep disorders move towards inclination the morbidity and death rate from the expanding disasters, cardiovascular problems, hypertension, obesity and learning inability. A few sleep disorders are very serious to put great effects on physical, psychological, cognitive and motor functioning of a person. There are no reliable figures on how many are diagnosed and treated for the sleep disorders. According to a survey, total 40 million U.S. people have chronic sleep disorders, due to which \$18 billion loss of productivity is estimated among them and 30% of all adults have insomnia problem Marcus. A large

number of 1550 is estimated for car crashes/ major accidents due to falling asleep. By 2030, the number of older adults will be rise to 1.578 million, in which more than 260 million people probably facing sleep problems. Thus, the estimates propose that sleep disorders may exhibit a powerful and obscure problem among older people in low-monetary comforts. Theses judgments further highlighted the global height of sleep problems as a developing public health issue.

- In our article, we use the web application-based Django framework are implemented to predict the sleep apnea disease based on present and absent condition of the patient of the system.
- The Existing system uses same techniques, but different algorithms to predict the Obstructive Sleep Apnea (OSA) .
- The algorithms used in the existing systems are Support Vector Machine (SVM) and KNN

1.1 SLEEP APNEA

Sleep Apnea is a common phenomenon of sleep disorder, which is faced by millions of people across the countries. The condition is about how a person stops breathing during the sleep, in periodical instances. The cessations of breathing might take place regularly and the intensity and frequency of cessations decide the categorization as mild or medium or high levels of sleep apnea problem. The impact of the problem is about the brain are not allowed to deeper stages of sleep to prevent choking for breathing in the patient. When there are frequent interruptions, the quality of sleep gets affected, thus leading to more health complications. While there are many who are familiar with the distinct forms of sleep apnea conditions, OSA (Obstructive Sleep Apnea) is the major challenge that goes often unrecognized.

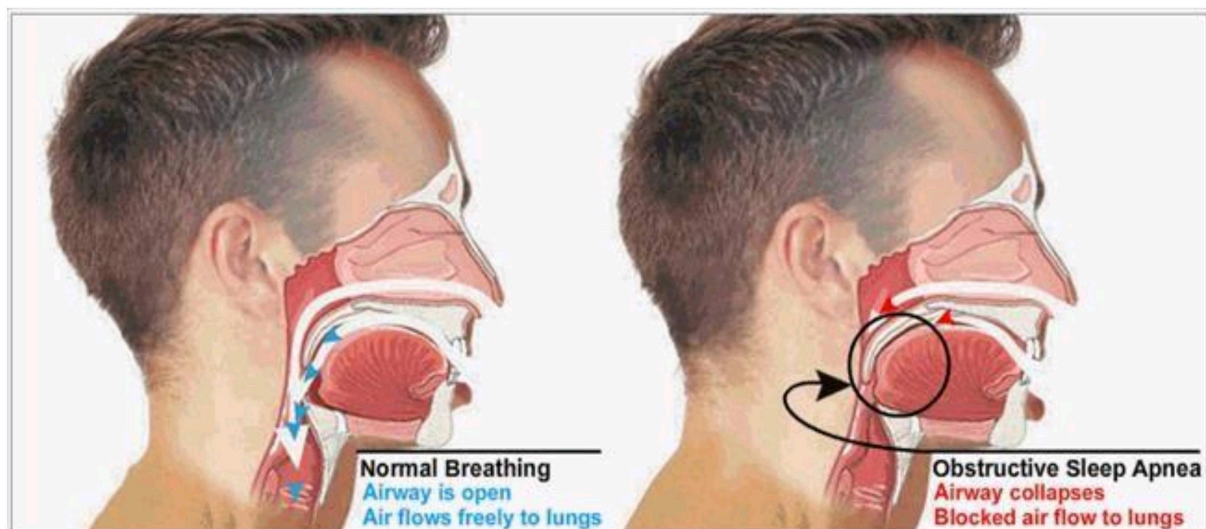


Fig 1.1 Obstructive sleep Apnea

1.2 SLEEP AND ITS TYPES

Sleep is a naturally occurring state identified by decreasing or missing awareness of surrounding and suspension of sensational activities. In this state, all muscles are in the relaxed state. It is an increased anabolic state which helps in the development of strong immune, nerve, muscles and skeletal system. It is found in all well-evolved creatures, birds and numerous reptiles, creatures of land and water and fish. Sometimes, sleep is supposed to aid preserve energy.

Types:

Basically, sleep has been categorized into two forms

- Rapid eye movement (REM)
- Non-rapid eye movement (NREM)

Every form has a set of identified physiological and neurological features. As per the American Academy of Sleep Medicine, NREM has been divided into three parts: N1, N2, and N3 as explained below. One does not go straight from deep sleep to REM sleep, however. Rather, a sleep cycle progress through the stages of non-REM sleep from light to deep sleep, then reverse back from deep sleep to light sleep, ending with time in REM sleep before starting over in light sleep again. After REM sleep, the individual returns to stage 1 of light sleep and begins a new cycle.

NREM stage 1: This is a stage between sleep and wakefulness. It is a light sleep (alpha activity) and a person can wake up easily at this stage. Eyes move very gradually while muscles activities slow down and people mostly remember the visual images after awakening from this stage.

NREM stage 2: Also known as theta activity. It gradually becomes harder to awaken the sleeper in this stage. The eye movement and brain activities become slow due to the sleep spindles and K-complexes which intercede the alpha waves of stage 1. Out of the total sleep time, 50% time is spent in this stage.

NREM stage 3: It is also called as slow-wave sleep (SWS) and delta waves begin to appear with high amplitude at less than 3.5 Hz. The sleeper is less responsive to the environment. When stage 4 arrives, then almost exclusively delta waves are generated by the brain. During stages 3 and 4, it is very difficult to wake someone, which collectively known as deep sleep. Eye movements or muscle activities are stopped at this stage. People can't adjust themselves after awakening from this stage and feel dizzy and unbalanced for a few minutes. A few minors encounter bedwetting, night fear or sleepwalking in deep sleep.

1.3 TYPES OF SLEEP DISORDERS

Sleep Apnea: It is a sort of sleep disorder defined by stops in breathing or infrequent breathing amid sleep. Every stop in breathing known as apnea that can retain from no less than ten seconds to minutes and may happen 5 to 30 times or increasingly 60 minutes. Fundamentally, sleep apnea is a sleep-related breathing disorder. The below Figure 4 demonstrates the consequences of sleep apnea.

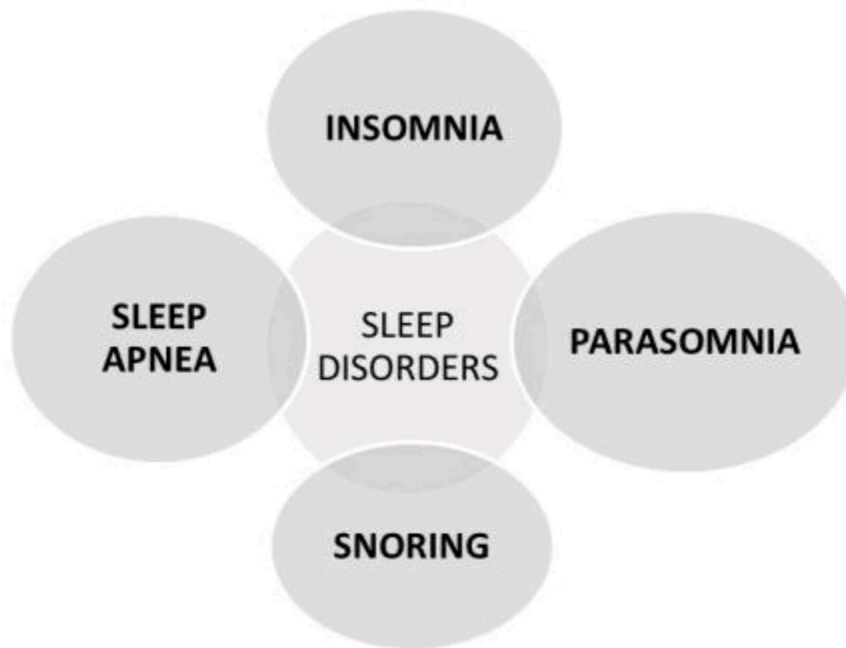


Fig 1.3 Types of Sleep Disorders

It is treatable; still, around 90% of patients are unknown and consequently untreated. They encounter daytime lethargy and tiredness that leads to car crashes, sadness, and memory loss. Moreover, it is viewed as a hazard factor for morbidity and mortality because of its long-haul consequences on the cardiovascular system. This impact is identified with various physiological components like hypertension that in a long haul compromises the well-working of the heart. It is related to heart failure which is 12-16% more pervasive in apnea patients. It has additionally been watched that roughly 60-70% of rest apnea patients are obese. Patients in danger for sleep apnea should be distinguished for symptomatic testing and treatment .

Insomnia: The presence of this disorder happened regularly in OSA patients and consistently related with poor sleep quality yet had no impact on long-haul 7 inconveniences and as indicated the half patients experienced insomnia which goes from moderate to serious.

Parasomnia: It refers to physical disturbance during sleep that involves the skeletal, motor and autonomic nervous systems. Adults with parasomnia often report the behavioral, perceptual, emotional, and dreamlike disturbances that may erroneously suggest psychiatric disorder

Snoring: It is a sound delivered because of obscured air movement amid breathing during sleep. Sometimes, this sound might be delicate, however in different cases; it can be heavy and undesired. It is a syndrome and an indication of sleep-related upper aviation route deterrent and is exceptionally normal, influencing over 9% to half of the grown-up population. It alludes to an issue of bed-partner. Numerous do not view snoring alone to be a morbidity. Only with other disorder is snoring considered pathologic. It has been reported as a risk factor for the growth of more problems such as brain infraction, hypertension, and sleep disturbances etc.

1.4 IMPACT OF SLEEP APNEA

It is a sort of sleep disorder defined by stops in breathing or infrequent breathing amid sleep. Due to these disorders, many bad impacts put on our various body parts



Fig 1.4 Impact of Sleep Apnea

The below is the brief description of the few impacts which put bad effects on various parts of the body.

Impaired Moral Judgement: Bad sleep always put an adverse effect on physical wellbeing and passionate prosperity of an individual. A sleep-deprived patient always takes more time to give the answers of questions than a normal one.

Heart Rate Variability: Heart rate changes during various sleep stages. If an individual suffers from any sleep disorders like in sleep apnea where pauses occur during breathing then these pauses affect the heart. Similarly, in snoring, heart rate varies due to the air obstruction.

Risk of Heart Diseases: The person suffering from sleep apnea and snoring is more likely to be suffering from cardiovascular diseases.

Decreased Accuracy: A sleep disorder patient are more tend to be a tired person. Due to this tiredness, an individual is not able to give the best efforts and the overall performance or growth would be degraded.

Increased Reaction Time: A sleep-deprived patient always takes more time to give a response as per the assigned task than the normal human being. Hence, the effectiveness of the task would be less.

Impaired Immune System: An individual suffered from sleep loss will suffer from cold, flu and other ailments and when it is not functioning properly, the person will fail to do the job.

Hallucinations: Due to sleep apnea, sometimes a person feels hallucination or sleep paralysis in which a person is not able to move for some minutes/seconds.

Severe Yawning: Due to tiredness, drowsiness and sleep loss, a person moves towards severe yawning.

Memory Loss: Sleep apnea occurs when a blocked airway repeatedly halts the sleeper's breathing, resulting in loud bursts of snoring and chronic daytime fatigue. Memory loss and difficulty focusing are the common complaints in sleep apnea patients.

Irritation: The Individuals having sleep loss and sleep deprivation tend to be more irritated. Due to this, they are not able to give the best efforts towards their tasks.

Diabetes: It has shown to be associated with higher incidence of sleep disorders, which may be due to the disease itself or because of secondary complications or associated comorbidities associated with diabetes.

Obesity: Decreased sleep duration and quality is associated with an increase in body weight.

Tremors: People with sleep apnea experience a range of symptoms, including tremor (shaking), rigidity (stiffness), slowness of movement, and problems with balance and coordination. They may also have memory problems, depression, and sleep complaints.

Aches: Sleep disorders such as sleep apnea or insomnia also can trigger bouts of muscle pain that make sleeping difficult.

Growth Suspension: The sleep breathing disorder also influences the growth hormone secretion in adults as well as in children.

Decreased Temperature: In this sleep occurs when the core temperature is dropping. Sleep usually begins when the rate of temperature change and body heat loss is maximal.

1.5 RISK FACTORS

Rapidly increasing prevalence of OSA is a concern of paramount importance worldwide which demands the identification the risk factors responsible for the onset of OSA in order to ensure effective management OSA and associated consequences like cardiovascular disorders (CVD).

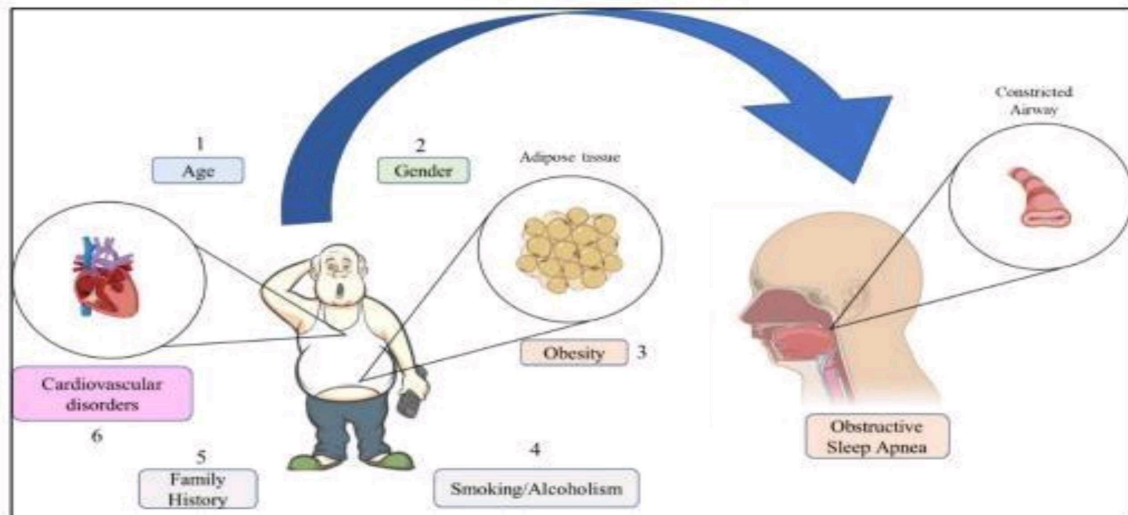


Fig 1.5 Risk Factors for OSA

Obesity: Obesity has been a constant burden, exponentially rising across the globe with nearly 40% of the world's adult population being obese. A person is termed obese when the BMI is more than or equal to 30. Obesity has been regarded as a causative factor for many disorders from CVD to cancer and OSA. It is the most common and prevalent risk factor for OSA covering approximately 65-70% of the total patients screened.

Obese OSA patients present with enlargement of soft tissue structures in the upper airway that result in obstruction of airflow. Furthermore, fat deposition around the neck leads to the narrowing of the airway ultimately causing it to collapse. The lung volume also diminishes, destabilizing the upper airway passage. Studies suggest that obesity directly influences the OSA severity which is further proportional to the risk of CVD. Furthermore, mild OSA patients who gain weight equivalent to 10% of their baseline weight are six times more likely to be at risk for OSA progression. Moreover, the prevalence of obesity associated OSA is not limited to just adults. The prevalence of OSA in obese children has been estimated to be 46% as compared to the general pediatric population. It has been reported that childhood obesity increases the likelihood of developing OSA in the middle age.

Age: Age is a crucial factor responsible for influencing the onset of OSA in human beings. Although, OSA can develop in any person of any age, certain age groups are at a higher risk of being diagnosed with OSA. OSA targets all age groups, from children to middle aged adults to older people above 60 years of age and is reported to progress with increasing age.

Gender: Evidences reveal a trend of inclination towards gender selectivity in OSA patients. In other words, the prevalence of OSA is somewhat biased towards the gender of a person. The male to female ratio of OSA ranges between 3:1 to 5:1 in the general population indicating that OSA is primarily a male biased disorder. Evidence states that women have a different threshold of feeling sleepy than men (68).

Under-reporting of OSA symptoms such as sleepiness and snoring whereas increased prevalence of symptoms such as insomnia, headache, anxiety and depression in women can be a reason of under-evaluation of OSA in women (69, 70). It is noteworthy that anatomically men generally exhibit increased airway resistance and are more susceptible to airway collapse than women.

Life style related factors- Alcoholism and Smoking Consumption of alcohol induces evident snoring, thus worsening pre-existing OSA by increasing the frequency of apneic events and associated hypoxia. Reports on neuregulin-1 (NRG-1) gene polymorphisms indicate its involvement in the manifestation of OSA.

Craniofacial Anatomy: Facial abnormalities such as distorted mandible and tongue, enlarged bone, wrongly positioned hyoid bone, decreased position airway and even increased distance between mandibular plane and hyoid can narrow down the airway and promote apnea events further increasing the risk for OSA. Assessment of upper airway using endoscopy for the location of obstruction in patients with OSA revealed that in most cases (89%), it is the velopharynx that hinders the flow of air. Interestingly, most patients suffer from obstruction at multiple sites (72%) and not only velopharynx.

Genetics/Family: History Familial studies indicate that sleep disordered breathing and other associated symptoms are significantly common in family members of patients with OSA than the general population suggesting a genetic cause. According to the Cleveland Family Study, OSA was found to have a prevalence of 21% in relatives of OSA patients. Moreover, the relatives of OSA patients reported symptoms of sleepiness, tiredness and fatigue.

1.6 OBJECTIVE

The main objective of this project is to predict the sleep apnea disease prediction by using Django Framework and machine learning.

1.7 OUTLINE OF THE PROJECT

Sleep apnea is a sleep-related breathing disorder that causes respiratory problems and arousals due to a reduction or rise in airflow during sleep. Obstructive sleep apnea (OSA) is the most common form of sleep apnea. In our Proposed method, to predict the sleep apnea disease by using Django Framework as well as machine learning model of the system. With the explosive growth of machine learning (ML) and artificial intelligence and its increasing use in healthcare, recently, the focus has turned to applications of ML in developing predictive models to improve the screening strategy for OSA and increase its accuracy of the system. In the Web Application part, user can enter the symptoms of the patient detail. Finally, to predict the disease based on sleep apnea present or sleep apnea absent of the system.

CHAPTER 2

AIM AND SCOPE OF THE PROJECT

2.1 AIM OF THE PROJECT

The main aim of the project is to predict the sleep apnea disease prediction by using Django Framework and machine learning.

2.2 SCOPE OF THE PROJECT

Obstructive sleep apnea (OSA) is a prevalent but severely undiagnosed sleep disorder that impacts the natural breathing cycle during sleep with decreased breathing periods or no airflow at all. New sleep apnea classification techniques are nowadays being developed by bioengineers for most comfortable and timely detection. This project focuses on the machine learning algorithm are random forest and SVM as well as to create the web application of Django framework to predict the sleep apnea disease of the patient. Experimental results shown the better performance of the system.

In the Existing system, The Existing system uses same techniques, but different algorithms to predict the Obstructive Sleep Apnea (OSA) . The algorithms used in the existing systems are Decision Tree and KNN.

CHAPTER 3

LITERATURE SURVEY

3.1 LITERATURE SURVEY

3.1.1 Aiyer, I Mehmet Recep, and Muhammed Kursad Ucaet al., “Use of machine learning to Develop an Anthropometry Based Screening Model for Obstructive Sleep Apnea”. (2020)

Obstructive sleep apnea (OSA) is a common sleep disorder with a 6-17% prevalence range. However, it is estimated that over 80% of patients with moderate to severe OSA remain undiagnosed. Current screening methods depend heavily on patient self-reporting of symptoms such as snoring or excess sleepiness. However, these may be unreliable and tend to have low predictive values. The purpose of this study is to explore the advantages of using machine learning techniques to develop an anthropometry-based screening tool for OSA for use in the general population. Methods: Subjects were adults without previously diagnosed OSA, referred to a community sleep center for suspicion of OSA. Epworth Sleepiness Scale (ESS) was completed. A physical examination utilizing airway assessment using a modified Friedman (MF) grade, body mass index (BMI), and neck circumference (NC) was performed before polysomnography. OSA was defined by an apnea-hypopnea index ≥ 15 . We studied two machine learning methods, logistic regression (LR) and adaptive boosting (AB). For creating the diagnostic model, we split the data to 80% for training the model and 20% for testing, respectively. The main attributes used to develop the OSA diagnosis model were based on the B.A.N. score - BMI >30 , Airway size >2 , and NC >17 in men and 16 in women. Sleep apnea was defined as an AHI of ≥ 15 .

Results: The patient's samples included 1002 patients - 437 did not have OSA vs. 565 positives for OSA. The two adopted ML models provided robust classification accuracy in both training and testing cases. Evaluation criteria to assess the developed models include classification accuracy, Precision, Recall, and F1. AdaBoost showed the best recall/sensitivity values. Adaptive boosting showed AUC of 0.72/0.72, F1 0.67/0.73, Precision 0.68/0.70 and Recall 0.81/0.79 values for the training data and testing data respectively. Conclusions: Two ML-based diagnosis models utilizing only three anthropometric variables generated accurate classification results, with the best results seen with the Ada boost algorithm.

These ML models can be deployed as a software prototype via a mobile application for home use and can help create a screening strategy for OSA. This can be especially relevant in test/triage decisions in high-risk populations such as commercial drivers, where self-reporting of symptoms may be unreliable.

PROS: K-Nearest Neighbour performs better than others.

CONS: developing fewer features and higher performance systems.

3.1.2 Ramesh, J et al, Sheikh Shanawaz Mostafa, Joao Paulo Carvalho “Towards validating the effectiveness of obstructive sleep apnea classification from electronic health records using machine learning”. (2020)

Obstructive sleep apnea (OSA) is a common, chronic, sleep-related breathing disorder characterized by partial or complete airway obstruction in sleep. The gold standard diagnosis method is polysomnography, which estimates disease severity through the Apnea-Hypopnea Index (AHI). However, this is expensive and not widely accessible to the public. For effective screening, this work implements machine learning algorithms for classification of OSA. The model is trained with routinely acquired clinical data of 1479 records from the Wisconsin Sleep Cohort dataset. Extracted features from the electronic health records include patient demographics, laboratory blood reports, physical measurements, habitual sleep history, comorbidities, and general health questionnaire scores. For distinguishing between OSA and non-OSA patients, feature selection methods reveal the primary important predictors as waist-to-height ratio, waist circumference, neck circumference, body-mass index, lipid accumulation product, excessive daytime sleepiness, daily snoring frequency and snoring volume. Optimal hyper parameters were selected using a hybrid tuning method consisting of Bayesian Optimization and Genetic Algorithms through a five-fold cross-validation strategy. Support vector machines achieved the highest evaluation scores with accuracy: 68.06%, sensitivity: 88.76%, specificity: 40.74%, F1-score: 75.96%, PPV: 66.36% and NPV: 73.33%. We conclude that routine clinical data can be useful in prioritization of patient referral for further sleep studies.

PROS: Accuracy=97% Genetic algorithm used.

3.1.3 Vuolo et al., “Promoting Sleep Health Through Identification and Management of Obstructive Sleep Apnea” (2018)

There is a high prevalence of obstructive sleep apnea in the United States, which left untreated can lead to increased cardiovascular risk. The current practice standard is to use a questionnaire to evaluate a patients' sleep health, but this is not done regularly in every clinical setting. This DNP project aimed to bridge the gap in practice by implementing regular screening of obstructive sleep apnea in an urgent care center in Massachusetts.

Methods: This DNP project was conducted by having adult patients complete the Epworth Sleepiness Scale to determine the presence of a sleep health issue. The patients then completed an additional survey to determine if they have been screened in the past, and their attitudes toward the screening. The urgent care manager provided the screening tool to patients based on the inclusion criteria of being 18 years or older and the ability to read/speak English. **Results:** Data was collected from 54 patients 18 years or older over a three-month period. Eleven were excluded because they had sleep apnea, were already being treated, or did not answer all questions of the survey. A total of 18 patients Screen positive for sleep apnea with 88% of participants reporting not having been screened for sleep health issues prior to this screening and 72% of participants reporting the tool was beneficial and easy to complete. **Conclusion:** Most people with sleep health issues in this urgent care clinic were not aware of their risk and had not been screened prior indicating a need for regular screening in Urgent Care practice settings. At this time the urgent care center will not be implementing a change in practice, but they are interested in the possibility and will consider implementing routine screening in the future.

PROS: Accuracy of up to 88.2%.

CONS: It is difficult to learn the characteristics.

3.1.4 Kim et, Ramiro Casal, Gastón Schlotthauer “Diagnostic Accuracy of Different Machine Learning Algorithms for Obstructive Sleep Apnea”. (2018)

The objective of this study was to develop models for predicting obstructive sleep apnea (OSA) based on easily obtainable clinical information of patients using various machine learning techniques. Methods: We used a data set that included the records of 1,368 patients, in which 1,074 patients were male (78.5 %), and 294 patients were female (21.5 %). We randomly divided the data into a training set (1,000) and test set (368). Five machine learning methods, i.e., support vector machine model, lasso logit model, naïve bayes, discriminant analysis, and K-nearest neighbor (KNN), with a 10-cross fold technique were used with the proposed model to predict OSA. We evaluated the accuracy, sensitivity, specificity, and precision of each model for three thresholds [Apnea-Hypopnea Index (AHI) ≥ 5 , AHI ≥ 15 , and AHI ≥ 30]. Results: Among the machine learning techniques, KNN showed the best results compared to the other techniques. The accuracy, sensitivity, specificity, and precision of OSA prediction were 87.0%, 91.0%, 74.4%, and 91.9%, respectively, based on AHI ≥ 5 . When the threshold of OSA was AHI ≥ 15 or AHI ≥ 30 , KNN provided lower accuracy (79.6% each) and precision (79.0% and 68.7%), which were still higher than those of the other techniques. Conclusions: The model derived from the KNN technique exhibited the best performance based on its highest level of accuracy. We demonstrate that this model is a useful tool for predicting OSA.

PROS: Accuracy 79% support vector machine is used.

CONS: The estimation of total sleep time will allow to improve the existing algorithms.

3.1.5 Gillan, G et al, Muhammed Kursad Ucar, Mehmet Recep Bozkurt“Primary Care Obstructive Sleep Apnea Screening” (2020)

Obstructive Sleep Apnea (OSA) is a common sleep disorder characterized by long pauses in breathing over the course of a night's sleep, leading to significant daytime fatigue and long-term pathologies if left untreated. While a sleep study is the diagnostic tool of choice for OSA, this test is costly. To maximize cost effectiveness, we developed a screening protocol to identify patients at high risk for OSA for referral for a sleep study. To identify high risk individuals, we screen patients identified in the EMR with pre-existing risk factors of OSA. We contact them to complete the full screening test: the widely accepted STOP-Bang questionnaire. In our study, we are using the score of six or more to identify high risk individuals. If a patient scores six or higher following our contact, he/she/they are referred for a sleep study. We are still gathering and analyzing data, but our current findings are very promising. We have found that the combination of poor patient response and the high score of six or greater has eliminated 91% of the starting patient population. However, every participant identified as high risk following our positive screening protocol (n=6) has been diagnosed with sleep apnea following their sleep study. While the study's patient population is small (n=210) thus far, our findings are promising and support the usefulness of our new OSA screening protocol with the STOP-Bang questionnaire.

PROS: Accuracy=89.4% KNN used.

CONS: Studies are transformed into a rule-based system and presented for the use of attending physicians.

3.1.6 Sheikh Shahnawaz Mostafa, Joao Paulo Carvalho, Fernando Morgado-Dias, Antonio Ravello-García, “Optimization of sleep apnea detection using SpO2 and AN” (2020)

Repetitive respiratory disturbance during sleep is called Sleep Apnea Hypopnea Syndrome and causes various diseases. Different features and classifiers have been used by different researchers to detect sleep apnea. This study is undertaken to identify the better performing blood oxygen saturation features subset using an Artificial Neural Network classifier for sleep Apnea detection. A database of 8 subjects with one-minute annotation is used to test the proposed system. The optimized system has seven features chosen from a total set of sixty-one features presenting a high accuracy rate using a genetic algorithm. Artificial Neural Network was able to achieve 97.7 percentage of accuracy with only seven features chosen by the Genetic algorithm.

CHAPTER 4

PROPOSED METHODOLOGY

4.1 SOFTWARE REQUIREMENTS

Operating System	Windows 7 or later
Simulation Tool	Anaconda (Jupyter notebook)
Documentation	MS – Office

4.2 HARDWARE REQUIREMENTS

The hardware requirements are needed to serve as the basis for implementation of the system and hence should be an absolute and coherent specification of the entire system. The software engineers use the hardware requirements as the starting point for the system design. It indicates what the system performs and what the system should execute.

CPU type	I5
Ram size	4GB
Hard disk capacity	80 GB
Keyboard type	Internet keyboard
Monitor type	15 Inch color monitor
CD -drive type	52xmax

4.3 PYTHON

Python is a dynamic, high level, free open source and interpreted programming language. It supports object-oriented programming as well as procedural oriented programming. In Python, we don't need to declare the type of variable because it is a dynamically typed language.

For example, `x=10`. Here, `x` can be anything such as String, int, etc.

Python is an interpreted, object-oriented programming language similar to PERL that has gained popularity because of its clear syntax and readability. Python is said to be relatively easy to learn and portable, meaning its statements can be interpreted in a number of operating systems, including UNIX-based systems, Mac OS, MS-DOS, OS/2, and various

versions of Microsoft Windows 98. Python was created by Guido van Rossum, a former resident of the Netherlands, whose favorite comedy group at the time was Monty Python's Flying Circus. The source code is freely available and open for modification and reuse. Python has a significant number of users.

4.4 APPLICATION OF PYTHON

- Web Development.
- Game Development.
- Machine Learning and Artificial Intelligence.
- Data Science and Data Visualization.
- Desktop GUI.
- Web Scraping Applications.
- Business Applications.
- Audio and Video Applications.

4.5 MACHINE LEARNING

Machine learning is a growing technology which enables computers to learn automatically from past data. Machine learning uses various algorithms for building mathematical models and making predictions using historical data or information. Currently, it is being used for various tasks such as image recognition, speech recognition, email filtering, Facebook auto-tagging, recommender system, and many more. Machine Learning is said as a subset of artificial intelligence that is mainly concerned with the development of algorithms which allow a computer to learn from the data and past experiences on their own.

The term machinelearning was first introduced by Arthur Samuel in 1959. We can define it in a summarized way as: "Machine learning enables a machine to automatically learn from data, improve performance from experiences, and predict things without being explicitly programmed". A Machine Learning system learns from historical data, builds the prediction models, and whenever it receives new data, predicts the output for it. The accuracy of predicted output depends upon the amount of data, as the huge amount of data helps to build a better modelwhich predicts the output more accurately.

Suppose we have a complex problem, where we need to perform some predictions, so instead of writing a code for it, we just need to feed the data to generic algorithms, and with the help of these algorithms, machine builds the logic as per the data and predict the output. Machine learning has changed our way of thinking about the problem.

The below block diagram explains the working of Machine Learning algorithm:

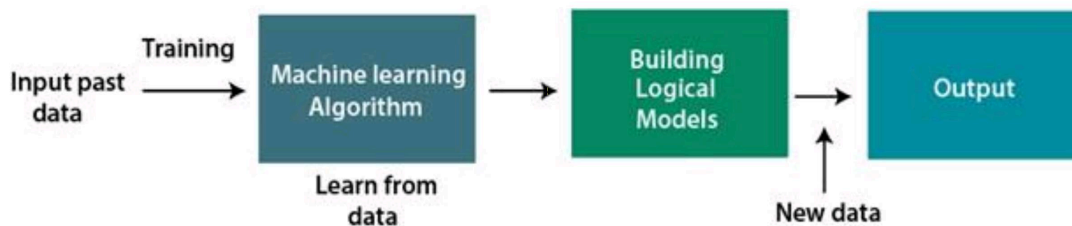


Fig 4.5.1 WORKING OF MACHINE LEARNING ALGORITHM

4.6 DJANGO FRAME WORK

Django is a web application framework written in Python programming language. It is based on MVT (Model View Template) design pattern. The Django is very demanding due to its rapid development feature. It takes less time to build application after collecting client requirement. This framework uses a famous tag line: The web framework for perfectionists with deadlines. By using Django, we can build web applications in very less time. Django is designed in such a manner that it handles much of configure things automatically, so we can focus on application development only.

Django is an MVT web framework that is used to build web applications. The huge Django web-framework comes with so many “batteries included” that developers often get amazed as to how everything manages to work together. The principle behind adding so many batteries is to have common web functionalities in the framework itself instead of adding latter as a separate library. One of the main reasons behind the popularity of Django framework is the huge Django community. The community is so huge that a separate website was devoted to it where developers from all corners developed third-party packages including authentication, authorization, full-fledged Django powered CMS systems, e-commerce add-ons and so on. There is a high probability that what you are trying to develop is already developed by somebody and you just need to pull that into your project.

Python is arguably one of the easiest programming languages to learn because of its simple language constructs, flow structure and easy syntax. It is versatile and runs websites, desktop applications and mobile applications embedded in many devices and is used in other applications as a popular scripting language.

4.7 ALGORITHM STEPS:

Here, we use the machine learning algorithm are **RANDOM FOREST AND SVM ALGORITHM USED**

4.7.1 WORKING OF RANDOM FOREST ALGORITHM

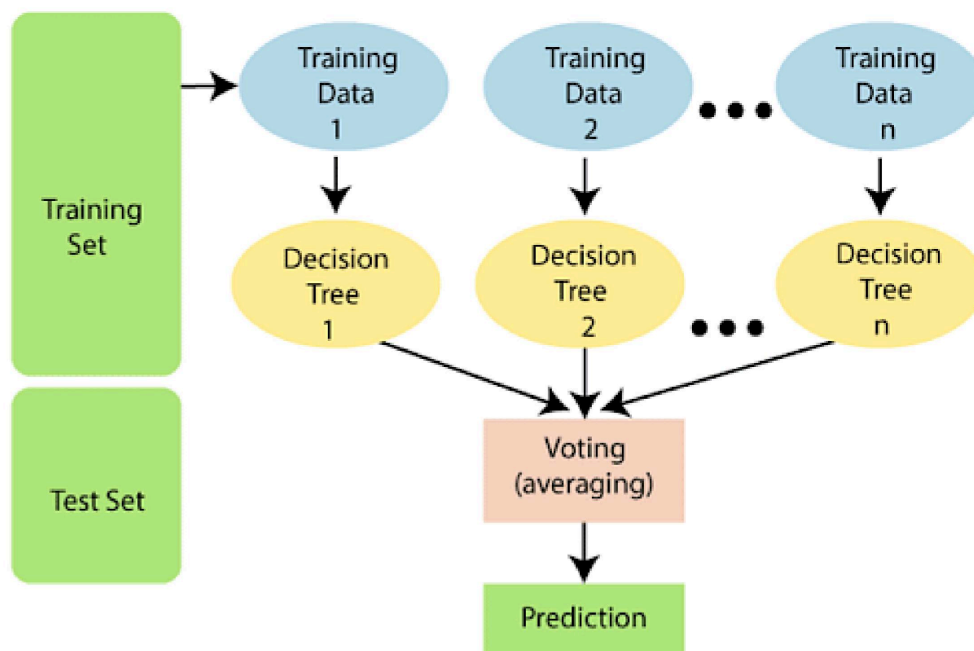


Fig 4.7.1.1 WORKING OF RANDOM FOREST ALGORITHM

The following steps explain the working Random Forest Algorithm:

- Select random samples from a given data or training set.
- This algorithm will construct a decision tree for every training data.
- Voting will take place by averaging the decision tree.
- Finally, select the most voted prediction result as the final prediction result.

This combination of multiple models is called Ensemble. Ensemble uses two methods:

- Bagging: Creating a different training subset from sample training data with replacement is called Bagging. The final output is based on majority voting.
- Boosting: Combining weak learners into strong learners by creating sequential models such that the final model has the highest accuracy is called Boosting. Example: ADA BOOST, XG BOOST.

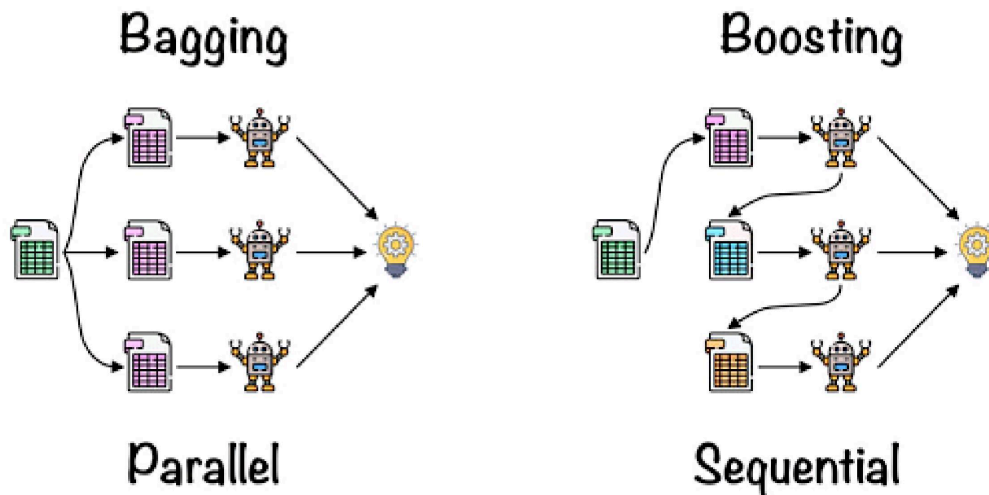


Fig 4.7.1.2 DIFFERENCE OF BAGGING & BOOSTING

Bagging: From the principle mentioned above, we can understand Random Forest uses the Bagging code. Now, let us understand this concept in detail. Bagging is also known as Bootstrap Aggregation used by random forest. The process begins with any original random data. After arranging, it is organized into samples known as Bootstrap Sample. This process is known as Bootstrapping. Further, the models are trained individually, yielding different results known as Aggregation. In the last step, all the results are combined, and the generated output is based on majority voting. This step is known as Bagging and is done using an Ensemble Classifier.

4.7.2 WORKING OF SUPPORT VECTOR MACHINE ALGORITHM

Support Vector Machine” (SVM) is a supervised learning machine learning algorithm that can be used for both classification or regression challenges. However, it is mostly used in classification problems, such as text classification. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is the number of features you have), with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the optimal hyper-plane that differentiates the two classes very well (look at the below snapshot).

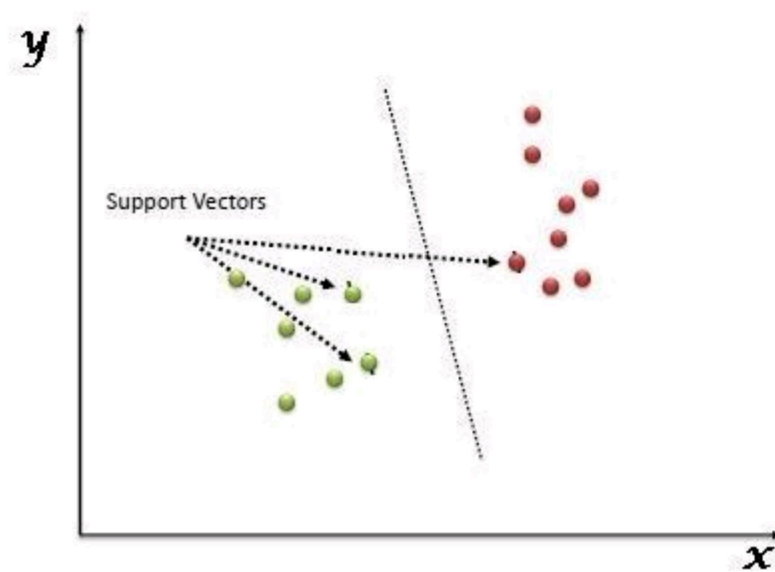


Fig 4.7.2 WORKING OF SUPPORT VECTOR MACHINE ALGORITHM

Support Vectors are simply the coordinates of individual observation, and a hyper-plane is a form of SVM visualization. The SVM classifier is a frontier that best segregates the two classes (hyper-plane/line).

CHAPTER 5

PROJECT DESIGN AND IMPLEMENTATION

5.1 EXISTING SYSTEM

This Existing paper focuses on an automated classification algorithm which processes short technique is based on support vector machines (SVM) and has been trained and tested on sleep apnea recordings from subjects with and without OSA. which is tested through polysomnography (PSG) at sleep labs. PSG is both expensive and inconvenient as an expert human observer is required to work over night. New sleep apnea classification techniques are nowadays being developed by bioengineers for most comfortable and timely detection. This paper focuses on an automated classification algorithm which processes short duration epochs of the electrocardiogram (ECG) data. The presented classification technique is based on support vector machines (SVM) and has been trained and tested on sleep apnea recordings from subjects with and without OSA.

5.2 EXISTING MODEL DISADVANTAGES

- Less number of Data set collection
- Feature handled is little complex
- Consuming huge time

5.3 OBJECTIVE OF THE PROJECT

The main objective of this project is to predict the sleep apnea disease prediction by using Django Framework and machine learning.

5.4 FLOW CHART

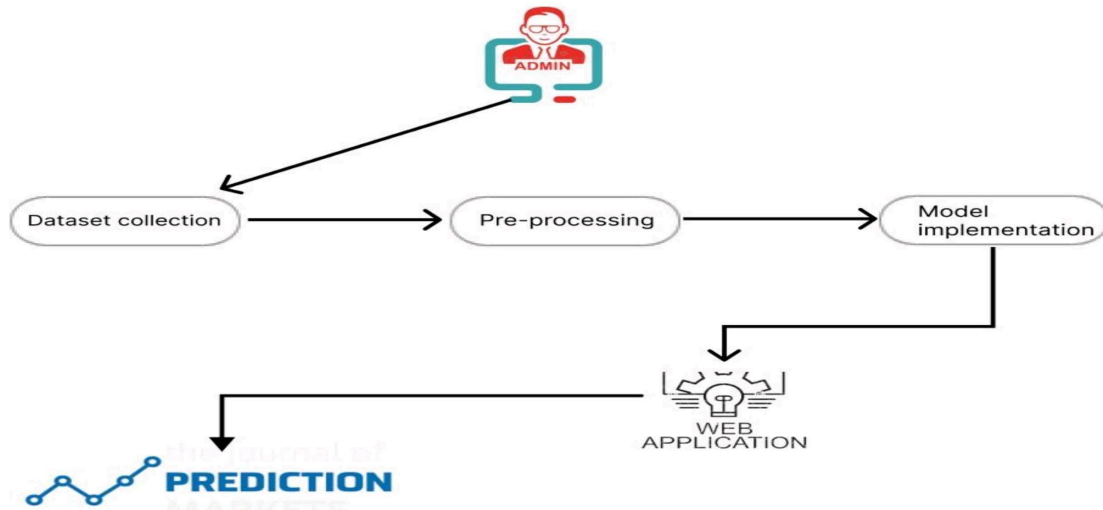


Fig 5.4 FLOWCHART REPRESENTING THE INITIAL STEPS OF THE MODEL

- The process starts with the user, who defines the problem statement and the data required to solve the problem.
- The user collects the dataset and prepares it for analysis.
- The dataset goes through pre-processing, which includes cleaning, transforming, and manipulating the data as required.
- Next, a predictive model is implemented using the pre-processed dataset.
- The model is integrated into a web application that can be accessed by users for predictions.

Finally, the web application provides predictions based on user input, and the process ends.

5.5 IMPLEMENTATION / PROPOSED WORK

Sleep apnea is a sleep-related breathing disorder that causes respiratory problems and arousals due to a reduction or rise in airflow during sleep. Obstructive sleep apnea (OSA) is the most common form of sleep apnea. In our Proposed method, to predict the sleep apnea disease by using Django Framework as well as machine learning model of the system. With the explosive growth of machine learning (ML) and artificial intelligence and its increasing use in healthcare, recently, the focus has turned to applications of ML in developing predictive models to improve the screening strategy for OSA and increase

its accuracy of the system. In the Web Application part, user can enter the symptoms of the patient detail. Finally, to predict the disease based on sleep apnea present or sleep apnea absent of the system.

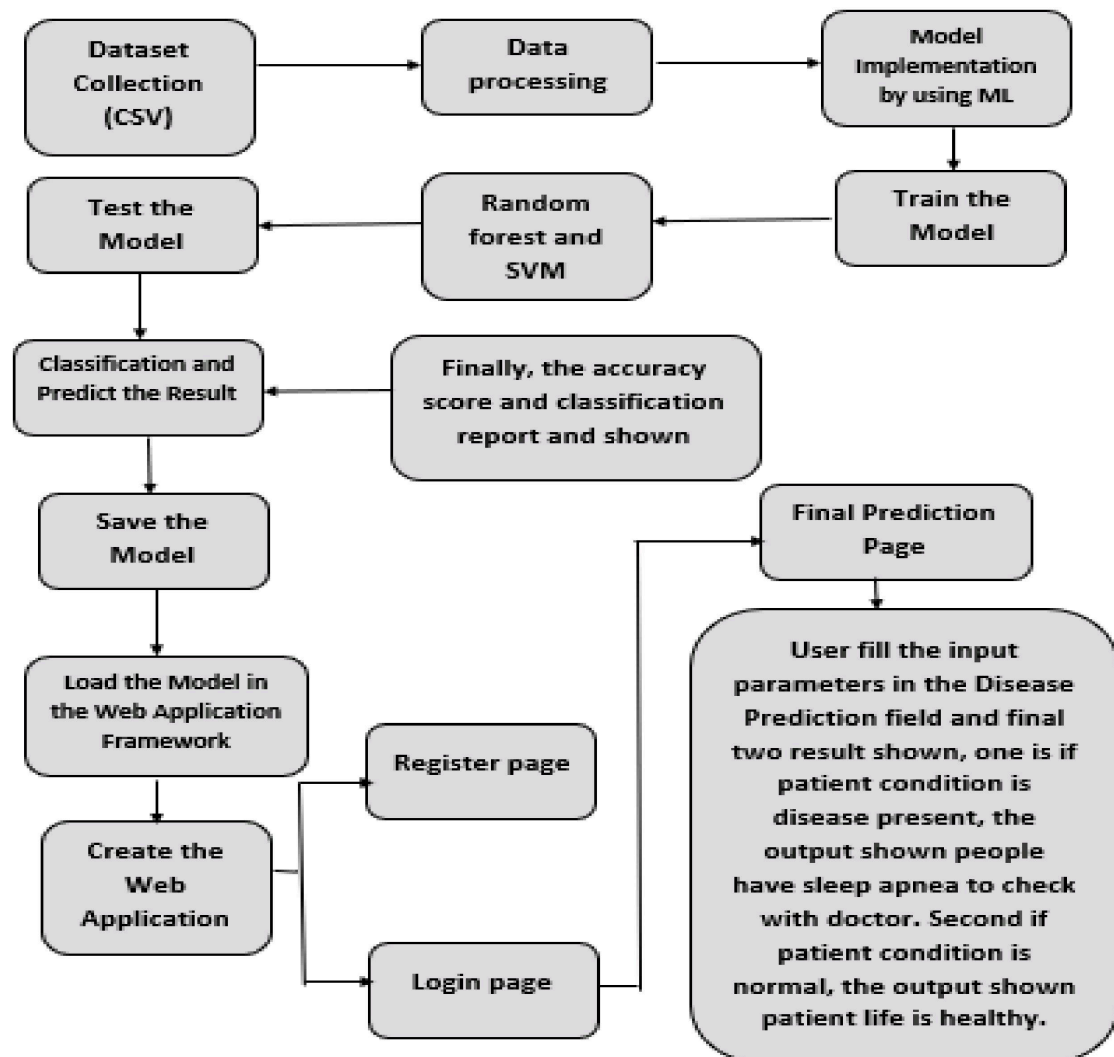


Fig 5.5 SYSTEM ARCHITECTURE OF THE SLEEP APNEA DISEASE AND PREDICTION

5.6 MODULES

- Dataset collection
- Pre-processing
- Model implementation
- Web Application
- Prediction

5.6.1 DATA COLLECTION

A dataset (or data set) is a collection of data, usually presented in tabular form. Each column represents a particular variable. Each row corresponds to a given member of the dataset in question. It lists values for each of the variables, such as height and weight of an object. Each value is known as a datum.

We have chosen to use a publicly-available patient's data which contains a relatively small number of inputs and cases. The data is arranged in such a way that will allow those trained in disciplines to easily draw parallels between familiar statistical and novel ML techniques. Here, we use the random forest and svm algorithm are used to predict the disease of the system.

5.6.2 PRE-PROCESSING

In this step, we use various types of pre-processing techniques to handle the missing, noisy and inconsistent data. There are a number of pre-processing techniques such as case folding, character erase, tokenization, slang word handling, stop word removal, stemming and number handling. The sklearn pre-processing package provides several common utility functions and transformer classes to change raw feature vectors into a representation that is more suitable for the downstream estimators of the system. Data preprocessing involves transforming raw data to well-formed data sets so that data mining analytics can be applied.

5.6.3 MODEL IMPLEMENTATION

Here, we use the machine learning model are random forest and svm algorithm are used to generate and save the model for further process of the system.

The Machine Learning algorithm is used to train a model.

The prediction result is then saved as a H5 model to predict the values for future.

5.6.4 WEB APPLICATION

A web framework is an architecture containing tools, libraries, and functionalities suitable to build and maintain massive web projects using a fast and efficient approach. They are designed to streamline programs and promote code reuse. To create the server-side of the web application, you need to use a server-side language. Python is home to numerous such frameworks, famous among which are Django and Flask.

Django:

Django is a high-level Python web framework that enables rapid development of secure and maintainable websites. Built by experienced developers, Django takes care of much of the hassle of web development, so you can focus on writing your app without needing to reinvent the wheel.

5.7 PREDICTION

By using the saved model, we are implementing the concept of web application using Django frame work.

User, enter the values of symptom of sleep apnea patient as well as normal patient data. Next to click the enter button.

Finally, the result shown based on sleep apnea present or absent of the person.

5.8 ADVANTAGES OF PROPOSED WORK:

- Web Application used
- Prediction Proper
- Better Accuracy

CHAPTER 6

RESULTS AND DISCUSSIONS

6.1 RESULTS

The web application for the detection of the Sleep Apnea Disease is developed. The following images show the pages of the web application which are developed for the project.



FIG 6.1.1 User Login Page

The user login page consists of username and password, which must be entered by the user in order to login to their respective account. If the user does not have an account, the sign up button must be clicked to create a new account. An account can be added as a sub account, by clicking the relative account and registering in the relative account login page.

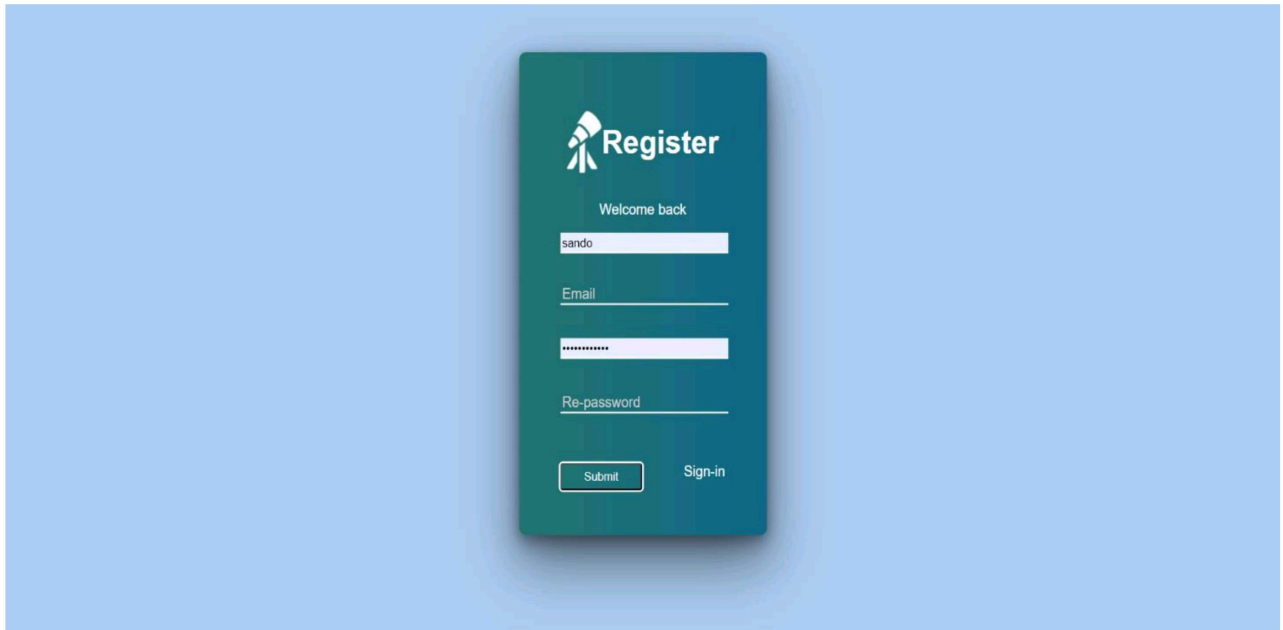


FIG 6.1.2 User Registration Page

The user registration page consists of the required details of the user.

PREDICTION FORM

SLEEP APNEA PREDICTION USING SUPERVISED MACHINE LEARNING TECHNIQUES
[Home](#)

AGE

63

GENDER

Male

CHEST_PAIN

3

REST_BPS

145

CHOLESTERAL

233

FBS

1

REST_ECG

0

HEART_RATE

150

EXANG

0

OLDPEAK

2.3

SLOPE

0

CA

0

THAL

1

Submit

FIG 6.1.3 Prediction Form Page Presence of Healthy patient Data

The prediction form page is an interface provided for the user to enter their input and results of the system's Sleep Apnea Healthy Patient Data

SLEEP APNEA NOT OCCUR SO, GIVEN CARE PLAN FOLLOWING THIS CONDITIONS	SLEEP APNEA MIGHT NOT OCCUR IN THIS CONDITION Prevention Lifestyle Modification: Encourage the patient to adopt a healthy lifestyle including weight management, regular exercise, and a balanced diet. Excess weight can contribute to obstructive sleep apnea. Avoidance of Sedatives and Alcohol: Educate the patient about the effects of sedatives and alcohol on sleep quality and their potential to exacerbate sleep apnea. Sleep Positioning: Recommend sleeping on the side instead of the back to reduce the severity of sleep apnea symptoms. Regular Sleep Schedule: Encourage the patient to maintain a consistent sleep schedule, ensuring they get adequate sleep each night. Precautions Continuous Positive Airway Pressure (CPAP): Advise the patient to use CPAP therapy consistently if prescribed. CPAP helps keep the airway open during sleep. Oral Appliances: Discuss the option of using oral appliances, such as mandibular advancement devices, to help keep the airway open. Regular Follow-up: Schedule regular follow-up appointments with healthcare providers to monitor the effectiveness of treatment and make any necessary adjustments. Avoid Smoking: Emphasize the importance of avoiding smoking, as it can worsen sleep apnea symptoms and increase the risk of other health complications. Effects Daytime Fatigue: Educate the patient about the potential effects of sleep apnea on daytime functioning, such as excessive daytime sleepiness, difficulty concentrating, and irritability. Cardiovascular Risks: Discuss the increased risk of cardiovascular problems associated with untreated sleep apnea, including hypertension, heart disease, and stroke. Mental Health Impacts: Highlight the link between sleep apnea and mental health issues like depression and anxiety. Treatment Continuous Positive Airway Pressure (CPAP): Ensure the patient understands how to use CPAP equipment correctly and encourage compliance with treatment. Oral Appliances: Provide information on oral appliances and refer the patient to a dentist specializing in sleep medicine for evaluation and fitting if appropriate. Surgery: Discuss surgical options with the patient if conservative treatments are ineffective or if there are anatomical issues contributing to sleep apnea. Education and Support Patient Education: Provide educational materials about sleep apnea, its causes, effects, and treatment options. Support Groups: Offer information about local or online support groups where patients can connect with others facing similar challenges and share experiences. Family Education: Educate family members about sleep apnea and its impact on the patient's health to garner support and understanding. Monitoring and Evaluation Sleep Studies: Arrange for regular sleep studies to assess the effectiveness of treatment and monitor any changes in the severity of sleep apnea. Symptom Tracking: Encourage the patient to keep a sleep diary to track symptoms and assess the effectiveness of interventions over time. Follow-up Appointments: Schedule periodic follow-up appointments to review progress, address any concerns, and make adjustments to the care plan as needed.	
---	---	--

FIG 6.1.4 Output of Normal patient page

The results of the Sleep Apnea Disorder Not Present Patient are displayed.

PREDICTION FORM

SLEEP APNEA PREDICTION USING SUPERVISED MACHINE LEARNING TECHNIQUES

[Home](#)

AGE

5

GENDER

Female

CHEST_PAIN

5

TREST_BPS

5

CHOLESTERAL

5

FBS

5

REST_ECG

5

HEART_RATE

5

EXANG

5

OLDPEAK

5

SLOPE

5

CA

5

THAL

5

Submit

FIG 6.1.5 Prediction Form Page Presence of Sleep Apnea in Our Data

The prediction form page is an interface provided for the user to enter their data Selection Depending on the presence of sleep apnea in our data.

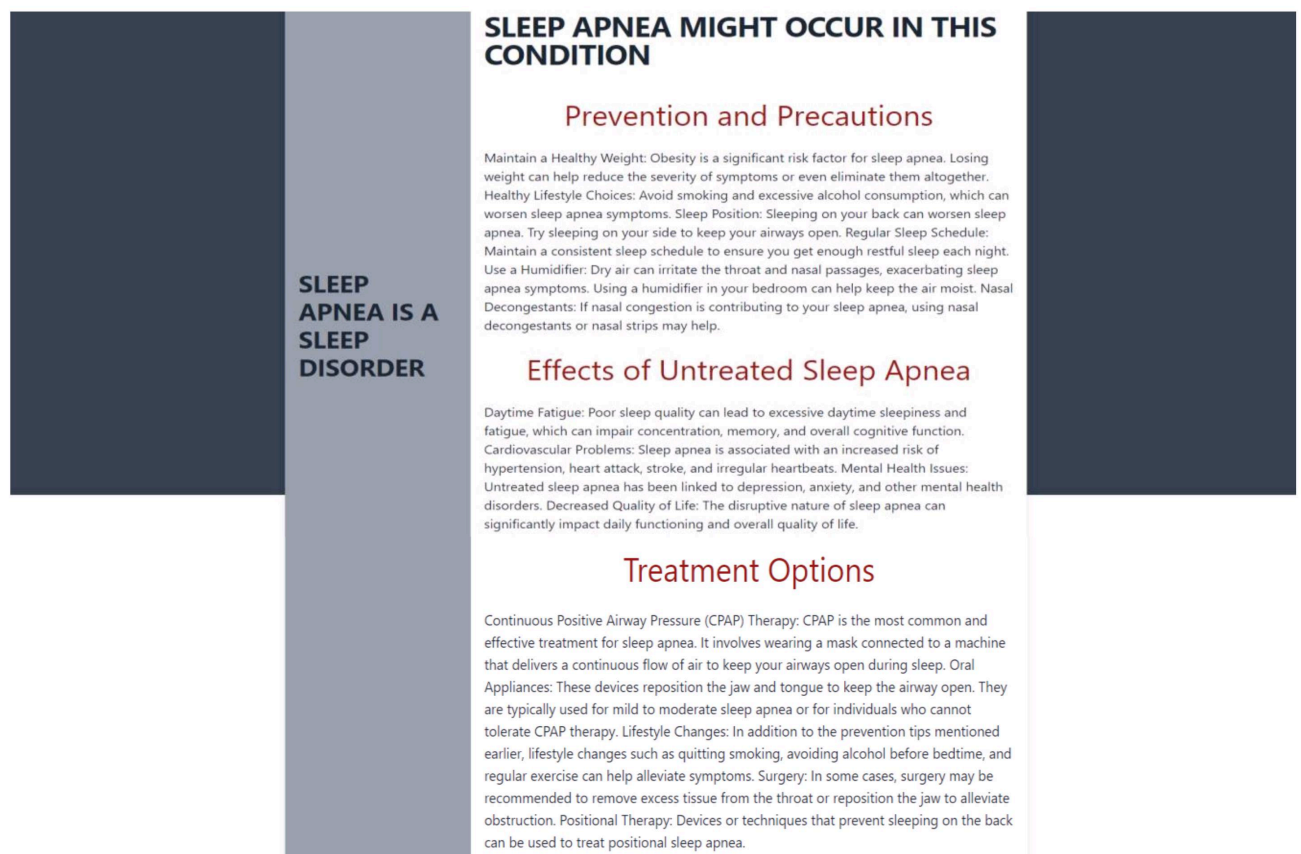


FIG 6.1.6 Output of sleep Apnea Present Page

The results of the Sleep Apnea Present Patient Data are displayed.

Algorithm	Specificity	Sensitivity	Accuracy
CNN	88.9	85.45	86.23
CNN+LSTM	92.32	93.1	93.44
Kernel Extreme Learning Machine	80.3	84.11	87.66
RUSboot	90.78	91.2	92.3
Adaboost	91.89	92.55	93.13
Random Forest +SVM	96.22	97.44	98.89

Comparison of Algorithms

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 CONCLUSION

In The proposed Work machine learning as well as web application-based Django framework for predicting OSA based on present or absent of the patient . We are on the next wave of approaches to better detect sleep apnea in the general population, with the more widespread use of ML. The experimental results show that the Web application-based Django model is more appropriate than the traditional neural network detection method. Our results showed promising findings with respect to recognition of apnea (Present or absent), which could be of significant interest to sleep specialists of the system. Our method shows comparable performances to the state-of-the-art results in terms of getting prediction using end-to-end machine learning as well as Django Framework.

7.2 FUTURE ENHANCEMENTS

Multiple Algorithms can be deployed for effective filtering. A toggle button can be used to enable formula-based detection transactions (for ex: the user can choose to enable or disable the transaction limit). Counterfactual analysis can be deployed. Hardware implementation can also be interfaced using NFC (Near Field Communication) for easy transactions.

REFERENCES

- [1] A Hedge, D.O., Horges, R Olson, E.J., Nykodym, J., Karan, T., Somer, V 2020 Obesity, obstructive sleep apnea, and the possibility of unexpected atrial fibrillation.
- [2] White, D. 2021 Sleep apnea. Proceedings of the American Thoracic Society 3, 124–128.
- [3]. Peppard PE. increased incidence of adult sleep breathing disorders. 2021.
- [4]. Heinzer R, Marque-Vidal P. sleep disturbed breath. frequency in the overall population. 2020
- [5]. McNicholas WT The Management Committee of EU COST ACTION B26. Evidence currently available, fundamental causes, and future research directions regarding sleep apnea as a standalone cardiovascular disease risk factor.2020
- [6] M.Vijay Kalli et al., " Predictive Analytics for the Detection of Obstructive Sleep Apnea". 2021
- [7] Mencar, Corrada, et al. " Machine learning used to predict the severity of sleep apnea obstructive syndrome." 2019.
- [8] S. Aswath et al., " Using anthropometrics, the Obstructive Sleep Apnea Severity Predictive GUI ". 2021
- [9] Wen-Te Liu et al., "SVM Prediction of Obstructive Sleep Apnea Severity Using Anthropometric Features," 2021
- [10] Young Jae Kim et al., "Machine Learning-Based Prediction System for Severe Sleep Disorders in Korean Adults Diagnostics", 2020.
- [11]Troncoso-García, A. R., Martínez-Ballesteros, M., Martínez-Álvarez, F., & Troncoso, A. (2022). Explainable machine learning for sleep apnea prediction.
- [12]Mostafa, S. Morgado, F. (2021). An analysis of deep learning's effectiveness in detecting sleep apnea.
- [13] Punjabis, M. (2020). Review of sleep disorder apnea diagnosis and treatment. Jama, 323(14), 1389-1400.

APPENDIX:

A. SOURCE CODE

```
#!/usr/bin/env python

"""Django's command-line utility for administrative tasks."""

import os
import sys

def main():
    """Run administrative tasks."""
    os.environ.setdefault('DJANGO_SETTINGS_MODULE', 'sleep_apnea.settings')
    try:
        from django.core.management import execute_from_command_line
    except ImportError as exc:
        raise ImportError(
            "Couldn't import Django. Are you sure it's installed and "
            "available on your PYTHONPATH environment variable? Did you "
            "forget to activate a virtual environment?"
        ) from exc
    execute_from_command_line(sys.argv)

if __name__ == '__main__':
    main()

from django.contrib import admin
from .models import *
# Register your models here.
admin.site.register(UserProfile)
admin.site.register(Almodel)
from django.apps import AppConfig

class AppConfig(AppConfig):
    default_auto_field = 'django.db.models.BigAutoField'
```

```

name = 'app'

from django import forms
from . Models import *
class PredictionForm(forms.Form):
    age = forms.IntegerField()
    sex = forms.IntegerField()
    cp = forms.IntegerField()
    tresbps = forms.IntegerField()
    chol = forms.IntegerField()
    fbs = forms.IntegerField()
    restecg = forms.IntegerField()
    thalach = forms.IntegerField()
    exang = forms.IntegerField()
    oldpeak = forms.IntegerField()
    slope = forms.IntegerField()
    ca = forms.IntegerField()
    thal = forms.IntegerField()
from django.db import models
from django.contrib.auth.models import User
# Create your models here.
class UserProfile(models.Model):
    user = models.ForeignKey(User,on_delete=models.CASCADE)
    # email = models.EmailField()
    def __str__(self):
        self.user.username
class Almodel(models.Model):
    """
    age sex cp trestbps  chol  fbs restecg thalach exang  oldpeak
slope  ca  thal  target

```

```

From django.shortcuts import render,redirect
from django.views.generic import CreateView,TemplateView
from django.contrib.auth.forms import UserCreationForm
from sklearn.preprocessing import StandardScaler
import numpy as np
from django.http import *
from .forms import *
from django.urls import reverse_lazy
from .models import *
import pickle
# Create your views here.
model = pickle.load(open('model.pkl','rb'))
class HomeView(TemplateView):
    template_name = "index.html"
class SignUpView(CreateView):
    form_class = UserCreationForm
    success_url = reverse_lazy("login")
    template_name = "signup.html"
def PredictionView(request):

    if request.method == "POST":
        form = PredictionForm(request.POST)
        if form.is_valid():
            scale = StandardScaler()
            data =
[form.data["age"],form.data["sex"],form.data["cp"],form.data["tresbps"],form.data["chol"]
,form.data["fbs"],form.data["restecg"],form.data["thalach"],form.data["exang"],form.data[
"oldpeak"],form.data["slope"],form.data["ca"],form.data["thal"]]
            predict = scale.fit_transform(np.array(data,ndmin=2))
            final = model.predict(predict)
            return render(request,"final.html",{"final":final})

```

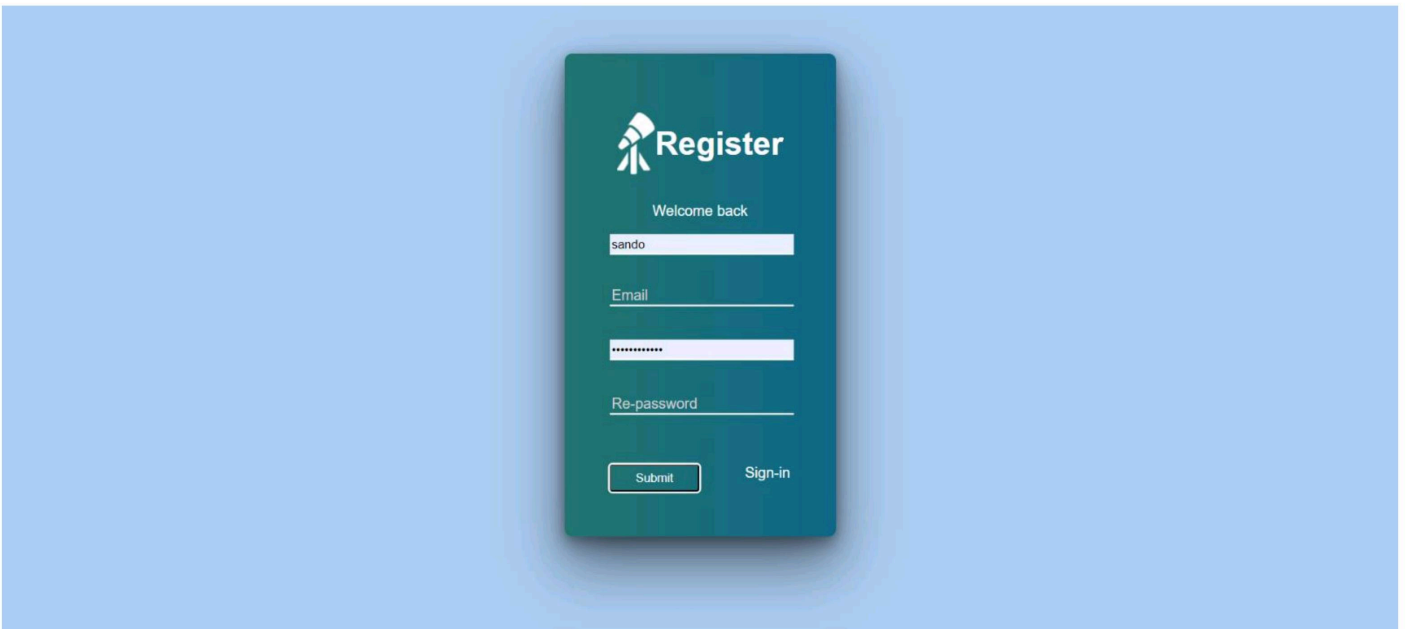
```
    else:
        HttpResponseRedirect(form.errors)
else:
    form = PredictionForm()
    return render(request, "prediction.html", {"form": form})

def aboutus(request):
    return render(request, "aboutus.html")
```

B. SCREENSHOTS



User Login Page



User Registration Page

PREDICTION FORM

SLEEP APNEA PREDICTION USING SUPERVISED MACHINE LEARNING TECHNIQUES	
Home	
AGE	63
GENDER	Male
CHEST_PAIN	3
REST_BPS	145
CHOLESTERAL	233
FBS	1
REST_ECG	0
HEART_RATE	150
EXANG	0
OLDPEAK	2.3
SLOPE	0
CA	0
THAL	1
Submit	

Prediction Form Page Presence of Healthy patient Data

	SLEEP APNEA NOT OCCUR SO, GIVEN CARE PLAN FOLLOWING THIS CONDITIONS	SLEEP APNEA MIGHT NOT OCCUR IN THIS CONDITION Prevention Lifestyle Modification: Encourage the patient to adopt a healthy lifestyle including weight management, regular exercise, and a balanced diet. Excess weight can contribute to obstructive sleep apnea. Avoidance of Sedatives and Alcohol: Educate the patient about the effects of sedatives and alcohol on sleep quality and their potential to exacerbate sleep apnea. Sleep Positioning: Recommend sleeping on the side instead of the back to reduce the severity of sleep apnea symptoms. Regular Sleep Schedule: Encourage the patient to maintain a consistent sleep schedule, ensuring they get adequate sleep each night. Precautions Continuous Positive Airway Pressure (CPAP): Advise the patient to use CPAP therapy consistently if prescribed. CPAP helps keep the airway open during sleep. Oral Appliances: Discuss the option of using oral appliances, such as mandibular advancement devices, to help keep the airway open. Regular Follow-up: Schedule regular follow-up appointments with healthcare providers to monitor the effectiveness of treatment and make any necessary adjustments. Avoid Smoking: Emphasize the importance of avoiding smoking, as it can worsen sleep apnea symptoms and increase the risk of other health complications. Effects Daytime Fatigue: Educate the patient about the potential effects of sleep apnea on daytime functioning, such as excessive daytime sleepiness, difficulty concentrating, and irritability. Cardiovascular Risks: Discuss the increased risk of cardiovascular problems associated with untreated sleep apnea, including hypertension, heart disease, and stroke. Mental Health Impacts: Highlight the link between sleep apnea and mental health issues like depression and anxiety. Treatment Continuous Positive Airway Pressure (CPAP): Ensure the patient understands how to use CPAP equipment correctly and encourage compliance with treatment. Oral Appliances: Provide information on oral appliances and refer the patient to a dentist specializing in sleep medicine for evaluation and fitting if appropriate. Surgery: Discuss surgical options with the patient if conservative treatments are ineffective or if there are anatomical issues contributing to sleep apnea. Education and Support Patient Education: Provide educational materials about sleep apnea, its causes, effects, and treatment options. Support Groups: Offer information about local or online support groups where patients can connect with others facing similar challenges and share experiences. Family Education: Educate family members about sleep apnea and its impact on the patient's health to garner support and understanding. Monitoring and Evaluation Sleep Studies: Arrange for regular sleep studies to assess the effectiveness of treatment and monitor any changes in the severity of sleep apnea. Symptom Tracking: Encourage the patient to keep a sleep diary to track symptoms and assess the effectiveness of interventions over time. Follow-up Appointments: Schedule periodic follow-up appointments to review progress, address any concerns, and make adjustments to the care plan as needed.
--	---	--

Output of Normal patient page

PREDICTION FORM

SLEEP APNEA PREDICTION USING SUPERVISED MACHINE LEARNING TECHNIQUES
[Home](#)

AGE

5

GENDER

Female

CHEST_PAIN

5

TREST_BPS

5

CHOLESTERAL

5

FBS

5

REST_ECG

5

HEART_RATE

5

EXANG

5

OLDPEAK

5

SLOPE

5

CA

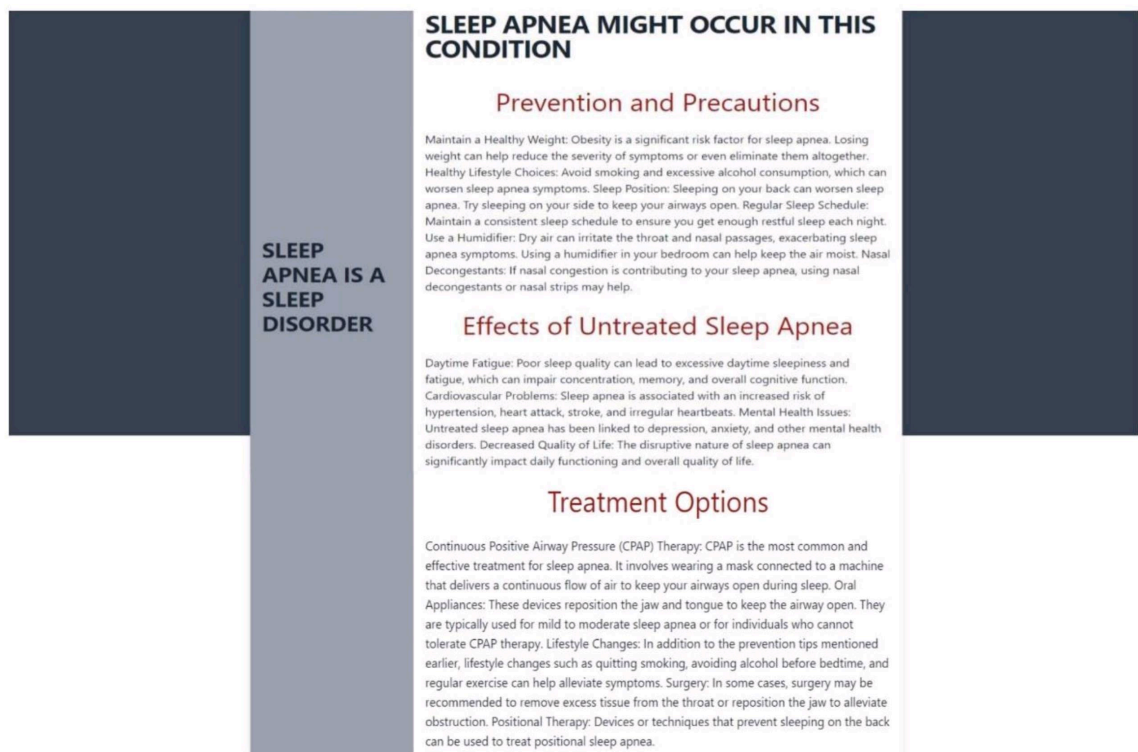
5

THAL

5

Submit

***Prediction Form Page Presence of Sleep Apnea in
Our Data***



Output of sleep Apnea Present Page



14th International Conference on Science & Innovative Engineering - 2024

ORGANIZED BY

**PRINCE SHRI VENKATESHWARA PADMAVATHY ENGINEERING COLLEGE
PRINCE DR. K. VASUDEVAN COLLEGE OF ENGINEERING & TECHNOLOGY**

IN ASSOCIATION WITH

**MANIPAL UNIVERSITY COLLEGE, MALAYSIA
ORGANIZATION OF SCIENCE & INNOVATIVE ENGINEERING TECHNOLOGY**

Certificate of Registration

This is to certify that Dr./Mr./Ms. **VELAN S** from
Sathyabama Institute of Science and Technology, Chennai has presented a
paper titled **Obstructive Sleep Apnea Detection Using Machine Learning**
in the "14th International Conference on Science & Innovative Engineering" held on 27th & 28th April 2024 at
Prince Dr. K. Vasudevan College Of Engineering & Technology

Dr. Antony V. Samrot, M.E., Ph.D.,
Director (Research, Innovation and Postgraduate Studies)
Manipal University College, Malaysia

Dr. A. Krishnamoorthy, M.E., Ph.D
Convener - ICSIE

K. Janani, M.Tech.,
CEO, OSIET

Obstructive Sleep Apnea Detection Using Machine Learning

¹Tuffin Sando
U.G Scholar
Department of Information
Technology
Sathyabama Institute of Science and
Technology
Chennai, India
jesustuffin@gmail.com

L.Mary Gladence
Associate professor
Department of Information
Technology
Sathyabama Institute of Science and
Technology
Chennai, India
lgladence@gmail.com

¹Velan
U.G Scholar
Department of Information
Technology
Sathyabama Institute of Science and
Technology
Chennai, India
velansenthilkumar23@gmail.com

ABSTRACT

OSA (Obstructive Sleep Apnea) presents a significant challenge to sleep quality, described by disruptions in breathing and the hallmark of irregular airflow during sleep. Prevalent among middle-aged individuals, statistics indicate that around 2% of middle-aged women and 4% of middle-aged men are impacted by this respiratory disorder. The diagnostic journey for OSA involves a two-step process overseen by physicians, initially focusing on the review of medical records attained through the polysomnography system. Acknowledging the limitations of existing diagnostic procedures, the study introduces innovative approaches leveraging HRV (Heart Rate Variability) and ECG (Electrocardiography) signals. This involves collecting ECG records from both patient and control groups and subsequently utilizing an optical filter to refine ECG signals and HRV variables. The intricacies of the electrocardiographic data are further explored as the ECG signal is applied to compute the HRV parameter, and functionality is extracted from both signals.

Keywords: Graphical User Interface, Python Programming Language, Obstructive Sleep Apnea Prediction, Django Framework, Web Application, Machine Learning, Artificial Intelligence.

I. INTRODUCTION

The predominant form of sleep-related respiratory anomalies is encapsulated in OSA, a condition with profound implications for one's social and personal life. The effectiveness of sleep is jeopardized by airway blockages, giving rise to disruptive phenomena such as loud snoring, gasping, and choking for air during sleep, accompanied by headaches and daytime lethargy. If left unaddressed, these manifestations can lead to a spectrum of health afflictions, ranging from Liddle syndrome and cardiac infarction to obesity and premature mortality. Sleep apnea, characterized by chronic respiratory interruptions during sleep, imposes a significant burden on an individual's well-being, disrupting the normal breathing pattern with pauses lasting seconds to minutes. The linkage between sleep apnea, obesity, and impaired cardiopulmonary function is underscored, as patients grapple with symptoms like memory loss, irritability, dizziness, and daytime drowsiness, hindering routine activities such as work, learning, and driving. Despite its prevalence, obstructive sleeping syndrome (OSAS) often goes untreated and undetected, affecting persons between the ages of 30 and 70 at a projected rate of 5 to 14 percent. Notably, recent research reveals that nearly 23 percent of women and 50 percent of men may experience sleep apnea episodes unrelated to sleepiness. The clinical ramifications of OSAS extend beyond sleep disruptions, encompassing higher morbidity and mortality rates, along with an elevated risk of cardiovascular diseases.

The intricate nature of sleep disturbances is explored, emphasizing the potential severity of cases based on the frequency and severity of breathing pauses. The repercussions extend to the brain's reluctance to allow deeper sleep stages, posing a risk of choking on respiration. Amidst awareness of various sleep apnea symptoms, the central concern of OSA is underscored, contributing to a rising fatality rate associated with diverse sleep disorders. A staggering 93 percent of Indians experience sleep-related problems, yet only 2% discuss these issues with doctors, highlighting a concerning lack of awareness and communication.

The economic impact of sleep disturbances is illuminated, emphasizing the substantial costs incurred on financial, social, and personal fronts. While healthcare remains a global concern, the increasing complexity and interplay of various health issues, including trauma-related concerns, obesity, and contemporary issues such as sleep apnea, further complicate the quality of life. The paper delves into the scientific proof of sleep deprivation breathing, emphasizing the role of Polysomnography in diagnosing OSA. Surprisingly, despite the proliferation of Machine Learning (ML) algorithms for early disease detection, few studies focus on OSA prediction.

To estimate the likelihood of SA based on a patient's medical history, the study presents a web application built on a classification model inside the Django framework. The findings of the test validate the system's enhanced performance. The subsequent sections of the paper promise an extensive exploration, comprising a literature review, a proposed methodology, a discussion of results, and the overall impact of the article on the system.

II.RELATED WORKS

The comprehensive literature review navigates through a diverse array of studies, each offering distinct perspectives and methodologies in the domain of OSA detection. Alireza Pedram Razi and team [1] SA stands as one of the widespread sleep-related illnesses, characterized by a disruption in airflow through the airways lasting at least 10 seconds. This condition is recognized to be related to various cardiovascular diseases. The conventional method for diagnosing

sleep apnea involves polysomnography (PSG), a costly and time-consuming approach. In this study, we explore an alternative diagnostic method utilizing ECG signals, involving the extraction, selection, and classification of features. The classification was carried out with RF ("Random Forest") classifier, whose performance was compared with SVM ("Support Vector Machine") and DT("Decision Tree") classifiers. The findings indicated that the RF and LDA combination yielded the highest accuracy (95.01%), sensitivity (92.17%), and specificity (94.79%). This method demonstrated superior efficiency than other approaches utilizing the same datasets.

Dr. Jianming Zhu and team. [2] SA, a predominant sleep disorder, has the potential to adversely impact the human physiological system. Consequently, there is a pressing need for early SA diagnosis. The conventional method, involving overnight polysomnography (PSG) evaluation, may face limitations in "availability, prompting exploration into automatic SA screening along with fewer signals. RFECV("Recursive Feature Elimination with Cross-Validation") was applied to identify features, and an RF classifier was then applied to distinguish between apnea and normal events. With a specificity of 98.4%, an accuracy of 97.5%, a sensitivity of 95.9%, and an AUC of 0.992 in per-s 11 nent classification, the tests carried out on the Apnea-ECG database produced impressive results that outperformed earlier methods.

The study underscores the complementary nature of ECG and SpO2 in SA detection. Consequently, the proposed method stands as a promising alternative to conventional detection methods.

Kandala. N. V. P. S. Rajesh and team [3] OSA is a widespread sleep disorder affecting approximately 10 percent of middle-aged individuals, leading to disruptions in normal organ functioning, particularly the heart. Left untreated, OSA is linked to heightened risks of cardiovascular diseases, stroke, diabetes,

and hypertension, significantly rising mortality risk. Consequently, early detection of sleep apnea is crucial to mitigate its adverse health effects and improve overall patient outcomes.

Anju Prabhaand and team [4] the objective of Sie present study to devise a non-intrusive system for automated detection and categorization of SA events, leveraging the single-channel AbdRES ("Abdomen Respiratory Effort Signal") from the ISRUC sleep database. A classifier system is built by extracting characteristics from te Abd RES, including Shannon entropy, time domain respiratory rate variability, and discrete wavelet transform energy. Comparative analysis between linear multi-class SVM as well as RF classifiers is conducted. Additionally, an enhanced random forest (IRF) classifier is introduced, addressing dataset imbalance through a combination of data re-sampling, RF method, and a threshold-moving technique. Individual feature sets yield distinct system designs, yet the fusion of features enhances classification accuracy. The IRF-based system achieves a maximum accuracy of 89.66%, utilizing a decreased feature set attained through a principal component study. This suggested approach offers an effective, cost-efficient, and accessible screening tool for SA. Ahmed I. Sharaf and team [5] OSA significantly impacts human life, affecting sleep quality. While Polysomnogram is a potent method for OSA detection, it's time-consuming and costly. This paper introduces an innovative automated approach, utilizing single-lead ECG signals for apnea detection and classification. Employing WST ("Wavelet Scattering Transformation"), the ECG signals are decomposed into smaller segments. A RF classifier processes these features to categorize ECG segments. Validation through 10-fold and hold-out cross-validation yields accuracies of 91.65% and 90.35%, respectively. Comparative analysis with different classifiers underscores the importance of the suggested method, showcasing superior performance compared to existing methodologies.

Bruno M. C. Silva and team [6] This article delves into the efficacy of various classifiers in detecting sleep apnea moments through minute-to-minute Electrocardiogram (ECG) signals. It meticulously compares the accuracy of different classifiers, employing a Sgolay filter to extract EDR (ECG-Derived Respiration) and HRV from each ECG signal. These features are utilized for training, testing as well as validation of the classifiers. In a subsequent phase, an extended set of features is explored to assess their importance. Results reveal the optimal accuracy

at 82.12%, accompanied by a specificity of 72.29% and sensitivity of 88.41%. This analysis underscores the critical role of selecting appropriate classifiers and features, offering insights for improved accuracy. The promising early-stage outcomes warrant further studies to enhance classifiers for potential real-world applications. Comparative analysis with other sleep apnea detection approaches validates the performance of the suggested method.

Nader Salari and team [7] SA, a prevalent sleep disorder with elusive detection, has gained attention for diagnosis through Electrocardiogram (ECG) analysis. Given the imperceptible changes induced by SA on the ECG, innovative diagnostic methods are imperative. Machine Learning (ML) emerges as a successful avenue for computer-aided diagnosis, leveraging past clinical outcomes. This study systematically reviews English articles, published before October 2020, and indexed in IEEE, Web of Science, Scopus, and PubMed databases, yielding 48 selected articles. ML algorithms, predominantly SVM and DL neural networks (CNN, DNN), are employed in binary classifications distinguishing SA from normal states, either based on full ECG records or one-minute segments. Key features include frequency, time series, and statistical metrics. SVM achieves 100% specificity, sensitivity, and accuracy, in full-record detection, while a RNN ("Residual Neural Network") attains 99% specificity, sensitivity, accuracy, and ECG segment classification. Overall, ML techniques grounded in ECG characteristics demonstrate robust capabilities in SA diagnosis, potentially enhancing early detection and averting complications.

Ahnaf Rashik Hassan and team [8] This article addresses the imperative need for computerized obstructive sleep apnea detection to enhance diagnostic speed and support medical professionals. The focus is on developing a low-power, portable device for monitoring sleep apnea, necessitating a reliable detection scheme. The proposed automate approach utilizes electro cardiogram (ECG) signals. Data-adaptive signal decomposition using the TQWT ("Tunable Q Factor Wavelet Transform") is utilized to extract statistical characteristics from TQWT sub-bands to create train and test matrices. A novel ML technique called RUSBoost ("Random Under-

Sampling Boosting") is presented to classify an unprecedented combination of TQUT for SA diagnosis. The method's algorithmic performance is systematically evaluated across various TQWT parameter values, demonstrating optimal parameter selections. The efficacy of RUSBoost is underscored, outperforming conventional classification models. With its reliance on a single ECG channel, this method holds promise for practical device implementation, alleviating manual data analysis burdens on clinicians and expediting sleep apnea diagnosis.

Nicole L. Molin and team [9] This study aims to predict the risk of OSA using overnight breath recordings obtained through smartphone app, ZeeAppnea. Applying 4 data mining multi-level classifiers on the FFT ("Fast Fourier Transform") of each time series, SVM and RF classifiers exhibit superior performance, achieving total multilevel prediction accuracies of 90% and 93%, respectively. In comparison, manual interpretations by medical personnel yield an overall accuracy of 55%. Notably, binary accuracies for severe OSA classification reach 95% (SVM), 69% (manual interpretations), and 98% (RF). These results emphasize the efficacy of RF or SVM over time-consuming manual interpretations, showcasing the potential for improved prediction accuracy and the automation of OSA screening through the ZeeAppnea application.

V. Ankitha and team [10] OSA, a respiratory disorder causing interruptions in breathing during sleep, significantly impacts sleep quality. Affecting around 4 percent of middle-aged men and 2 percent of middle-aged women, the disorder is diagnosed through a two-step process involving polysomnography. Recognizing the need for improved diagnostic procedures, this study employs HRV and ECG signals. ECG records from control and patient groups are subjected to optical filtering for signal cleaning. HRV parameters are computed from ECG signals, and features are extracted. Utilizing ML approaches like SVM, RF, and KNN (K-nearest neighbors) for classification, the system achieves impressive accuracies of 82.5%, 97%, and 89%, respectively, with 11 HRV and ECG features. This approach presents a promising avenue for implementing a practical sleep/awake detection

method, utilizing ML and signal processing on ECG signals for obstructive sleep apnea diagnosis.

Corrado Mencar, Crescenzo Gallo [11] The escalating significance of OSA syndrome as a public health concern necessitates efficient diagnostic approaches. While polysomnography is a well-established tool for assessing syndrome severity and sleep fragmentation, its multiple steps make it costly and time-consuming. The objective of this research is to assess the effectiveness and clinical application of various machine learning techniques. These techniques use questionnaire responses and demographic data to forecast the degree of obstructive sleep apnea syndrome. By exploring alternative approaches, this research seeks streamlined and accessible diagnostic solutions for a condition of growing public health importance.

Xiaoyun Zhao and team [12] SAS ("Sleep apnea syndrome"), described by recurrent pauses in respiratory airflow during sleep, prompts physiological changes in the electroencephalogram (EEG) signal. This study introduces an automated method to discern sleep apnea events, specifically categorizing OSA, Central SA (CSA), and normal breathing events. An Infinite Impulse Response Butterworth Bandpass filter is used to separate the EEG signals from C4-A1 and C3-A2 into five sub-bands. For every sub-band, characteristics like variance and sample entropy are taken out. Feature selection is conducted with the NCA ("Neighbor Composition Analysis") method, and the outcomes serve as input coefficients for classification with RF, K-NN, and SVM classifiers. The accuracy for normal breathing, CSA, and OSA events reaches 95.24%, 84.85%, and 80.43%, respectively. The suggested approach exhibits significant potential for automatically classifying respiratory events during clinical studies, offering a new avenue for the expansion of an expert-free automatic classification system for SA and normal events.

Stein Kristiansen and team [13] OSA is a common, but frequently underdiagnosed sleep disease that causes periods of decreased respiration or airflow stoppage during sleep by interfering with the normal breathing cycle. Our overarching objective is to enhance OSA diagnosis rates and expedite the diagnostic process

through user-friendly and cost-effective home-based sleep analysis tools that can effectively identify apnea events, we evaluate the efficiency of ANNs, SVM, DT, KNN, and RF on data from the MIT-BIH and Apnea-ECG databases from PhysioNet. The emphasis is on respiratory signals from the oxygen saturation, chest, abdomen, nose, and with minimal preprocessing. Results show a promising accuracy of 96.6% for Apnea-ECG using a combination of chest and nose respiration data, with over 90% accuracy for all signal combinations. Notably, even the single KNN method performs well. While MIT-BIH results are lower due to noise and smaller dataset size, the study indicates that one signal may suffice for effective disrupted breathing detection, emphasizing the preference for abdomen respiration data considering classification performance and patient comfort.

Anita Ramachandran and team [14] SA, a disruptive sleep disorder described by shallow or interrupted breathing during sleep, poses significant health risks, including liver problems, neurological complications, hypertension, cardiovascular issues, and diabetes. The global occurrence of SA necessitates effective diagnosis and treatment. The clinical detection of sleep apnea is typically done through the PSG (Polysomnography) test, which determines numerous biomedical parameters like EEG, ECG, and SpO2 (oxygen saturation) throughout a full night's sleep. Recently, ML applications for SA detection, leveraging the ability to learn from training datasets and generalize estimations, have gained traction. This paper assesses the performance of six ML classifiers—SVM, ANN, KNN, XBoost, and RF—in Detecting apneic events using datasets with ECG signals.

Yao Wang and team [15] Hypopnea, characterized by inadequate alveolar ventilation leading to a more than 50% reduction in respiratory airflow during night sleep, serves as a precursor to more severe respiratory events like sleep apnea. This study introduces a method combining discrete wavelet transform and approximate entropy of EEG signals for the identification of sleep apnea and hypopnea events. Utilizing data from Tianjin Chest Hospital, EEG record datasets undergo preprocessing and decomposition into alpha, beta, gamma, theta, and

delta bands using an IIR ("Infinite Impulse Response") Butterworth bandpass filter. Descriptive features, including the estimated entropy of high-frequency coefficients, are extracted on the basis of sub-bands discrete wavelet transform.

IV. PROPOSED METHODOLOGY

Our proposed methodology aims to elucidate the conceptual framework and operational steps guiding our research endeavors. At its core, we leverage the Django Framework and a ML system to craft a predictive model for sleep apnea. Recognizing the transformative impact of ML and AI in healthcare, our approach amalgamates these technologies to enhance OSA prediction accuracy.

The process unfolds through several interconnected modules, each playing a pivotal role in shaping the system's outcome. That is revealed in fig 1.

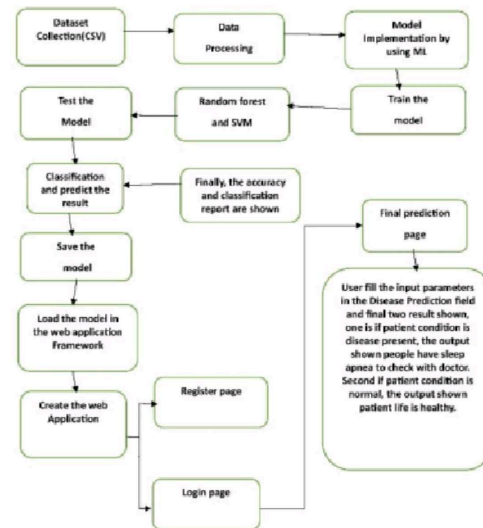


Fig 1 Block Diagram of our Proposed method

A. Dataset Gathering

In this foundational phase, we curate a dataset, a tabular representation of data where each column signifies a distinct variable, and each row encapsulates an individual data point. The chosen dataset, openly accessible and structured with clarity, accommodates a finite number of entries. Employing SVM and Random Forest algorithms, we forecast the system's response to sleep apnea.

B. Data Preparation

Handling the intricacies of data, we embark on a preprocessing journey. Techniques such as stemming, case folding, and tokenization are applied to address misplaced, noisy, and inconsistent data. Leveraging sklearn. preprocessing utilities, raw data is transformed into refined datasets, laying the groundwork for subsequent analytics.

C. Exemplary Execution

This phase orchestrates the ML method.SVM and RF algorithms are used to construct, train, and store the predictive model. Rigorous qualification processes ensure the model's reliability. The outcome, a preserved H5 model, serves as a predictive tool for future values.

D. Internet Application

We transition to the realm of web application development, employing the Django Framework to expedite the creation of a robust and secure platform. The framework's efficacy, crafted by seasoned programmers, streamlines web development complexities, enabling a focus on application enhancement without reinventing the wheel.

E. Predictions for Our Outcome

Actualizing the web application concept, users input patient data and sleep apnea symptom values. The system, guided by the saved model; determines the likelihood of sleep apnea. This dynamic interaction culminates in a conclusive assessment of whether a participant exhibits signs of sleep apnea.

V. RESULTSAND DISCUSSION

This section serves as the reflective narrative of our system's response to the proposed methodology. "Fig 2" visually represents user inputs based on the presence of sleep apnea in the dataset. Subsequently, "Fig 3" unfolds the results concerning patients with confirmed sleep apnea. This symbioticintegration of technology, methodology, and practical application positions our research asa comprehensive and forward-thinking approach in the domain of sleep disorder diagnostics.

Prediction Form

Name	Age
Sex	Cp
Tresbps	Chol
Fbs	Restecg
Thalach	Exang
Oldpeak	Slope
Ca	Thal

Predict

Fig 2 Input from SAPresent

The findings of the SA Disorder Present Patient are shown in Fig 3.

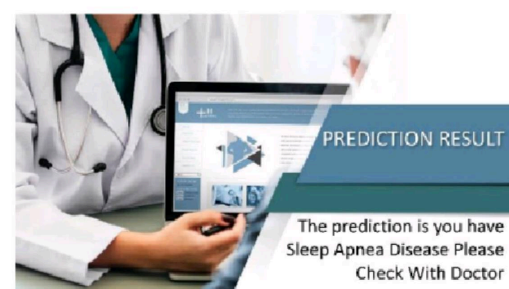


Fig 3 Output of SA Present

The input and findings of the sten⁹ SA
Healthy Patient Data are revealed in Fig 4 and Fig 5.

Prediction Form

Name	Age
Sex	Cp
Tresbps	Chol
Fbs	Restecg
Thalach	Exang
Oldpeak	Slope
Ca	Thal

Predict

Fig 4 Input of Normal Patient

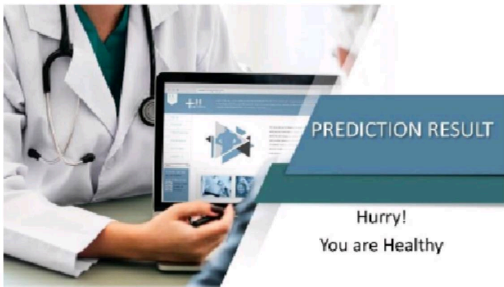


Fig 5 Output of Normal Patient

Table 1. Comparison of Algorithm

ALGORITHM	SPECIFICITY	SENSITIVITY	ACCURACY
CNN	88.9	85.45	86.23
RUSboot	90.78	91.2	92.3
Kernel Extreme Learning Machine	80.3	84.11	87.66
CNN + LSTM	92.32	93.1	93.44
Adaboost	91.89	92.55	93.13
Random Forest + SVM	96.22	97.44	98.89

VI. CONCLUSION

In conclusion, this multifaceted project unveils a holistic approach to OSA detection, amalgamating advanced technologies and methodologies. Commencing with an exploration of the intricacies of OSA in the introduction, the research strategically pivots towards a nuanced investigation of existing literature, highlighting the transformative potential of machine learning and signal processing methods in diagnosing OSA through electrocardiogram (ECG) signals.

The project unfolds in distinct modules, seamlessly interwoven to create a robust system. From dataset gathering and meticulous data preparation to exemplary execution of machine learning algorithms, each module contributes to the systems predictive prowess. The utilization of the Django framework in crafting an intuitive web application adds an element of accessibility to the diagnostic process, ensuring a user-friendly interface for input and prediction.

The Results and Discussion section encapsulates the culmination of these efforts, providing a comprehensive examination of the system's response to varying inputs, ultimately determining the presence or absence of sleep apnea. This intricate exploration sheds light on the system's strengths, fostering a deeper understanding of its potential applications and areas for refinement.

In essence, this project represents a significant stride towards leveraging technology for accurate and accessible sleep apnea diagnosis. Its multidimensional approach, combining medical insights, machine learning, and web application development, positions it as a pioneering venture in the intersection of healthcare and technology.

VII. REFERENCES

- [1]. Alireza Pedram Razi and ZahraEinalou, "Sleep Apnea Classification Using Random Forest via ECG".2021
- [2]. Dr. Jianming Zhu, "Detection of Sleep Apnea from Electrocardiogram and Pulse Oximetry Signals Using Random Forest".2022
- [3]. Kandala.N.V.P.S. Rajesh , "Obstructive sleep apnea detection using discrete wavelet transform-based statistical features".2021
- [4]. Anju Prabha, "Respiratory Effort Signal Based Sleep Apnea Detection System Using Improved Random Forest Classifier".2021
- [5]. Syed Jamalullah, R., Mary Gladence, L., Rajalakshmi, V., "Development of end – to – end encoder-decoder model applying voice recognition system in different channels" in International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8, Issue-2S11, September 2019.
- [6]. Venkateswara Rao, K., Mary Gladence, L., Raja Lakshmi, V., "Research of feature selection methods to predict breast cancer" , in International Journal of Recent Technology and Engineering(IJRTE) ISSN: 2277-3878, Volume-8, Issue-2S11, September 2019.
- [7]. Ahmed I. Sharaf, "Sleep Apnea Detection Using Wavelet Scattering Transformation and Random Forest Classifier".2023
- [8]. Bruno M. C. Silva, "Classifier Precision Analysis for Sleep Apnea Detection Using ECG Signals".2020
- [9]. Nader Salari, "Detection of sleep apnea using Machine learning algorithms based on ECG Signals: A comprehensive systematic review".2022
- [10]. Ahnaf Rashik Hassan, "An expert system for automated identification of obstructive sleep apnea from single-lead ECG using random under sampling boosting".2017
- [11]. Nicole L. Molin. "Prediction of obstructive sleep apnea using Fast Fourier Transform of overnight breath recordings".2021
- [12]. V. Ankitha, "Literature Review on Sleep APNEA Analysis by Machine Learning Algorithms Using ECG Signals".2021
- [13]. Corrado Mencar, Crescenzo Gallo, "Application of machine learning to predict obstructive sleep apnea syndrome severity".2019
- [14]. Xiaoyun Zhao, "Classification of sleep apnea based on EEG sub-band signal characteristics".2021
- [15]. Stein Kristiansen, "Data Mining for Patient Friendly Apnea Detection".2018
- [16]. Anita Ramachandran, "Performance Analysis of Machine Learning Algorithms for Sleep Apnea Detection Using ECG".2021
- [17]. Yao Wang, "An Efficient Method to Detect Sleep Hypopnea- Apnea Events Based on EEG Signals".2020

RE-2022-205311-plag-report

ORIGINALITY REPORT

5%

SIMILARITY INDEX

3%

INTERNET SOURCES

4%

PUBLICATIONS

2%

STUDENT PAPERS

PRIMARY SOURCES

1

T Raghul Sudharsan, Gowtham S, S. Revathy, T. Bernatin, L. Mary Gladence, V. Maria Anu. "Smart Farming using IoT", 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), 2022

Publication

1%

2

www.nature.com

Internet Source

1%

3

V. Ankitha, P. Manimegalai, P. Subha Hency Jose, P. Raji. "Literature Review on Sleep APNEA Analysis by Machine Learning Algorithms Using ECG Signals", Journal of Physics: Conference Series, 2021

Publication

1%

4

extension.msstate.edu

Internet Source

<1%

5

Stein Kristiansen, Mari Sonsteby Hugaas, Vera Goebel, Thomas Plagemann, Konstantinos Nikolaidis, Knut Liestol. "Data Mining for

<1%

Patient Friendly Apnea Detection", IEEE Access, 2018

Publication

6

Nicole L. Molin, Clifford Molin, Rohan J. Dalpatadu, Ashok K. Singh. "Prediction of obstructive sleep apnea using Fast Fourier Transform of overnight breath recordings", Machine Learning with Applications, 2021

Publication

<1 %

7

Wang Yao, Ji Siyu, Yang Tianshun, Wang Xiaohong, Wang Huiquan, Zhao Xiaoyun. "An efficient method to detect sleep hypopneaapnea events based on EEG signals", IEEE Access, 2020

Publication

<1 %

8

link.springer.com

Internet Source

<1 %

9

Yang Cao, Disheng Wu, Mingrui Hu, Shu Chen. "Chapter 49 Detection andDefense Schemes forCache Pollution Attack inContent-Centric Network", Springer Science and Business Media LLC, 2023

Publication

<1 %

10

doaj.org

Internet Source

<1 %

11

Atiya Khan, Saroj K. Biswas, Chukhu Chunka. "ESAD: Expert System for Apnea Detection

<1 %

Using Enhanced DWT Feature Extraction and Machine Learning Algorithms", 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2023

Publication

12

www.researchgate.net

Internet Source

<1 %

Exclude quotes On

Exclude matches Off

Exclude bibliography On