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RESEARCH ARTICLE

"BREATHING NEW LIFE: ARTIFICIAL INTELLIGENCE'S ROLE AND CHALLENGES IN OBSTRUCTIVE SLEEP APNEA DIAGNOSIS"

Arkaja Singh[1], Mashal Maheshwari[2], Sameer Rao[3], Warda Shahnawaz[4], Manas Gunani[5], Srushti Gopani[6], Shivaram Poigai Arunachalam[7]

1. Mahatma Gandhi Medical College, Jaipur, Rajasthan, India.
2. Sawai Man Singh Medical College, Jaipur, Rajasthan, India.(Corresponding Author)
3. Department of Medicine, Rutgers New Jersey Medical School, Newark, New Jersey, USA.
4. Jinnah Sindh Medical University, Karachi, Pakistan.
5. Department of Medicine, Allegheny Health Network, Pittsburgh, Pennsylvania, USA.
6. Government Medical College, Surat.
7. Assistant Professor of Medicine, Mayo Clinic, Rochester, Minnesota, USA.Assistant Professor of Radiology, Mayo Clinic, Rochester, Minnesota, USA.

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Abstract

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Obstructive sleep apnea (OSA) is a common and underdiagnosed condition that significantly impacts patients' quality of life and poses health risks. Artificial intelligence (AI) in OSA care offers promising opportunities for improved diagnosis, treatment, and patient monitoring. This article explores different AI-based approaches to OSA diagnosis, such as machine learning algorithms to analyze oximetry, airflow, and other variables, smartphone apps to detect sleep-related disorders, and heart rate variability analysis. Despite its potential, integrating AI into OSA care presents challenges such as data quality, model interpretability, clinical validation, and ethical considerations. Strategies to improve AI usage include generating rich datasets, ensuring model interpretability, obtaining regulatory approvals, continuously learning and adapting models, integrating with electronic health records, and facilitating human-AI collaboration. Additionally, validation across diverse populations, user-friendly interfaces, and an ethical approach to patient data are critical to successful AI implementation. By addressing these considerations, AI can revolutionize OSA diagnosis and treatment, leading to better patient outcomes and more efficient healthcare delivery.

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Introduction:-

Obstructive sleep apnea (OSA) is a prevalent clinical disorder that affects a significant portion of the global population, impacting nearly one-seventh of individuals aged 30-69 worldwide (1). It is a condition marked by episodes in which the upper airway partially (hypopnea) or completely (apnea) collapses during sleep, reducing oxygen levels and often causing the affected person to briefly wake from sleep, which results in disturbed, fragmented sleep. Patients with OSA have unwanted ramifications of the conditions, along with common complaints of snoring, excessive daytime sleeping, and deleterious effects on mental health, quality of life, and the

Corresponding Author:- Mashal Maheshwari
Address:- Sawai Man Singh Medical College, Jaipur, Rajasthan, India.

cardiovascular system (2). The pathology behind the condition is the progressive narrowing of the pharyngeal space, which can result from a blend of diminished ventilatory response coupled with neuromuscular considerations and anatomical risk factors. These factors collectively heighten the likelihood of breathing issues during sleep. In the United States, it has been noted that 25-30% of men and 9-17% of women meet the diagnostic criteria for obstructive sleep apnea (OSA). Along with that, there has been an upward trend in OSA prevalence, which is strongly associated with the increasing rates of obesity, which range from 14% to 55% (3). However, despite its prevalence, many cases go undiagnosed and untreated, partly due to a lack of cost-effective, accurate diagnostic modalities. At present, the established benchmark for OSA diagnosis is polysomnography (PSG), a method that is both expensive and time-intensive. Unfortunately, access to PSG is often constrained by prolonged waiting lists at sleep laboratories, making it an impractical option for many individuals (4). The parameters, such as airflow, breathing incidents, snoring, blood oxygen saturation (SpO2), electrooculography (EOG), electroencephalography (EEG), and electrocardiography (ECG), are all part of the monitoring conducted during polysomnography (PSG) (5). While it is highly effective for diagnosis, its utilization is hindered by limitations, including the high cost of equipment, the need for extensive labor, and the continuous monitoring required for numerous body sensors (6).

Consequently, a pressing need arises for alternative approaches, such as using artificial intelligence (AI) in diagnosing OSA. In recent years, the convergence of artificial intelligence (AI) and healthcare has opened up promising opportunities for transforming sleep medicine, particularly in the context of OSA. AI's capacity to analyze extensive datasets and emulate human intelligence positions it as a formidable tool for enhancing OSA diagnosis and treatment. Through the utilization of sophisticated algorithms and computational capabilities, AI has the potential to catalyze transformative changes across multiple dimensions of OSA care. These potential advancements encompass not only improved diagnosis and treatment selection for OSA but also the integration of precision medicine, vigilant patient monitoring, and comprehensive health management. The realm of sleep medicine has witnessed the exploration of diverse AI-based approaches in recent years. These include automatic sleep stage classification facilitated by computational frames and power spectral density (PSD) features derived from sleep electroencephalograms (EEG) (7), ultra-short-term analysis to assess autonomic nervous system (ANS) activity (8), and predicting sleep apnea using heart rate variability (HRV) and classification models (9). These innovative strategies are directed at enhancing the diagnosis and treatment of OSA. The continuous monitoring of OSA patients assumes paramount importance in gauging treatment effectiveness and detecting potential disease progression. Furthermore, these AI-driven monitoring systems yield valuable insights into patient well-being, enabling timely and appropriate interventions that significantly improve patient care and outcomes.

In addition to achieving high accuracy, there have been extensive efforts to enhance convenience, reduce the number of required sensors, and even explore non-contact methods for assessing obstructive sleep apnea (OSA). Sound-based OSA assessment is particularly promising, as it can be seamlessly integrated with smartphones and smart speakers, enabling comprehensive non-contact monitoring of OSA (10). Breathing sounds during sleep are influenced by airway patency. As the upper airway dilator muscle activity decreases during sleep, the upper airway becomes more collapsible, leading to potentially louder breathing sounds. Apnea events result in no breathing sounds due to breath cessation, but a loud breathing sound can occur when the apnea ends. In contrast, hypopnea can narrow the airway without vibration, causing quieter and irregular breathing sounds. Detecting respiratory events during sleep using sound can be a promising aspect to look into (11,12).

While integrating AI into OSA care presents a plethora of opportunities, it also presents certain challenges that warrant attention. These challenges encompass safeguarding patient privacy and security, addressing ethical considerations, aligning with regulatory frameworks, and fostering effective synergy between AI systems and healthcare providers. By acknowledging and tackling these challenges head-on, the complete potential of AI in the domains of OSA diagnosis, treatment, and management can be fully harnessed.

This comprehensive literature review delves into the specific applications of AI within OSA care, delves into the challenges at hand, and explores the way for future directions. The article aspires to provide insights into how AI has the capacity to revolutionize OSA care, thereby kindling further research in this swiftly evolving field.

AI used in OSA:

1. Joint analysis of at-home oximetry and airflow recordings utilizing machine-learning algorithms:

The study by Daniel Álvarez et al. demonstrated that oximetry alone could achieve notably high accuracy, particularly in confirming severe cases of illness. However, the combination of oximetry and airflow exhibited strong synergies, leading to a significant performance enhancement compared to single-channel techniques. Through the utilization of machine learning, their combined analysis presented a precise method for at-home OSA screening. The study focused on a population displaying moderate-to-high clinical suspicion of OSA, evident by symptoms such as severe daytime hypersomnolence, loud snoring, nocturnal choking and awakenings, and/or observed apnoeas. This clinical profile raised a substantial suspicion of moderate to high levels of OSA. The levels of spo2 (oxygen saturation) and airflow were measured using polysomnography (PSG) and subsequently processed. Nonlinear algorithms known as Support Vector Machines (SVMs) were employed to discern patterns from signals originating from ECG or oximetry.The researchers created three distinct regression models to estimate the Apnea-Hypopnea Index (AHI) using different types of data. The first model, SVMSpO2, uses single-channel oximetry data. The second model, SVMAF, uses single-channel airflow data. The third model, SVMSpO2+AF, uses a dual-channel approach combining features from oximetry and airflow data to estimate the AHI.

These models were then subjected to a prospective evaluation in a separate test dataset. The results of their research led to the conclusion that the joint analysis of both spo2 and airflow, facilitated by artificial intelligence, yielded an accurate estimation of AHI. This promising approach has the potential to serve as a valuable diagnostic tool for OSA, offering improved accuracy and reliability in diagnosis (13).

2. Obstructive sleep apnea syndrome detection based on ballistocardiogram and Piezo-electrical sensor

The study conducted by Weidong Gao et al. aimed to address the limitations associated with using traditional polysomnography (PSG), wherein electrode detachment can occur. To overcome this, they adopted a non-contact mattress approach. They employed piezoelectric ceramic sensors to record body pressure variations across the chest and abdomen. These pressure data were then transformed into impulse waveforms and respiration waveforms, enabling the retrieval of heart rate and breathing rate information. The processed heart rate signals were subsequently used to compute Heart Rate Variability (HRV). To achieve this, the researchers separated the Ballistocardiogram (BCG) data and respiration signals to isolate cardiac impulses and respiratory rhythms. By analyzing the time-domain and frequency-domain components of both BCG and respiratory signals over specific time intervals, they generated characteristics indicative of sleep apnea. Subsequently, a machine learning-based classification method was employed to detect obstructive sleep apnea (OSA), with model fusion technology implemented to enhance recognition accuracy.

The proposed method for sleep apnea detection offers several advantages. Notably, it is cost-effective and does not disrupt individuals' regular sleep patterns. By using non-contact mattress-based sensors and innovative signal processing techniques, this approach holds promise for accurate and convenient OSA diagnosis (9).

UrtnasanErdenebayar et al. conducted a study with a similar methodology. They employed a piezoelectric sensor, a compact device designed to detect snoring, a prevalent trait among individuals with OSA. Previous studies utilizing microphones for this purpose had proven to be expensive and uncomfortable for patients. The utilization of piezoelectric sensors offered a cost-effective alternative; however, the challenge of patient discomfort persisted despite the cost-effectiveness of this approach (14).

3. OSA diagnosis using a hybrid acoustic smartphone app

The "Firefly" app uses the patient's subtle breathing patterns and utilizes advanced detailed sleep stages, respiratory rate, snoring, and OSA patterns. A completely unattached device allows the patient to rest and sleep without disturbance. The app can be easily downloaded on Apple or Android devices and allows patients to test at home in their comfortable environment. The study showed promising results but had a few downsides with the number of false positives and negatives, which can be due to the knocking of the phone by the duvet during sleep or sleeping positions that are not controlled in an unconstrained setting. Besides the limitations, the app allows daily patient monitoring, which can be ideal and reliable to identify the condition (15). (Figure - 2)

4. Automatic segmentation algorithm to delineate the fat pads from magnetic resonance images in a population-based study

Utilization of MRI images of the head and neck showing multiple segmented sections of parapharyngeal fat pads for OSA epidemiology, would help us investigate OSA in large cohort studies. Muhammad Laiq Ur Rahman Shahidet al, created a segmentation method that is entirely automated and used their algorithm to analyze population-based epidemiological studies that could generate a lot of data in a short span of time. On the other hand, manual segmentation of fat pads is tedious and individual dependent, given that the individual is a skilled radiologist who has to take the slice by slice to contour. Manual segmentation got promising results with 3D scans, but the data set was small. Whereas, the suggested automatic segmentation method could be used for accurate and dependable analysis of massive amounts of data in epidemiological studies in order to comprehend the pathophysiology of the obstructive sleep apnea condition (16).

5. Nonobstructive multiple ultra-wideband radar sleep posture recognition system

The incidence and severity of sleep apnea can be affected by different sleep postures and therefore, a couple of methods have been utilized to detect these postures to enhance assessment of OSA. However, these methods including sensors, cameras and wearable devices have limitations to their practical use such as interfering with sleep and being cost-ineffective. Derek Ka-Hei Laiet studied sleep posture recognition by ultra-wideband radars with the help of machine learning systems to assess and track sleep positions that are observed in patients diagnosed with OSA and in those undergoing rehabilitation. They used the deep learning system, ViT (Vision Transformer) to analyze spatio-temporal graphs by mapping multiple radar signals from dynamic sleep postures observed in their study participants. In addition, they compared different radar configurations and various AI systems to conclude that the Swin Transformer model with a side and head radar configuration was most accurate in predicting the sleep postures in patients with underlying OSA. The study had limited data for model training and further studies with a larger dataset could pave the way for implementation of this technique (17).

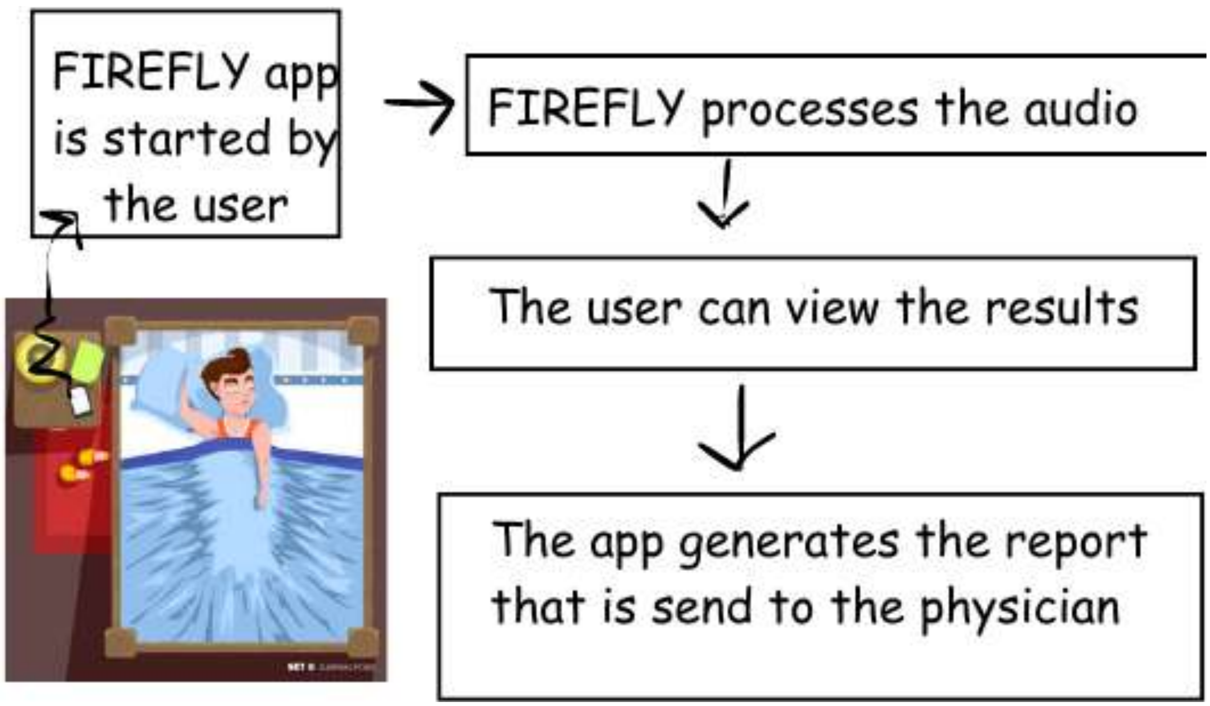

Figure 1:- A pictorial image of how the hybrid acoustic smartphone app “Firefly” operates, where hybrid nature signifies the ammalgamation of active sonar and passive acoustic signal. Sonar signal would detect breathing movement and acoustic signal would detect frequency changes due to snoring.

6. Automated multi-model deep neural network for sleep stage scoring

Xiaoqing Zhang et al. tried to create an automated framework using deep learning, an advanced machine learning system that uses EEG signals, PSG for sleep stages, EOG, EMG, and spo2. Sweating, environmental sensitivity, limb movement, and other factors can all affect the clinical PSG's signal quality. As a result, the likelihood of aberrant signal capture during nightly sleep PSG is considered in this study's model design. They tried to overcome the issues faced by previous studies and provide a robust and reliable model in which the inter-rater agreement nears that of human experts. In future research, it would be essential to address the above-mentioned limitations, explore the evaluation criteria for neural network models, and develop a lightweight version to make it work in wearable and smart devices (18).

RikuHuttunen et al. tried to assess OSA-related sleep fragmentation based on a photoplethysmography (PPG) signal. Their hypothesis that PPG-based sleep signals can be used to identify sleep stages was proved. Since PPG measurements are simple to do, it is possible to acquire more extensive PPG signal datasets without the need for manually graded PSGs. As a result, it is now possible to use semi-supervised learning with vast volumes of unlabeled PPG signals and a small number of PPG signals with manual PSG-based labeling. Thus, independent of the availability of the relevant hypnograms, any dataset containing PPG signals might be utilized to enhance the quantity of training data (19).

7. Diagnosing Sleep-related disorders using bio-signal processing using machine learning.
DelaramJarchi et al used machine learning classifiers to evaluate ECG and EMG signals in healthy and diseased subjects. They used unobtrusive principals involved in extracting breathing signals from ECG to detect OSA and incorporated them into polysomnography, which reduced the intrusive nature of wearable devices. EMG signals were crucial to identify restless leg syndrome, which has an established association with OSA and therefore simultaneously detected both disorders through recognition of body movements by deep learning models. They did not use the training data for the same participant when testing, also called cross-subject recognition, which established a practical scenario in their study. Their proposed Deep Neural Learning Network was trained to process EMG with raw data extraction and ECG with peak pulse and modulated respiration signal extraction. Although their method resulted in an accuracy of 72%, they proposed that recruiting higher sample data would further improve these results. (20)

8. Ultra Short-term HRV analysis in OSA diagnosis
Heart rate variability is used to assess Autonomic Nervous activity and can be used to further assess the over-activation of sympathetic stimulation in OSA. For the study, sleep stage and respiratory events were scored according to the American Academy of Sleep Medicine. They used the Epworth Sleep scale to analyze the data and found that both ESS and age were higher in patients with severe OSA. They looked at the efficacy of ultra-short-term techniques in the detection of ANS abnormalities in patients with OSA in order to address the limitations of short-term methodology in HRV analysis. Ln VLF, Ln LF, and Ln HF are the three parameters that are commonly used in the frequency analysis of HRV. Additionally, the total spectral power may be used to calculate Ln TP, which is assumed to represent the global autonomic function. During HRV analysis, the Ln LF/HF ratio, a key indicator of sympathovagal balance, may also be determined. Numerous investigations on HRV in OSA have shown that the Ln LF/HF ratio, or Ln LF, accurately reflects the shift in ANS balance towards sympathetic predominance. Increases in Ln HF were associated with a change in ANS function from sympathetic to parasympathetic dominance. Therefore, the change towards sympathetic predominance seen in HRV study of OSA patients may indicate a greater cardiovascular risk (8).

9. The real-time diagnosis of sleep apnea facilitated by a Smartphone-based tool Internet of Things (IoT) and cloud computing architecture incorporating Support Vector Machine (SVM) learning.
IoT strategies have extensive application in various domains, spanning from sensor-related applications to detection systems. Moreover, the integration of IoT, cloud computing, and machine learning has demonstrated its efficacy in achieving accurate, real-time detection and diagnosis of sleep apnea. Cloud computing serves to minimize costs associated with servers, hardware, software licenses, and security maintenance. For example, Bsoul et al. proposed a sleep apnea monitoring system as an illustrative case (22,23). The authors proposed a Support vector machine using the IoT framework to diagnose sleep apnea. (Figure-2)

The authors felt that the method has several advantages, including first Cloud computing offers both cost-effective, consistently accessible storage and a reliable pool of computational resources crucial for the analysis of physiological data. Furthermore, the IoT architecture-based sleep monitoring system is designed for user-friendliness and enabling remote monitoring that supports real-time diagnosis. Moreover, the algorithm has the potential to detect significant and potentially severe apnea events even before consulting a medical professional for an initial diagnosis. Lastly, an experimental assessment of the system's ability to diagnose Obstructive Sleep Apnea Syndrome (OSAS) using real-world clinical data demonstrates its efficiency, with impressive sensitivity, accuracy, and specificity rates of 87.6%, 90.2%, and 94.1%, respectively (22).

10. Wearable monitoring devices for diagnosis
Gabriele B Papini et al. introduced an automatic, non-intrusive AHI estimation approach that relies entirely on wrist-worn reflective photoplethysmography (rPPG). This method employs a deep learning model to harness information

related to cardiorespiratory and sleep patterns extracted from the rPPG signal and is trained for accurate AHI estimation. The results imply that wrist-worn rPPG measurements, which can be incorporated into wearables like smartwatches, hold promise in augmenting conventional OSA diagnostic methods by enabling unobtrusive monitoring of sleep and respiratory function (24).

Kristin McClure et al. created a non-intrusive breathing analysis system that automatically identifies clinically significant breathing patterns. This system gathered data from accelerometers and gyroscopes placed on the chest and abdomen of 100 healthy volunteers who mimicked various breathing events like central sleep apnea, coughing, obstructive sleep apnea, sighing, and yawning. To develop their system further, they generated synthetic datasets by introducing labeled instances of these different patterns into segments of normal breathing. The outcomes reveal that employing deep learning to analyze chest and abdomen movement data collected by wearable sensors offers a non-invasive approach for tracking breathing patterns. This innovation holds potential for various crucial medical scenarios, including detecting apneas during home sleep monitoring and monitoring breathing events in critically ill patients undergoing mechanical ventilation in the intensive care unit (25).

Florent Baty et al. used a wearable electrocardiogram (ECG) acquisition system, referred to as the ECG belt, which was designed and assessed for its applicability in categorizing the severity of sleep apnea. This evaluation was carried out by employing heart rate variability analysis, with and without data pre-filtering. Multiple classification algorithms were evaluated, and the support vector machine emerged as the preferred choice due to its simplicity and overall solid performance. Throughout the study, whole-night ECG signals were recorded from patients suspected of having sleep apnea. These signals were collected using both the ECG belt and conventional patched ECG during polysomnography (PSG) recordings. The results demonstrated that the device can be used to assess sleep apnea, especially for follow-up (26).

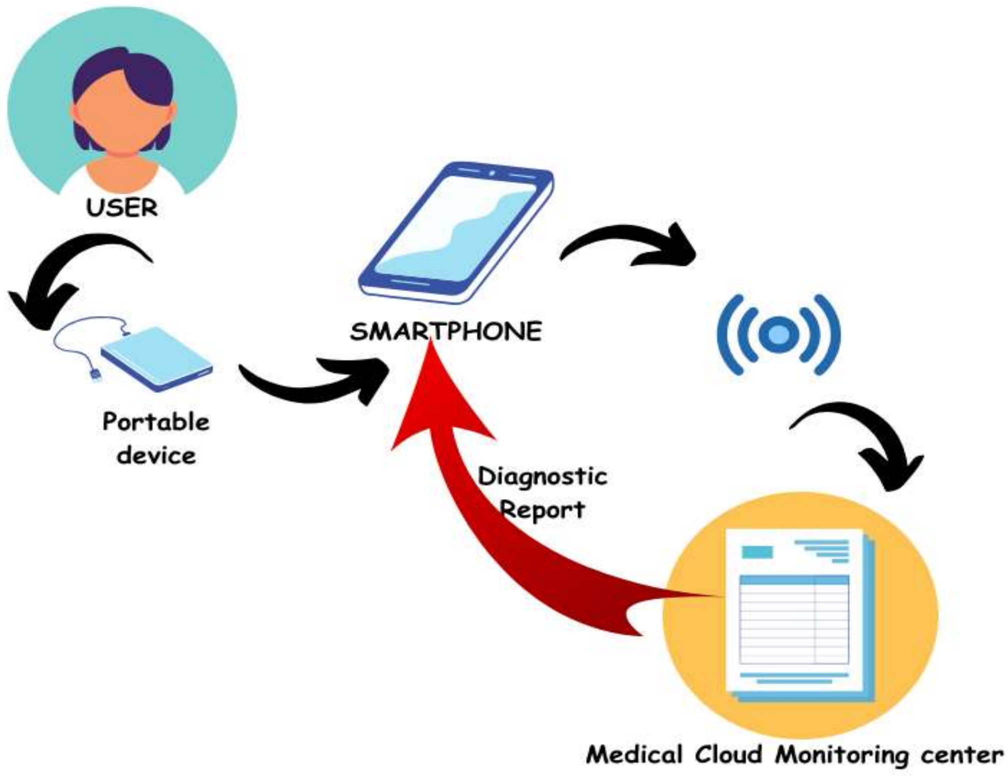

Figure 2:- A pictorial image of real-time diagnosis of sleep apnea facilitated by a Smartphone-based tool IoT and cloud computing architecture incorporating SVM learning - The portable pulse oximeter generated readings during sleep are sent to the android smartphone via bluetooth. The readings encapsulate three SpO2 classifiers- Mean, Minimum and Variance. These values are analyzed by an algorithm which differentiates apneic and normal breathing events. The data is stored and projected with cloud computing, and therefore communicated to both the patient and medical professional.

11. Recording sleep apnea non-invasively using a nocturnal 3D video system, followed by analysis through visual perceptive computing.

The authors used the Kinect-3D camera and then Visual Perceptive Computing (VPC), to suggest an alternate for home sleep testing in patients with a high pretest probability for OSA. The underlying concept was to detect movements during sleep and correlate them with the possibility of arousal caused by desaturation due to underlying OSA. The role of machine learning algorithm was to classify sleep stages based on Kinect data which provided motion analysis. In patients with obstructive sleep apnea (OSA), they found a strong and statistically significant correlation ($r = 0.823$, $p < 0.001$) between the apnea-hypopnea index (AHI) as measured by polysomnography and respiratory events detected using the 3D camera. When evaluating the ability to detect OSA, the receiver operating characteristic curve showed a sensitivity of 90% with a specificity of 71.4%. (27).

12. Developing an algorithm for real-time diagnosis of OSA based on breathing Sounds and Prediction Reinforcement Using normal home noises.

Numerous studies have explored the acoustic properties of breathing sounds. While these studies primarily examined the acoustic characteristics of typical breathing sounds, they employed whole-night nocturnal sounds as input to assess the severity of obstructive sleep apnea (OSA) for that night. However, a more accurate and natural approach to diagnosing OSA involves detecting and quantifying individual apnea and hypopnea events. Apnea detection systems validated in hospitals might not work well in homes due to potential interference from residential noises. Training and testing should involve data from home sleep studies to ensure the reliability of machine learning or deep learning models for home-based apnea assessment. Nevertheless, conducting these studies at home presents its own set of difficulties, mirroring challenges seen in other deep learning areas like speech recognition (28). In speech recognition, robust deep-learning models are trained using clean speech data that have been intentionally contaminated. By introducing various noises like alarms, door knocks, telephone ringing, and television sounds, the signal-to-noise ratio (SNR) can be randomly adjusted to create diverse combinations of distorted audio (28).

The authors included PSG, home noise, and smartphone data set to train the algorithm for a better diagnosis of breathing events, analyzing the model using epoch-by-epoch prediction accuracy and classifying the severity of obstructive sleep apnea (OSA) based on the apnea-hypopnea index (AHI) (29).

Discussion:-

In this paper, our objective is to provide a comprehensive understanding of the advantages and challenges associated with the utilization of Artificial Intelligence (AI). At present, a handful of machine learning systems, such as the WatchPat device, have exhibited diagnostic accuracy surpassing that of polysomnography (PSG), with a specificity of 93.63% and sensitivity of 100% (32,33). AI not only enables the timely identification of the disease but also facilitates the development of a scoring mechanism for assessing the necessary level of treatment for each patient. PSG, while widely used, does have limitations due to factors like sweating and limb movement. The integration of AI in sleep staging and the scoring of respiratory and movement events could potentially reduce the workload of sleep technologists. There are studies that center around using snoring as a primary indicator for testing OSA (utilizing piezoelectric sensors and microphones). However, these studies are based on the assumption that all OSA patients snore, leading to potential false negatives in cases where snoring is absent. Several algorithms rely on data from EEG, ECG, SpO2, and airflow measurements. However, these algorithms have faced challenges due to imbalanced training datasets, which impacts their overall effectiveness. Additionally, studies conducted within controlled laboratory environments may differ from real-world scenarios, introducing limitations in their applicability. In essence, this paper aims to offer a well-rounded understanding of the current landscape of AI in OSA diagnosis, highlighting its potential benefits and shortcomings.

It is important to acknowledge that there exist several barriers to the effective integration of AI, as reported in the literature (figure-3). Issues such as limited sample sizes or biases in data selection and reporting can pose challenges. Machine learning algorithms are disease-specific and are developed based on prior data related to that particular condition. For instance, an algorithm designed for obstructive sleep apnea (OSA) cannot be readily applied to a patient with central sleep apnea due to the distinct nature of these conditions. Nonetheless, incorporating control groups in real-world studies can be exceptionally challenging as it necessitates the meticulous matching of factors like age, sex, BMI, and comorbidities. In summary, while AI holds promise for medical applications like OSA diagnosis, these barriers and limitations underscore the complexity of implementing AI-driven solutions effectively (34).

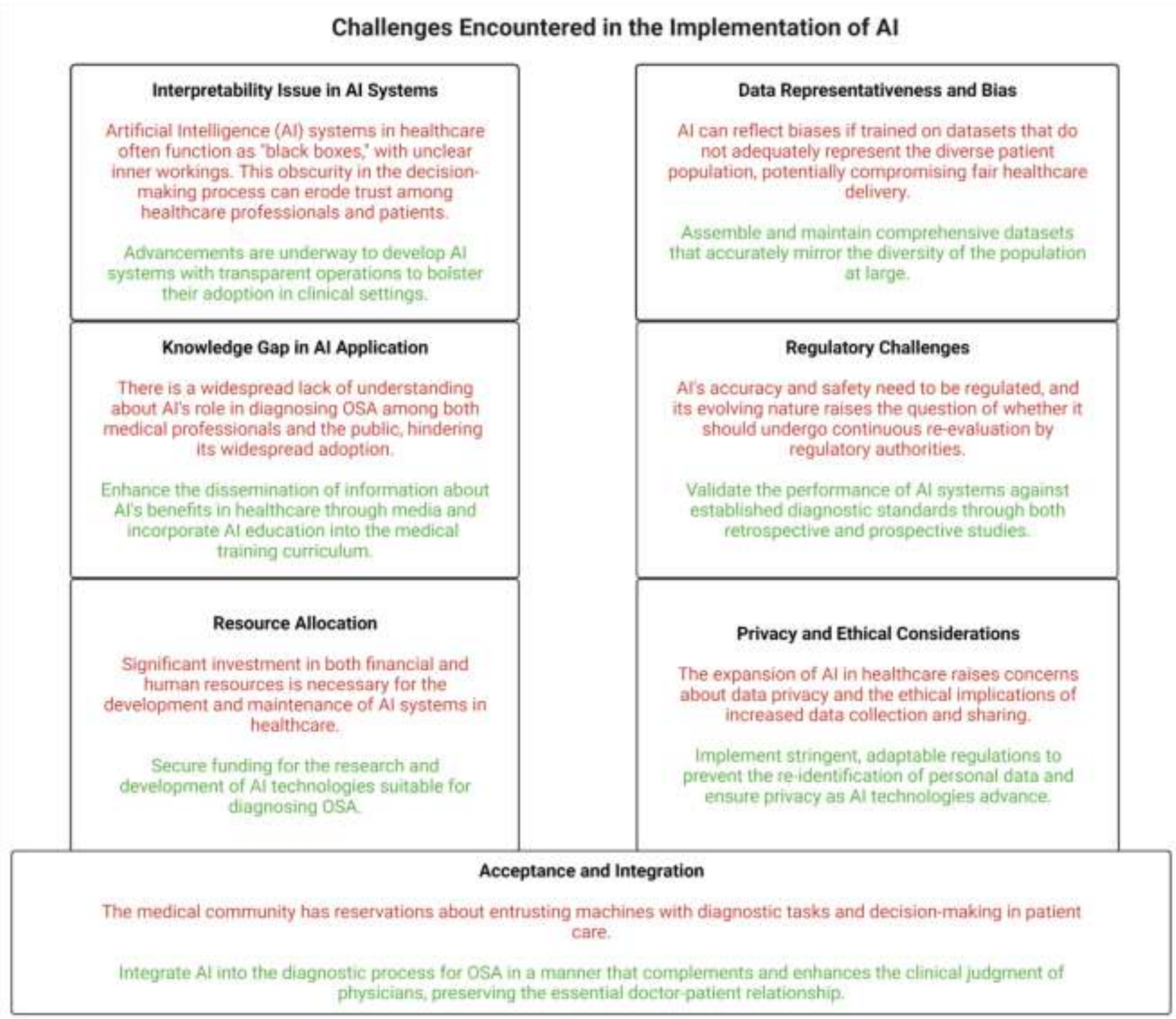

Figure 3:- Challenges encountered in the implementation of AI in OSA diagnosis.

We think in the realm of applying AI to the diagnosis and management of OSA, several key considerations come to the forefront. Collaboration among healthcare institutions becomes pivotal to generate high-quality and comprehensive datasets that encompass a diverse range of patient profiles and medical conditions. These datasets form the bedrock for AI models to learn from a wide spectrum of cases, thereby enhancing accuracy in diagnosing OSA and suggesting suitable treatments. To ensure the transparency and trustworthiness of AI in the medical context, efforts should be directed towards enhancing model interpretability. Developing explainable AI techniques holds the potential to provide insights into the decision-making processes behind AI-generated recommendations. This transparency aids healthcare professionals in having faith in AI-driven insights and applying them effectively in OSA care.

Moving forward, rigorous clinical validation studies become essential to assess the performance and safety of AI models specifically for diagnosing and managing OSA. Collaboration with regulatory bodies, like the FDA, is imperative to establish precise guidelines tailored to the unique characteristics of AI-based medical technologies within the domain of OSA. Continual learning and adaptability are paramount attributes for AI models in OSA. Regular updates and retraining ensure that these models remain in sync with the latest research findings and align with evolving best practices for OSA diagnosis and management.

Integration with electronic health records (EHR) emerges as a crucial step, as AI systems can capitalize on patient data to offer real-time insights to healthcare providers. The analysis of patient records, lab results, and imaging data by AI algorithms aids in accurate diagnosis, treatment planning, and ongoing monitoring of OSA. AI also holds the potential to give rise to clinical decision support systems, presenting evidence-based recommendations to healthcare professionals engaged in OSA diagnosis and treatment. These systems simplify the analysis of intricate medical data, suggest tailored treatment options, and craft personalized care plans based on individual patient attributes.

It's important to recognize that AI should work in tandem with human expertise, enhancing rather than replacing it. Effective collaboration between healthcare professionals and AI systems augments diagnostic precision and treatment outcomes in OSA. While AI assists in data analysis and pattern recognition, clinicians contribute clinical judgment to make well-informed decisions. Validating AI models across diverse patient populations becomes crucial to ensure their robustness for individuals of varying ages, ethnicities, and geographical locations. Efforts must be invested in identifying and addressing biases and disparities within AI algorithms to guarantee equitable OSA care for all. As AI tools are integrated into clinical workflows, they should come with user-friendly interfaces that seamlessly merge with existing systems. This empowers healthcare professionals to access and apply AI recommendations efficiently within their established OSA diagnosis and management processes.

Ethical principles must underscore the development and implementation of AI algorithms. Stringent data governance policies and robust security measures are essential to protect patient information while responsibly harnessing data for AI advancement in OSA. Upholding patient privacy and confidentiality remains a paramount concern throughout this journey.

Additionally, one of the most pivotal barriers confronting the integration of AI lies in bridging the gap between data collection, analysis, and the ethical deployment of that data. This gap underscores the vital role of the human ethical perspective, as ultimately, the practitioner bears the responsibility for patient outcomes. While AI can greatly expedite data collection and analysis, it is imperative that the clinical appraisal remains an integral part of the process. The ethical dimensions and intricacies of patient care necessitate that AI be utilized as a tool for augmenting decision-making rather than as a sole determinant. AI's outputs should be subjected to careful clinical evaluation and interpretation before any actions are taken. In this way, the synergy of AI's analytical power with human judgment ensures both accuracy and the preservation of ethical considerations in patient care.

AI holds the promise of revolutionizing the field of medicine, yet its effective application across research and patient care will require substantial funding to develop appropriate tools. The transition from research applications to practical patient care demands precise and reliable AI tools that can navigate complex medical scenarios.

It's noteworthy that AI has been identified as a critical research domain by organizations such as the American Academy of Sleep Medicine Foundation, as evidenced by their Strategic Research Award program for 2020. The profound impact of AI on healthcare lies in its ability to enhance the treatment of patients with sleep-related conditions. Through ongoing collaboration between the sleep disorders care team, researchers, and product developers, AI is poised to deepen our comprehension of disrupted sleep and its repercussions on health. This collective effort holds the potential to significantly enhance patient care outcomes in the realm of sleep medicine.

Conclusion:-

The integration of artificial intelligence (AI) into the treatment of obstructive sleep apnea (OSA) offers promising opportunities to improve diagnosis, treatment, and patient monitoring. AI-driven approaches such as machine learning algorithms and wearable devices have shown the potential to provide accurate and real-time solutions for OSA assessment. However, addressing challenges such as data quality, model interpretability, regulatory approval, and ethical considerations is critical to successful implementation. Collaboration between AI systems and healthcare providers and focus on user-friendly interfaces and patient privacy will pave the way for improved OSA management and better patient outcomes through AI technologies.

Declarations

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None.

Conflict of Interest Statement
The authors have no conflicts of interest to declare.

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None.

Data Availability
All data used in the analysis are available within the paper and its supporting information files.

Author Contributions
Arkaja Singh conceived the idea and developed the methodology for the study. Mashal Maheshwari, Sameer Rao, Warda Shahnawaz, ManasGunani and SrushtiGopani were equally involved in literature review, synthesizing results from the literature, writing, and editing of the manuscript. The first draft was written Arkaja Singh and all authors contributed to critically analyzing and editing it. Shivaram Poigai Arunachalam contributed to the overall structure and editing of the manuscript.

All authors read and approved the final manuscript.

Abbreviation:
AF= Airflow from nasal prong pressure
AASM= American Academy of Sleep Medicine
AHI= Apnea-Hypopnea Index
AI= Artificial intelligence
ANS= Autonomic nervous system
BCG= Ballistocardiogram
ECG= Electrocardiography
EEG= Electroencephalography
EOG= Electrooculography
EHR= Electronic health records
ESS= Epworth Sleep scale
HRV= Heart rate variability
IoT= Internet of Things
Ln HF= Natural logarithm High Frequency
Ln LF= Natural logarithm Low Frequency
Ln TP= Natural logarithm Total Power
Ln VLF= Natural logarithm Very Low Frequency
OSA= Obstructive sleep apnea
PPG= Photoplethysmography
PSD= Power spectral density
PSG= Polysomnography
rPPG= Reflective photoplethysmography
SNR= Signal-to-noise ratio
SpO2= Oxygen saturation
SVM= Support Vector Machine
ViT= Vision Transformer
VPC= Visual Perceptive Computing
WHO= World Health Organization

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