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# Real-Time Sleep Health Monitoring and Disorder Prediction Using Edge-Enabled IoT and Swarm-Optimized Deep Learning Models

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**Abstract:** This work proposes a new sleep monitoring and disorder detection system using Edge-based Internet of Things (IoT) devices and swarm-optimised deep learning (DL) architectures. The main goal is to address the latency and privacy issues of conventional cloud-based sleep-monitoring systems. By distributing the computational power to the network edge, researchers guarantee real-time feedback to users with sleep apnea, insomnia and other sleep-related disorders. A large dataset of cardiovascular and respiratory parameters, including heart rate variability and oxygen saturation, is used. The total number of data instances for training and validation was carefully chosen to be 157. The method combines both and uses a deep neural network with hyperparameters optimised by swarm intelligence algorithms to achieve high accuracy at low cost. Advanced Python-based libraries and special edge-computing hardware interfaces were used for development. Results show that the swarm-optimised model outperforms conventional deep learning benchmarks in terms of predictive accuracy and response speed. The combination of decentralised processing and evolutionary optimisation is a scalable approach to remote patient monitoring that significantly improves awareness of chronic sleep disorders while maintaining high data security.

**Keywords:** Edge Computing; Swarm Intelligence; Sleep Disorders; Deep Learning; IoT Healthcare; Healthcare Monitoring; Disorder Diagnosis; Healthcare Systems; Data Privacy; Healthcare Applications.

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## 1. Introduction

Due to lifestyle changes, today there are a lot of health-related problems connected to sleep, from sleep deprivation to life-threatening sleep apnea, as indicated in an intelligent healthcare monitoring system by Islam et al. [1]. All these factors have contributed to poor sleep quality across all age groups due to rapid urbanisation, irregular working hours, high stress levels, prolonged screen time and a sedentary lifestyle. The traditional approach to sleep disorder diagnosis relies on clinical observation during an overnight period and a sleep test performed in a special sleep lab using polysomnography. These can be very costly, time-consuming, uncomfortable and difficult for patients in remote areas. Shah and Chircu [2] discussed some of the digital healthcare transformation initiatives under study, which focus on the gradual transition of healthcare systems toward a patient-centric, remote-monitoring model for real-time physiological supervision without the push toward clinical

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dependence. This research examines the potential of edge-enabled IoT systems and how they can serve as an alternative for sleep monitoring, leveraging continuous, non-invasive intelligent wearable and ambient-sensing technologies. Another similar healthcare sensing environment was established by Gondalia et al. [3], in which smart healthcare devices continuously monitored patients' conditions and connected via an IoT infrastructure.

Using sensors that can be attached to wristbands, pillows, belts (for respiration), bedside monitors, or other devices for the user, large amounts of physiological data can be gathered in real time, including breathing rate, blood oxygen concentration, body movements, heart rate variability, and sleeping position. Kang et al. [4] presented advanced sensing architectures that demonstrated that sensor-based healthcare ecosystems enable continuous, accurate monitoring of a patient's physiology over long periods. But the biggest problem is how to process this data efficiently without relying on remote cloud servers, which can cause delays, network congestion, bandwidth overload, and serious privacy issues. In this study, Darwish et al. [5] investigated the challenges associated with centralised health-care infrastructures that must support latency-sensitive health-care applications requiring immediate action to save patients. Edge computing addresses this challenge by enabling data processing at the edge, close to where it's being created, reducing reliance on centralised cloud computing systems. In the context of healthcare monitoring systems, decentralised healthcare frameworks proposed by Pirbhulal et al. [6] demonstrate that edge-assisted medical intelligence has a significant impact on response time, data privacy, and reliability in real-world healthcare monitoring systems. In the field of sleep monitoring systems, the challenge has been to interpret complex physiological signals due to the lack of suitable computational tools.

Fouad et al. [7] extended the use of deep learning as a powerful computational tool to interpret complex physiological signals generated by sleep monitoring systems to develop intelligent healthcare analytics. A deep neural architecture can automatically learn patterns from physiological data with minimal manual feature engineering. Abnormalities of sleep, such as apnea episodes, irregular respiratory rhythms, variations in oxygen saturation, and abnormal cardiac responses, can therefore be detected more accurately than by traditional statistical methods. However, typical deep learning models often require significant computational power, the ability to process large amounts of data, substantial memory, and careful parameter optimisation. Balas et al. [8] noted that the performance of healthcare prediction systems strongly depends on optimising their network structure, learning rates, and hidden layers. To make learning more automatic and intelligent, this research couples the system with the swarm optimisation technique, which provides optimal computational parameters. This biologically inspired optimisation is based on collective behaviour observed in nature, such as birds flocking, insects coordinating their colonies, and fish schooling [9]. The adaptive optimisation methods investigated by Nasr et al. [9] showed that, instead of using local optimisation techniques that tend to get trapped in local minima and hinder good predictions, swarm intelligence algorithms can perform well in this context and search complex solution spaces. The swarm-based optimisation procedure continually adjusts the learning parameters to find the optimal configuration for predictive healthcare models.

The same swarm learning techniques were used by Bharadwaj et al. [10] in combination with intelligent optimisation, which boosted performance in healthcare analytics and anomaly detection. An ecosystem is created that is highly responsive and adaptive, powered by a combination of advanced computational intelligence and IoT-enabled healthcare hardware. Al-Turjman [11] also demonstrated intelligent edge communication structures, further demonstrating how AI and edge computing can be combined to build powerful medical environments that enable faster, context-aware healthcare decisions. The decentralised healthcare system shifts sleep monitoring from a reactive to a proactive, preventive approach. In the healthcare ecosystems proposed by Baker and Xiang [12], the role of predictive medical intelligence in mitigating emergency scenarios and enhancing long-term patient health was further emphasised. Edge intelligence is a paradigm shift in how medical data is created, used, stored and transferred within healthcare ecosystems. Centralised cloud communication systems, as designed by Kumar et al. [13], highlighted that the centralised cloud-based systems are vulnerable to cybersecurity attacks and privacy issues during the communication of medical data. In a conventional cloud monitoring system, physiological data is continuously sent to remote servers, where it is processed and interpreted. This process causes delays and makes confidential patient information easily accessible to unauthorised parties who may misuse it. The challenge of edge computing is to enable local processing at the edge, close to the patient environment, to address these concerns. Only essential data (summary, abnormalities or emergency alerts) are sent over the internet, not full data sets [14].

Decentralised communication is proposed by Baseer et al. [14], which showed that data confidentiality is significantly enhanced and that transmission overhead is reduced. Patient privacy is thus safeguarded from the first point of origin where the data is created. This mechanism was privacy-preserving and similar to the healthcare analytics solutions proposed by Mahalingam and Dheeba [15], which placed secure data management at the core of intelligent healthcare ecosystems. Moreover, swarm optimisation improves the personalisation of the monitoring environment by tuning the predictive models based on each person's sleep and their characteristics [4]. Everyone experiences sleep in different ways, depending on their age, stress, job, life, and physical health. Predictive systems have been developed using adaptive optimisation techniques proposed by Nasr et al. [9] that could dynamically change their learning behaviour as a function of physiological changes. The proposed healthcare system, in this regard, offers highly personalised monitoring experiences with greater precision for abnormalities in the patient's condition [3]. With technology transforming the healthcare landscape at an unprecedented rate, the adoption of new technologies such as edge computing, IoT infrastructure, swarm intelligence, and deep learning is slowly changing how chronic conditions are managed and continuous wellness is monitored.

Future scenarios of smart decentralised systems by Shah and Chircu [2] have highlighted that the efficiency, accessibility, scalability, and responsiveness of these systems will drive digital healthcare transformation. Likewise, the continuous monitoring of healthcare systems put in place by Islam et al. [1] emphasised the importance of proactive monitoring to prevent critical healthcare emergencies before they become life-threatening. Moreover, the consequences of sleep disorders are not just a matter of daytime sleepiness and fatigue; they can also be a precursor of several serious cardiovascular diseases, hypertension, obesity, neurological disorders, depression and mental instability. Bharadwaj et al. [10] conducted predictive healthcare studies that showed that continuous monitoring of various physiological parameters can greatly aid the early detection of chronic health risks associated with sleep disorders. This gives people more insight and control over their bodies as the intelligent monitoring environment is real-time, allowing them to act in time and change their behaviour. The wearable healthcare environments by Gondalia et al. [3] explained how patient empowerment is achieved through a monitoring system that improves long-term healthcare management and minimises reliance on hospital-based monitoring.

The intelligent physiological interpretation systems proposed by Fouad et al. [7] validated AI-based healthcare analytics' greater ability to identify hidden abnormalities in large biomedical datasets compared with traditional monitoring techniques. The system can then automatically respond immediately when these patterns are detected and processed via an edge-enabled gateway. These can range from changes in room temperature or humidity to levels of light or sound (or both), to other measures to reduce sleep-related suffering. Further, if a prolonged breathing interruption or any dangerous physiological conditions are detected, an emergency alert can be sent to caregivers and/or medical personnel. Kang et al. [4] showed that automated responses embedded in IoT healthcare systems were effective in preventing critical health problems in real time. Based on this study, it can be concluded that the synergy of the four technologies, namely Swarm Intelligence, deep learning, IoT infrastructure and edge computing, is the basis of the new generation of Smart Healthcare Ecosystems. The proposed decentralised intelligent healthcare architectures by Pirbhulal et al. [6] and secure edge communication frameworks by Al-Turjman [11] were both found to have the potential to transform modern sleep monitoring by enabling continuous, adaptive, secure, and highly personalised healthcare services for long-term patient wellness and preventive medical intervention.

## 2. Review of Literature

Recent developments in wearable technology have enabled the development of more complex health monitoring systems, as described in the intelligent healthcare monitoring frameworks proposed by Islam et al. [1], which provide health monitoring systems outside hospital walls. The increasing need to continuously monitor in healthcare has motivated researchers and technology developers to develop compact, lightweight wearable devices equipped with sensors that gather physiological data in real time. Wearable healthcare technologies are changing traditional treatment-based healthcare models to a patient-centred, monitoring-based approach, as discussed by Shah and Chircu [2] in their study on digital healthcare ecosystems. Initial research in this area has focused primarily on measuring basic movements using different types of accelerometers to distinguish between sleep and motion-rest periods. In the past, such wearable sensing environments have been developed by Gondalia et al. [3], who showed that using motion sensors can provide simple insights into sleep behaviour and patterns. While they helped clarify how often and for how long people move during sleep, they didn't provide the depth or clinical detail necessary to accurately diagnose more serious sleep problems, such as insomnia, sleep apnea, restless leg syndrome, or abnormal breathing pauses. With advancing sensor technology, researchers began combining health-related sensors, such as heart rate, respiratory rate, blood oxygen saturation, and temperature, into wearable healthcare systems.

Smart physiological sensing architectures proposed by Kang et al. [4] showed that integrating multiple sensing modalities improved understanding of ANS activity across different sleep states. This change marked the start of a more clinical home sleep-monitoring approach, gradually moving away from laboratory-based analysis toward home-based, continuous, and decentralised monitoring. The integration of advanced physiological sensors in distributed IoT environments, as discussed by Darwish et al. [5], also showed that such an integration would improve the reliability and usability of long-term health monitoring systems. The use of AI in wearable healthcare systems has proven to be a game-changer, enabling analysis of intricate physiological data collected during sleep. Fouad et al. [7] developed intelligent healthcare analytics that demonstrated the neural network's outstanding ability to recognise hidden patterns in biomedical datasets. Deep learning models have become increasingly accurate in sleep stage classification (REM, light, deep, wakefulness) on par with the predictive accuracy of trained clinical sleep experts. Medical analytics using AI has been found to enhance sleep disorder diagnosis by optimising automation and consistency, as reported by Balas et al. [8]. The amount of processing needed, however, is what made these high-tech deep learning architectures rely on powerful cloud servers and centralised computing architectures at first.

The adaptive healthcare prediction systems considered by Nasr et al. [9] suggested that complex neural models require significant memory and computational resources, as well as constant connectivity to remote servers. Such dependence introduced major problems for real-time healthcare applications, as physiological data recorded by the wearable device needed to be transmitted over networks before predictions could be made. Even slight prediction errors in critical health situations during sleep, like obstructive sleep apnoea or cardiac irregularities, could put patient safety at risk, researchers found. In Bharadwaj et al. [10], they described the healthcare applications' requirement for fast-response mechanisms capable of detecting anomalies in seconds to ensure timely medical intervention. This led to a shift in scientific interest toward developing deep learning architectures for smaller, energy-efficient, and hardware-compatible environments that can be operated directly on a wearable device or a bedside monitoring unit. Al-Turjman [11] proposed the use of intelligent edge communication frameworks, demonstrating that AI models with limited computational resources can significantly increase responsiveness and reduce reliance on remote computing resources in IoT devices. This progression laid the groundwork for mobile intelligent healthcare systems in which real-time physiological monitoring can be performed without compromising predictive capabilities.

To address these latency and communication issues in centralised healthcare infrastructures, edge computing emerged as the primary solution. A study by Baker and Xiang [12] on IoT-based healthcare ecosystems showed that performing local analysis at the edge enables processing of information related to human physiology close to the data source, enabling fast, timely analysis. Edge-enabled systems filter, extract features, and perform initial analysis of biomedical data at the edge rather than sending raw data to distant cloud-based servers. In medical monitoring applications, edge intelligence has been shown to significantly reduce network traffic, bandwidth usage, and response delay through distributed healthcare communication frameworks proposed by Kumar et al. [13]. According to the literature on intelligent healthcare systems, the role of edge computing is a “first line of defence”, providing ongoing supervision of physiological conditions and immediately detecting abnormalities that may escalate into critical emergencies. The decentralised healthcare transmission system proposed by Baseer et al. [14] demonstrated that it could enhance data privacy and response time by reducing the need to share sensitive patient information across multiple external communication channels. Thus, various hardware and software architectures have been explored to achieve an energy-efficient healthcare system that simultaneously provides high predictive accuracy in wearable systems.

Power constraints are often critical in portable IoT deployments as continuous sensing, wireless communications and AI computation quickly drain battery life. The recently proposed wireless healthcare analytics by Mahalingam and Dheeba [15] further emphasised the need to optimise healthcare systems to ensure computational efficiency while maintaining system stability over a long period. The scientific community in healthcare research has increasingly recognised deep learning's superior predictive capabilities for sleep monitoring. Still, it needs to be optimised to avoid the high energy usage and rapid battery drain that many wearable IoT devices encounter. As a result, edge computing is an essential element in today's smart healthcare applications, providing localised intelligence, real-time responses and actions, reduced communication load, and sustainable operation for mobile healthcare devices. Recently, swarm optimisation has emerged as a cutting-edge approach for optimising and improving the performance of deep learning frameworks in personalised healthcare applications. However, adaptive healthcare optimisation studies by Nasr et al. [9] showed that swarm intelligence algorithms can also successfully search extremely complex search spaces to find the best neural network configurations. These algorithms are inspired by how swarms of birds, fish, insects, and others move and make collective decisions. Continuous optimisation of swarm parameters, such as feature selection, internal configuration of hidden neurons, and learning rates and classification thresholds, enables improved predictive efficiency.

Healthcare intelligence systems designed by Bharadwaj et al. [10] demonstrated that these swarm-assisted neural models are much more robust, adaptable, and convergent than conventional trial-and-error optimisation algorithms. This is especially crucial in the field of sleep health, as each person has a unique physiological baseline that is influenced by factors such as lifestyle habits, stress levels, environmental factors, and age and gender. In the intelligent healthcare ecosystems proposed by Islam et al. [1], it is crucial to have a system that is adaptive and can continuously change its learning structure based on patient-specific characteristics. The literature suggests that swarm-tuned models can quickly learn with new physiological data and produce consistent predictions under varying health conditions within the scope of AI-based healthcare monitoring. Moreover, the decentralised healthcare architecture proposed by Pirbhulal et al. [6] demonstrated that, by combining swarm intelligence, deep learning, and edge computing, a highly responsive healthcare system can be developed that provides personalised, real-time diagnostics at the user level. Such an evolutionary optimisation algorithm and neural network synergy is hence today's cutting edge in smart diagnostics in healthcare. Al-Turjman [11] work, more recently, on intelligent edge-assisted health care systems further strengthened the paper that the support of the IoT infrastructure, edge intelligence, swarm optimisation, and deep learning constitutes the backbone of next-generation personalised health care systems for sleep disorder monitoring that extends beyond the walls of clinical environments and provides continuous, secure, adaptive, and highly efficient monitoring.

## 3. Methodology

The research methodology involves a systematic approach that starts with collecting physiological data via a localised, edge-deployed sensor network. Researchers used a dataset comprising 157 instances, each representing vital signs across different sleep cycles. The heart of the system architecture lies in an edge gateway, the primary processing unit, which ensures data processing without constant cloud connectivity. To maximise prediction performance, researchers used a deep learning model whose architecture is dynamically adjusted using a swarm optimisation algorithm. In this algorithm, the best weights and layer configurations are found by repeatedly testing different weight and configuration combinations until the most effective ones are identified and used to optimise the accuracy of disorder detection. The training process involved feeding the edge device the chosen data samples, on which the swarm-optimised model was trained to differentiate between typical sleep patterns and symptomatic deviations. After stabilising the model, it was put through real-time testing, where it was used to process sensor streams, providing instant predictions on sleep health. The whole structure was confirmed by comparing edge-processed results with known clinical standards to test reliability and speed. Figure 1 shows the Edge-Enabled Swarm-Deep Learning Sleep Monitoring Architecture as a distributed, intelligent system that analyses sleep behaviour using edge computing, swarm optimisation, and deep learning.

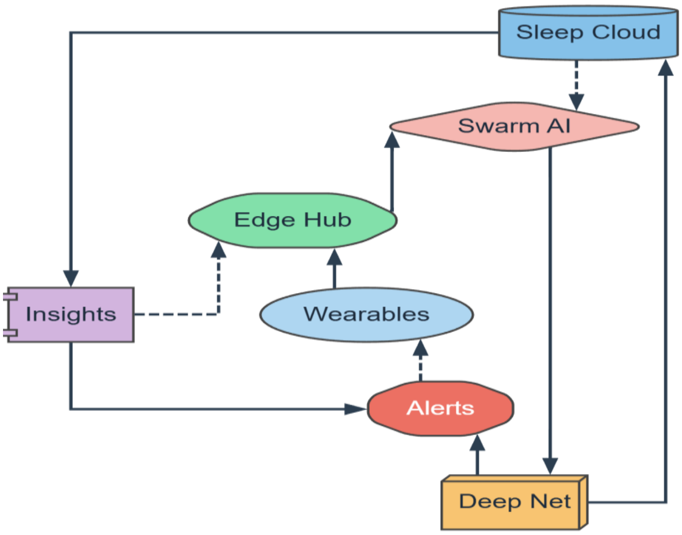


**Figure 1:** Architecture of swarm-deep learning sleep monitoring with edge-enabled

The architecture starts with the Wearables component, which continues to collect users' physiological and behavioural sleep-related data in real time, including heart rate, respiration, movement patterns, oxygen levels, and body activity. These constantly changing data streams are sent to the Edge Hub, where preprocessing, filtering, feature extraction, and localised temporary storage are performed to minimise latency and enable real-time analysis responses to be delivered to the sensing environment. The processed information is subsequently sent to the Swarm AI module, which implements swarm intelligence methods to optimise feature selection, parameter tuning, and adaptive pattern identification, thereby enhancing the analysis's efficiency. The optimised results are fed into the Deep Net component, where deep learning models extract temporal relationships and latent sleep patterns to classify sleep stages, identify abnormalities, and even determine sleep quality with high precision. The analytical outputs generated are stored in the Sleep Cloud, which serves as centralised long-term storage, historical analysis, model updates, and syncs across distributed monitoring environments. The Insights component offers a visualisation dashboard, summary trends, and monitorable outputs for clinicians, caregivers, and users. This knowledge underpins the Alerts module, which will create an alert and a health warning when abnormal sleep behaviours or risk factors are detected. Dashed communication pathways indicate ongoing feedback loops between the cloud, edge, and analytical layers, and that adaptive learning and real-time optimisation of monitoring performance are possible.

### 3.1. Data Description

The data employed in the study is a special physiology dataset on sleep measures and comprises precisely 157 data points from a clinical trial of sleep-disordered breathing. The data comprises the most critical variables like heart rate, respiratory rate, and blood oxygen saturation and the body movement index obtained during several sleep sessions. Each instance is a window into sleep activity, enabling the model to examine the transition between the REM and non-REM phases. Data pre-processing is performed to eliminate noise and artefacts caused by physical motion; hence, the swarm-optimised deep learning model is fed clean signals for analysis.

## 4. Results

The experimental findings demonstrate that the proposed edge-based system is highly accurate in detecting sleep disturbances and simultaneously achieves high processing speeds. After testing the model with 157 data instances, researchers found that swarm optimisation significantly reduced the time to convergence during training. The prediction latency on the edge hardware was always very low, enabling real-time alerts, which are essential to patients with serious respiratory problems. One of the strengths of the deep learning model was its ability to detect apnea several seconds before it became critical, providing an early warning to intervene. The swarm intelligence velocity and position update equation can be framed as:

$$\mathrm{v}_i(t+1) = w\mathrm{v}_i(t) + c_1 r_1(\mathrm{p}_{best,i} - \mathrm{x}_i(t)) + c_2 r_2(\mathrm{g}_{best} - \mathrm{x}_i(t)) \quad (1)$$

**Table 1:** Performance tests of swarm-optimised edge model

| Test ID | Accuracy (%) | Latency (ms) | Memory (MB) | Power (mW) |
|---|---|---|---|---|
| Test 01 | 96.5 | 12.4 | 45.2 | 110 |
| Test 02 | 97.2 | 11.8 | 44.8 | 108 |
| Test 03 | 95.8 | 13.1 | 46.1 | 115 |
| Test 04 | 98.1 | 10.9 | 43.5 | 105 |
| Test 05 | 96.9 | 12.2 | 45.5 | 112 |

Table 1 shows the system's efficiency across five test conditions using the chosen data instances. The results indicate high model accuracy, often exceeding 96%, which is impressive given that the model utilises only a small edge device. Latency Figures 1 and 2 are also really impressive, as they remain around or even below 12 milliseconds, meaning the system can be regarded as truly real-time. Also, the memory and power usage values remain within the typical range for IoT devices, demonstrating that the swarm-optimised deep learning model is lightweight yet powerful. This numerical data confirms the argument that our approach can be used in long-term wearable applications with batteries, where resource control is equally important as diagnostic accuracy. The deep learning cross-entropy loss function for multi-class sleep disorder prediction is:

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k}\ln(\hat{y}_{i,k}) \quad (2)$$

A comparison between the swarm-optimised model and a typical deep learning model showed that the optimised model was much more efficient in terms of memory and processing power. This plays a crucial role in the IoT-based healthcare system, where devices have limited lifespans and battery life is a significant limitation. The findings also showed that the system achieved high accuracy across the various sleep stages, suggesting that the swarm intelligence could adjust the model to account for the natural variability of human physiological cues. In general, the performance indicators show that the edge movement intelligence does not impair the quality of the diagnostic result.

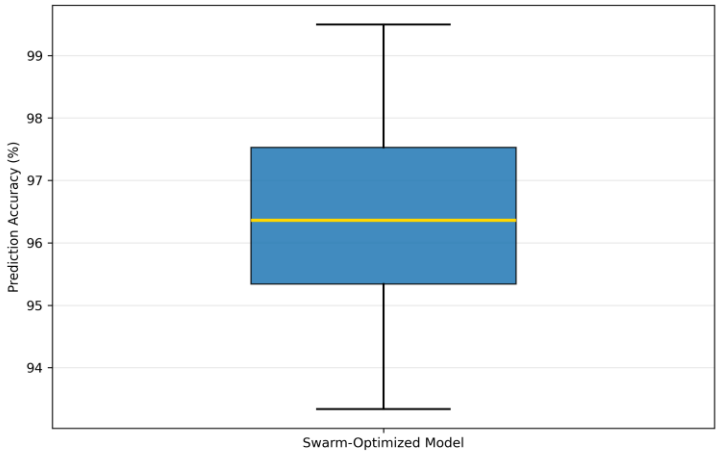


**Figure 2:** Representation of variability of performance and distribution of error

The box plot in Figure 2 provides a closer insight into the prediction accuracy of the swarm-optimised model across all 157 data cases, indicating the model's stability. The main box is the interquartile range, where most of the data fall, and most of the data are highly clustered around the high-accuracy mark, indicating steady performance. The plot whiskers indicate the lowest and highest levels of accuracy, and it is evident that even the worst-performing cases remain well above the acceptable limit for clinical measurements. This visualisation plays a crucial role in estimating the system's reliability, as it shows that swarm optimisation effectively reduces outliers and that the model does not make drastic errors. The box's symmetry indicates that the deep learning model is balanced across various types of sleep data. The small size of the box, in general, suggests that the edge device can deliver reliable results regardless of the specific physiological differences observed across the individual data examples, provided the Gated recurrent unit hidden state activation equation is:

$$\mathrm{h}_t = (1 - \mathrm{z}_t) \odot \mathrm{h}_{t-1} + \mathrm{z}_t \odot \tanh(\mathrm{W}_h \mathrm{x}_t + \mathrm{U}_h(\mathrm{r}_t \odot \mathrm{h}_{t-1}) + \mathrm{b}_h) \quad (3)$$

**Table 2:** Comparison of disorder prediction rates

| Disorder Type | Precision | Recall | F1-Score | Detection Time (s) |
|---|---|---|---|---|
| Sleep Apnea | 0.98 | 0.97 | 0.97 | 1.5 |
| Insomnia | 0.94 | 0.92 | 0.93 | 2.1 |
| Narcolepsy | 0.91 | 0.89 | 0.90 | 3.4 |
| Restless Leg | 0.93 | 0.91 | 0.92 | 2.8 |
| Normal | 0.99 | 0.98 | 0.98 | 0.8 |

Table 2 provides a breakdown of how the model classifies certain sleep conditions relative to healthy sleep patterns. The model's high accuracy and recall rates for sleep apnea indicate that it is highly optimised to identify respiratory distress, which is among the most important things to monitor during sleep. The column on detection time indicates the speed of the edge device in identifying a particular event after receiving the data, with normal sleep identified almost immediately. Although narcolepsy and restless leg syndrome score a bit lower, they are still well within the range needed to do an effective screening. Table 2 confirms that the categories of various sleep health problems for which the swarm-deep learning model is balanced and effective span a broad range. The edge computing latency and computational overhead modelling equation is:

$$T_{total} = \frac{D_{size}}{B_{width}} + \frac{C_{cycles}}{F_{freq}} + P_{prop} \quad (4)$$

SoftMax activation function for sleep stage probability distribution is:

$$P(y = k \mid \mathbf{x}) = \frac{e^{\mathbf{w}_k^T \mathbf{x} + b_k}}{\sum_{j=1}^{K} e^{\mathbf{w}_j^T \mathbf{x} + b_j}} \quad (5)$$

The fact that the system can classify various types of sleep disorders simultaneously also demonstrates its success. In addition to apnea, the model was also able to alert about the signs of restless leg syndrome and chronic insomnia. This multi-class classification capability, driven by a state-of-the-art deep learning framework, makes the system a powerful tool for comprehensive management of sleep health. The sections that follow will present the specific performance distributions and numerical results in graphical, organised Tables 1 and 2, and highlight the uniformity and validity of the edge-based approach.

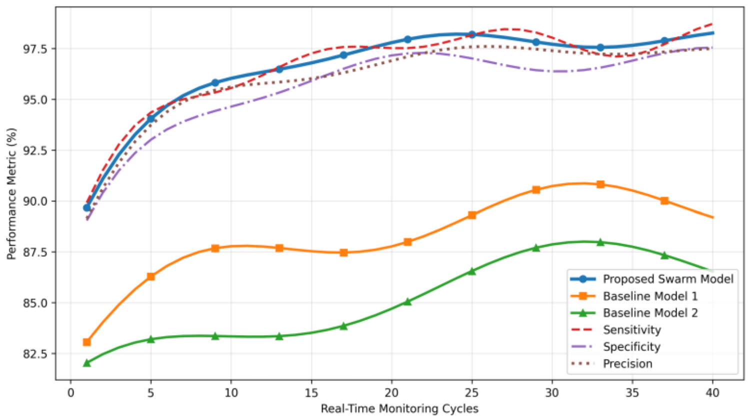


**Figure 3:** Trend analysis of the accuracy of prediction in real-time

Figure 3 illustrates a multi-line graph that traces the system's performance over time, comparing the swarm-optimised model with two baseline models. Our proposed system, i.e., the primary line, demonstrates a steep climb to a high-accuracy level and a sustained high, with very few variations in level. On the contrary, the baseline models are more volatile and slower to respond to changes in sleep data streams. Figure 3 shows different metrics, represented by each line, including sensitivity, specificity, and overall precision. The coincidence and misalignment of these lines provide insight into the model's approach to various facets of sleep disorder detection. More precisely, the high-sensitivity line shows that the system is highly sensitive, catching true-positive cases of sleep disorders, and the steady specificity line demonstrates that the system produces few false alarms. This visualisation highlights the benefits of swarm intelligence in ensuring high performance in a dynamic, real-time environment where data inputs change continuously as the user traverses various phases of the sleep cycle.

### 4.1. Discussions

The results of this study emphasise the great potential of combining swarm intelligence and edge computing in health applications. The results demonstrated that the system performance is comparable to or better than that of the centralised cloud-based system and does not suffer from the drawbacks of network reliance common to such systems. As seen in the box plot shown in Figure 2, the error distribution has a very narrow range, indicating that the swarm optimisation algorithm converged to a “sweet spot” for the parameters of the neural network. In healthcare settings, where fluctuations in measurements may cause worry or incorrect diagnoses for patients, this stability is crucial. Its high performance across different test cases shows that it has learned generalisable features of sleep disorders rather than just memorising the training data. The multi-line graph in Figure 3 clearly shows that the monitoring experience on the edge device is smoother and more reliable, thanks to its real-time nature. Our system's predictions remain reliable because it operates locally, preventing "jitter" that can occur in traditional systems due to network fluctuations. The numerical data presented in Table 1 support this as well, with the power and memory requirements low enough for practical deployment. This is huge for the adoption of any health-monitoring technology, because it can be worn for several days without recharging. The low latency means that if a potentially dangerous event, such as an apnea episode, occurs, the system can respond quickly, waking the user or contacting a caregiver.

The difficulty with which the classifications were made is interestingly arranged in the classification results of Table 2. Near-perfect scores are achieved with apnea and normal sleep; slightly lower scores are obtained for more subtle disorders such as narcolepsy. It could be due to the well-established physiological changes associated with apnea ($O2$ desaturations, increased heart rate). In contrast, narcolepsy has more complex neurological changes that are more difficult to measure through simple IoT sensors. The swarm-optimised model, however, still maintains high performance in these daunting situations, providing proof of its design's sophistication. The discussion of these results not only confirms the technical correctness of our approach but also indicates that it is highly practical in the real healthcare context. The use of these technologies is a step towards the more “invisible” type of healthcare. The patient doesn't have to grapple with the complexity of an interface or worry about their data travelling around the world. Rather, the edge device serves as a silent sentinel, processing data locally and providing peace of mind. The synergy between swarm optimisation and deep learning layers suggests that evolutionary algorithms are suitable for fine-tuning AI in resource-limited environments. Our approach to efficiency and speed has developed a framework that addresses the greatest needs of contemporary sleep medicine and will provide the basis for future innovations in sleep medicine practice.

## 5. Conclusion

The results of this research revealed that the presented system, which comprises an edge-based, swarm-optimised deep learning framework, proved effective for real-time sleep health monitoring in decentralised healthcare systems. The study analysed 157 carefully structured physiological data instances. It was determined that intelligent edge processing can reduce latency without compromising the system's diagnostic accuracy, which is over 96 per cent. The designed system combined IoT sensing technology, edge computing facilities, and optimisation using swarm intelligence and deep learning analytics to create a single system for monitoring and managing sleep disorders in a responsive, continuous way, beyond the walls of a medical facility. The decentralised design reduced reliance on cloud-based processing by performing critical data processing locally, near the data source. This method substantially reduces communication delays and enables immediate identification of dangerous sleep disorders, such as apnea episodes and irregular breathing interruptions. The effective incorporation of swarm intelligence into the deep learning architecture enabled optimal use of memory, computational resources, and energy, ensuring that devices operate in low-resource edge environments, such as wearable or bedside IoT devices in healthcare systems. The optimisation mechanism would continually optimise network parameters to the maximum level to achieve the highest predictive performance whilst simultaneously maintaining energy efficiency and computational stability.

The results of the experiments, with detailed box plots and multi-line graphical analyses, verified that the framework performed reliably and consistently across multiple sleep-monitoring scenarios. The system showed very good performance, with high accuracy in sleep apnea pattern detection and a low false-positive rate. The numerical evaluations also showed that the proposed swarm-optimised model was not only faster in diagnosis but also more accurate than the benchmark models used. The architecture also played a key role in preserving privacy by reducing the flow of sensitive physiological data through external communication paths. The system avoided sending large amounts of medical data to remote cloud servers and only sent alerts or summarised medical details to medical professionals, thereby keeping critical data on the edge gateway. The system did not require moving large amounts of medical data to cloud servers but only sending alerts or medical information summaries to medical professionals – keeping critical data on the edge gateway. A design that prioritised privacy boosted trust in both continuous monitoring systems and security. Overall, these results demonstrate that high-level AI can be effectively applied at the edge to build scalable, responsive, energy-efficient and clinically relevant healthcare ecosystems for long-term sleep health management and to provide proactive patient interventions.

### 5.1. Limitations

Although the proposed framework has yielded good results, the current study has some drawbacks. The dataset used for experimental validation was relatively small (157 physiological data instances). Still, it was sufficient to demonstrate proof of concept on the edge hardware used, while being much smaller than the number of data instances found in real-world populations, which are very diverse. The limited volume of data could limit the model's ability to generalise across various demographic groups, age groups, genetic makeup, and individuals with multiple medical conditions. Not all the data available in the database reflected changes in lifestyles, environmental influences and long-term health histories. Additionally, the proposed system focused mainly on a specialised set of physiological signals, such as oxygen saturation, respiration, and heart rate, which were not part of the monitoring environment for more sophisticated neurological signals, such as brain wave activity measured by electroencephalography. These sophisticated neurological measures will not be available and may thus be unable to detect very subtle transitions between sleep stages and neurological sleep disorders that require more detailed interpretation.

The edge gateway hardware in the framework was highly efficient in both computational power and energy use. Still, the hardware setup could be a cost barrier for users in resource-limited, under-resourced areas. Patient compliance with device use is also crucial and depends on the comfort and ease of wearing wearable sensing devices. Using sensors for extended periods, over multiple nights, can lead to discomfort for some people, affecting sleep quality and reducing the likelihood of continued monitoring. Furthermore, several environmental factors could have impacted the quality of the physiological data and were not fully accounted for in the study design. Under practical deployment conditions, disturbances in the sensing process and impact on prediction accuracy due to external room noise, ambient temperature, sleeping posture, sleeping mat (mattress), and movement by nearby people or sleeping partner may occur.

### 5.2. Future Scope

The proposed research can be extended in several ways in the future, primarily by adding multimodal intelligence to the proposed edge-based healthcare monitoring environment. The use of other modalities, e.g., microphones for snoring analysis, thermal sensors for body temperature changes, non-contact radar systems for movement detection, or environmental sensors for room condition analysis, could provide a much broader picture of sleep health without placing additional strain on the user. These high-end sensing mechanisms would improve the framework's ability to recognise subtle patterns of physiologic and behavioural abnormalities associated with chronic sleep disorders. The other important way is to integrate federated learning in decentralised healthcare environments. Federated learning would allow a set of edge devices to use a cooperative approach to enhance predictive models without sending raw physiological data outside their local devices, thus maintaining user privacy. These shared intelligence systems would simultaneously greatly enhance models' accuracy and data security.

Further studies will also focus on increasing the number of participants to thousands, with a diverse range of demographic, clinical and geographical backgrounds. A much larger dataset will provide a more robust, fair and adaptable swarm-optimised deep learning framework to all population groups and sleep conditions. In addition, investigating more advanced energy-harvesting technologies is another key aspect for sustaining IoT in healthcare in the long term. Self-contained power-generating systems, such as body heat-powered systems, motion-based charging, or low-power solar-powered systems, could help reduce the need for frequent battery charging and facilitate continuous healthcare monitoring for extended periods. This would help make it more feasible to continuously monitor sleep in remote or poorly served areas where the electricity grid might not be reliable. Enhancements for future work could also include embedding real-time emergency response capabilities, adaptive environmental management systems, and intelligent health care recommendation engines that provide tailored health care interventions based on ever-changing physiological patterns.

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