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Design and Analysis of an Effective and Intelligent Computing Method for Diagnosis of Sleep Disorders in Healthcare Monitoring

Adel Abdullah Basuliman[1], D. Kinslin[2], Mr. Sachin Gupta[3], Abhijit Ashok Patil[4], Nimisha[5], Muhammad Bagir[6]

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Abstract: However, the standard diagnostic procedure for sleep disorders is polysomnography, which is expensive, involves human professionals, and is performed in specialised labs. Hence, a less invasive and cheaper method of detecting sleep problems is required. Although people with sleep difficulties are more likely to develop hypertension, cardiovascular disease, etc., delayed detection of these conditions increases the overall mortality rate. The detection of all these ailments has previously relied heavily on signal processing and pattern recognition methods, but to improve accuracy, researchers have used a wide range of intelligent approaches and procedures. As a result, we take a step in the right path by offering an intelligent computing method called ANFUS (an integration of ANN, FCM, and SVM) to diagnose sleep disorders such sleep apnea, insomnia, parasomnia, and snoring by analysing ECG data and clinical recommendations. With this in mind, the primary objective has been to develop an intelligent computing approach to the diagnosis of four sleep disorders: apnea, insomnia, parasomnia, and snoring. Yet, there is more than one source of difficulty. It may also contribute to the emergence of related illnesses. Thus, stopping the spread of sleep disorders makes accurate diagnosis a top goal. As a result, ANFUS can be useful not only for patients but also for healthcare providers and institutions.

Keywords*: *ANFUS; ANN; FCM; SVM; ECG.

1. Introduction:

The death toll is rising steadily because of various sleep problems. Infectious sleep disorders are becoming increasingly common, not just in India but everywhere. It is well accepted that sleep disturbances are the leading cause of accidental death. An individual's carelessness with regards to their diet and way of life can quickly lead to the development of a sleep problem, which can then result in death. The rapid development of computer science has opened up new frontiers and advanced user interfaces for dealing with catastrophic situations, both of which can be of great use to the average person seeking a diagnosis and additional information about the potentially lethal sleep disorders from which they are suffering [1]. In addition, the financial consequences of sleep deprivation and sleep disorders are substantial. Also, the monetary burden of sleep problems is substantial. The financial, social, and personal costs that sufferers of sleep problems incur far outweigh the price of treatment. Direct medical costs, such as those associated with visits to the doctor, service fees, medication, etc., add up to an astronomical sum each year. Those who suffer from sleep deprivation, sleep disorders, or both are less productive and more likely to be involved in accidents as compared to healthy individuals. Twenty percent of all fatal car crashes are associated with drowsy driving rather than drunk driving. Sleep disturbances have a wide variety of immediate and future consequences [2]. Less thoughts are given to the consequences of a shortened lifespan, which might have negative effects on happiness, potential, and even lead to accidents. Long-term effects of sleep disorders trend towards tendency of morbidity and mortality from growing disasters, cardiovascular problems, hypertension, obesity, and learning incapacity. Only a small subset of

1Research Scholar, Department of Management Studies, NICHE Noorul Islam Centre for Higher Education Thucklay, India
basuliman.a@gmail.com
0000-0002-2166-4194
2Professor,Department of Management Studies,NICHE Noorul Islam Centre for Higher Education Thucklay, India
dkinslin@gmail.com
2https://orcid.org/0000-0002-9825-0168
3Chancellor, Department of Management Sanskriti University, Mathura, Uttar Pradesh, India
chancellor@sanskriti.edu.in
0000-0002-4900-0082
4Assistant Professor Bharati Vidyapeeth (Deemed to be University) Y. M. Institute of Management, Karad
abhijit.patil@bharatividyapeeth.edu
Orchid id: 0000-0003-0767-6436
5Assistant Professor Applied Sciences & Humanities ABES Engineering College, Ghaziabad ,UP, India
nimisha0305@gmail.com, nimisha@abes.ac.in
Orcid ID :0000-0003-4548-1365
6Lecturer, Information System Sekolah Tinggi Teknologi Informasi NIIT, Indonesia
alchirrid@yahoo.com

sleep problems are so severe that they significantly impair a person's ability to operate physically, mentally, cognitively, and motorically. Inaccurate estimates of the prevalence of sleep disorder diagnosis and treatment are widely available. Forty million adults in the United States suffer from a chronic sleep issue, according to a recent poll [3].

Problems falling asleep or staying asleep have a negative effect on regular physical activity. As a result, numerous studies and strategies for identifying sleep problems have been proposed. Scientists have relied on quantitative methods for the early diagnosis of sleep problems. The amount of people who participated in the study and the questions they asked in the survey posed the greatest difficulty, but accuracy in improving the current system was the primary goal of the analysis. As a result, the team used a wide variety of methods from the field of intelligent computing to boost the aforementioned performance indicators [4]. Artificial intelligence played a pivotal role in getting us here. All of the methods used in intelligent computing—be they ANN, FL, GA, SVM, MLPNN, DM, or BN—are based on learning rather than data control. Yet, in recent years, experts have embraced a plethora of information-control integration methods relevant to the healthcare industry [5].

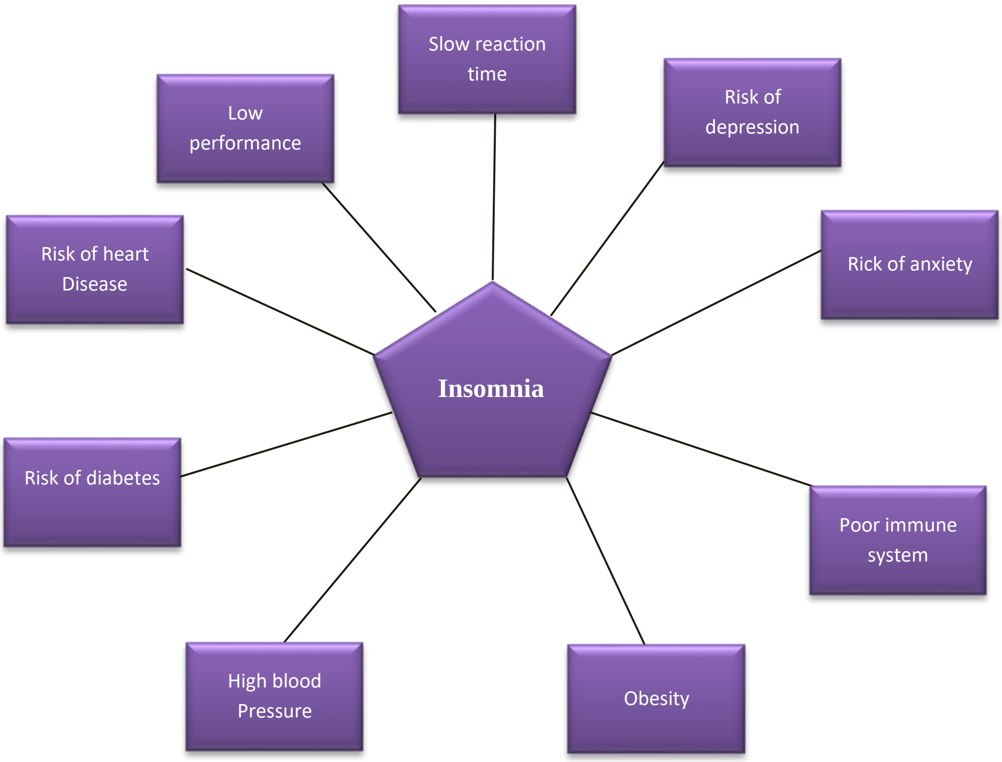

Fig 1: Influences of Insomnia.

The proposed intelligent computing method (ANFUS) uses an integrated technique of ANN, FCM, and SVM to diagnose sleep disorders like Sleep Apnea, Insomnia, Parasomnia, and Snoring problems; ANN and FCM have been used to test the trustworthiness of the automated learning system; and SVM is used to classify the sleep disorders. In real-world scenarios where neural networks strive for human-like performance and SVM performs the categorization of sleep disorders by computing the shortest distance among n nearest neighbours, the suggested method excels at identifying various sections of deficiency or error [6].

In this context, "artificial intelligence" refers to any form of mental ability that is not human. Artificial intelligence (AI) refers to the capacity of a machine to think and learn on its own. Machine learning, then, refers to the mechanisms by which machines can acquire such abilities. Predicting future events based on examples of desired behaviour or previous perceptions is a key component of machine learning. Manual labour becomes less efficient as the difficulty of the challenge rises [7]. As human error is inevitable when performing tasks by hand, this machine learning technique was developed to make life easier for everyone involved. Machine intelligence refers to the level of intelligence possessed by such systems.

Artificial neural network is what it means when you see the letters ANN. The goal of artificial neural networks

(ANN) training is to make the system more adept at predicting outcomes based on input from humans. All of the network's neurons function much like their biological counterparts do in a human brain. An analogy to the human brain can be drawn from this system. Several levels of neurons (processing elements) are included [8]. A weighted connection links each neuron to its immediate neighbours. The power of the links is in their masses. Adjusting these strengths in order to get the desired outcomes from the network is how the learning is accomplished.

When it comes to neural networks, the FFNN is the simplest possible design. It's a special case of acyclic networks in which the connections between nodes don't form any intentional loops. Only nodes at the next higher layer (layer L+1) are allowed to establish links with nodes at the same layer (layer L). The flow of information is unidirectional, beginning at the input nodes and continuing further through the intermediary nodes and finally arriving at the output nodes. It has become the go-to neural network for most applications. It can contain up to four layers, the first and final of which are used as input and output, respectively, while the layers in between are used for concealing information [9]. From the input layer, data is sent to the hidden layer, and from there it is passed on to the output layer, where the final result is displayed.

2. Existing Work Done:

PCA is used to filter features from ECG data, which are then fed into an LS-SVM classifier with an RBF kernel to automatically detect sleep apnea. This study includes 80 ECG recordings and has an accuracy of 85%, sensitivity of 84.71%, and specificity of 84.69%. The authors have implemented 10 machine learning algorithms to classify 25 nights of recorded sleep-disordered breathing. When applied to the same set of 25 suspects, the classifier combination of AdaBoost with Decision Stump, Bagging with REPTree, and either kNN or Decision Table achieved a sensitivity of 82%, a specificity of 82%, and an accuracy of 82%. Using principal component analysis (PCA), researchers have presented a method to identify snoring episodes in sleep sound recordings and label them as snores or non-snores [10]. When trained using only data from basic snorers, the system achieves an accuracy of 97.3%. In cases where both simple snorers and OSA patients are included in the training data, the accuracy drops to 90.2%.

The authors have combined NIG and TQWT for use in automated ECG analysis for sleep apnea detection using a computer. It has been classified using an adaptive boosting (AdaBoost) method. Success metrics include 87.33% accuracy, 81.99% sensitivity, and 90.72% specificity [11]. The authors suggest an artificially intelligent method for detecting sleep apnea from electrocardiogram (ECG) readings (ELM). Observable gains of 83.77 percent in performance have resulted from the proposed feature extraction method. In order to collect ECG data, scientists have developed a new online sleep apnea diagnosis approach using recurrence quantification analysis (RQA). Apnea has been distinguished from regular slumber by means of two distinct kinds of binary classifiers, namely the support vector machine and the neural network. It has been determined that the proposed system has an accuracy of 85.26 percent, a sensitivity of 86.37 percent, and a specificity of 83.74 percent [12].

Researchers have utilised a quadratic classifier to detect sleep in 30 test recordings, reporting an accuracy of 84.7%, sensitivity of 76.70 percentage, and specificity of 89.60 percentage. The authors have used wavelet-based features extracted from ECG signals as input to SVM, with results showing an overall accuracy of 83%, sensitivity of 80%, and specificity of 90% over the entire dataset [13]. Extraction of features from 2D-FFT using recurrence analysis has been applied to the problem of detecting sleep apnea from heart rate series by Maier et al., 2006, with improved findings such as an accuracy of 84.3%, a sensitivity of 77%, and a specificity of 78%.

Researchers have created an automatic snoring-signal identification system employing 2-layer fully-connected neural networks (FFNNs) with back propagation, and it has achieved a sensitivity of 82% and a positive predictive value of 90% for both typical snorers and those with OSAS. Researchers have employed SVM for automated recognition of sleep apnea based on features extracted from electrocardiogram recordings, and compared its performance to those of other classifiers such as KNN, PNN, and linear discriminant classifiers, achieving an accuracy of 70% by PNN and 83% by KNN [14].

Based on their research, the authors conclude that Janet Kolodner's CYRUS framework, which is a demonstration of Schank's dynamic memory theory, is the most prominent framework that may be referred to be a case-based system [15-17]. Sometimes it's tough to handle issues freely because of divergent points of view and the disservice of RBR and CBR. Its unique intersections, such as BOLERO and MIKAS, where RBR and CBR were brought together, introduced substantial benefits, but only if their interests were recognised and obstacles were removed.

Two approaches, PROTOS and CASEY, that combine CBR and MBR, have been proposed by the authors [18-20]. Recent studies have proposed a T-IDDM strategy, which combines RBR, CBR, and MBR. One major drawback of these approaches was that they forced us to convert secret information into hard and fast rules, which always resulted in the erasure and disorganisation of valuable information [21-23].

Researchers have devised a fully automated approach (called SAMOA) for identifying cases of sleep apnea syndrome. This method works well for rare diseases/disorders and self-governing symptoms, but it falls short when a person has more than one condition or when the symptoms of multiple diseases share a common cause of development [24-25].

The rest of the paper's structure is provided below. Part 2 provides a brief overview of the relevant literature, while Part 3 details the approach taken and the theory behind the approaches employed. Results and analysis from the simulations are reported in Section 4. The final portion of the chapter is titled "major findings," and it provides a brief overview of the most relevant findings.

3. The Proposed Work:

Physionet data is taken into account in this analysis. Physionet's widespread application in the modern written language makes it an appealing choice for many authors. Physiobank ATM provided us with all of these databases. The input ECG signal with sleep apnea is shown in below figure II.

Fig II: ECG Signals of Sleep Apnea.

The proposed work is shown in Figure III below.

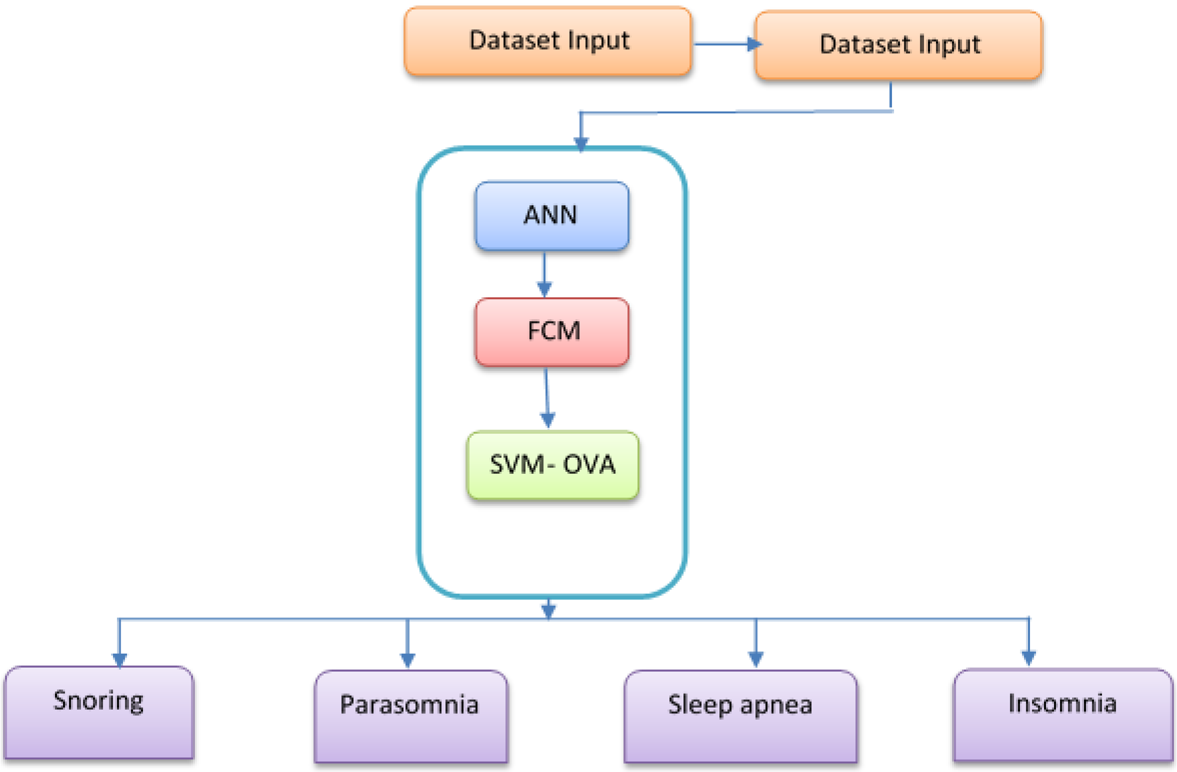

Fig III: block diagram of the Proposed ANFUS Algorithm.

The process of developing the intelligent computing approach can be broken down into the following stages.

Step 1: Retrieve data set from a repository on the web.

Step 2: split the data set in half, separating the ECG signals from the symptomatic guidelines.

Step 3: Separate the sorted dataset into training and testing sets.

Step 4: use 10-fold cross-validation to train the FFNN on a set of training data.

Step 5: ANN output is then sent to FCM.

Step 6: FCM segments the data into 4 regions and makes the necessary adjustments to the input values for each region.

The FCM output is fed into a support vector machine (SVM) alongside training data to establish a cut-off for all sleep disorders. We have discussed all the steps in detail in following sub section.

3.1. Pre-processing of the Input ECG Signal:

In medicine, an electrocardiogram (ECG) is used to record and analyse the minute electrical changes in skin resistance caused by the heart's contractions and electrical impulses. Indicating a wide range of heart conditions, this non-invasive test is quick and painless to perform. The diagnostic process is aided by the specialised tools developed by the medical industry. Oscilloscopes of sufficient accuracy are essential for the development and testing of such machinery. An electrocardiogram (ECG) is a graphical representation of the heart's electrical signals. P wave, QRS-complex, T wave, and U wave are the four components of an electrocardiogram. Several sleep problems can be identified based on the amplitude and duration of an ECG recording. The first stage is to identify different RR intervals, which measure the time between two peaks in a wave's progression. These intervals of RR values are used in various ways to derive the heart rate (HR). The rate of one's heartbeat can be used as an indicator of a variety of cardiovascular abnormalities. The P, Q, R, S, and T waves are the building blocks of the electrocardiogram. With a series of electrodes, it is possible to pick up the electrical impulses sent out by the human body. After that, the signals are amplified and transferred from analogue to digital format for further processing. It is the presence of noise in the original digital signal that causes the most trouble, and this noise can be eliminated in a number of ways. The signal must first be cleaned of these unwanted components before further analysis, such as heart rate frequency detection, can be performed. The ability to recognise certain frequencies is crucial for the early detection and diagnosis of a wide range of medical conditions. Standard threshold values for the PR interval, which can be used to detect p-waves, are 120–200ms, while those for amplitude (0.25%mV) and duration (80ms) are also common. QRS complexes typically occur between 80 and 120 milliseconds. The pre-processing is done through PCA algorithm and consequences is shown in Figure IV.

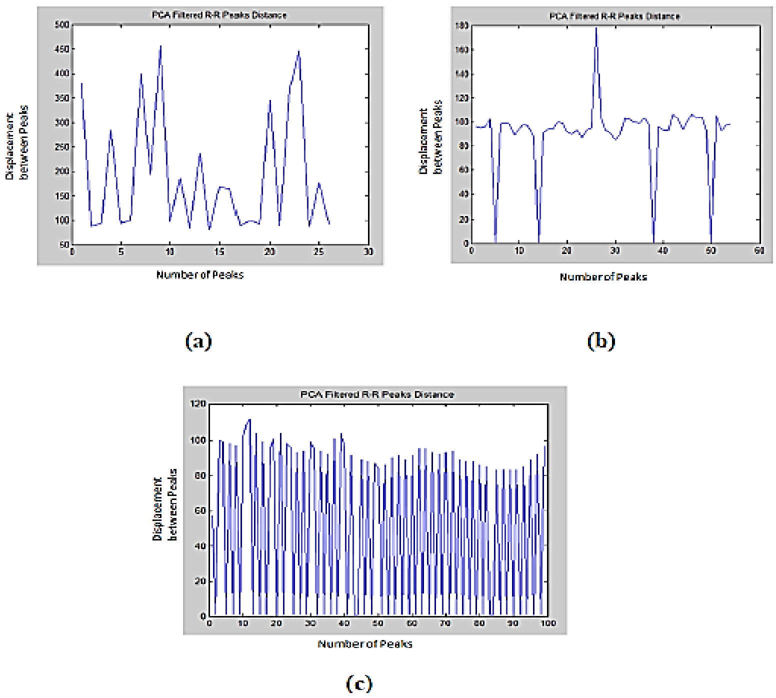

Fig IV: PCA Cleaned ECG Signals of (a) Snoring, (b) Sleep Apnea, (c) Parasomnia.

3.2. ANN and FCM: Artificial neural network is what it means when you see the letters ANN. One purpose of ANN is to teach the system how to forecast like humans. In a neural network, each layer's neurons function just like their counterparts in a human brain. This system closely resembles the structure of the human brain. It's built up from several different levels of neurons, or processing elements. When two neurons connect, they do so via weighted connections. These masses are the tensile forces that hold the links together. Achieving learning requires altering these strengths to get the desired responses from the network.

Here is a description of the ANN algorithm that will be employed in the proposed research.

Step 1: to create a neural network with a single hidden unit (h = 1). Adjust the network's base weights to fall inside a given interval.
Step 2: Constrain the function by training the system with the training set and an appropriate algorithm for some fixed number of iterations.
Step 3: If the validation set error function is acceptable, the system will order a sufficient number of samples from the test set to ensure that the effectiveness E is satisfactory.
Step 4: Assemble one hidden layer unit. A new hidden unit can be created by connecting existing input hubs to the output unit via a network whose weights are randomised (s). Prepare for Step 2 by setting h = h + 1.

In FCM method, a dataset is partitioned into a d-by-d grid, with each data point fitting into each cluster to some degree. Data points that stay close to the centre of a cluster have a much better probability of being fitted into that cluster than those that move farther away from the cluster's centre. Essentially, FCM is an iterative algorithm, and its primary responsibility is to locate the centre points that define the bounds of repetition in a given piece of work.

Combining a neural network with fuzzy logic could help address the shortcomings of each method taken alone.
Several methods have been utilized to put FCM into practise.
Step 1: Write a value of 0 for the membership matrix, which will serve as the initial state.
Step 2: Determine the midpoint
Step 3: refresh the membership matrices
Step 4: check if the membership matrix is equal to the threshold value (the maximum value of the input).
Step 5: Involves recalculating the middle value.
The adaptability of the neural network was arguably its greatest strength. But there was always a downside to things. It's unclear how a neural network makes its judgements, for example. In addition, fuzzy logic lacked the capacity to automatically learn the rules they had previously developed. Hence, integrating these two methods could assist eliminate the drawbacks of each and give more adaptable and satisfying outcomes.

3.3. SVM-OVA: Using the one-versus-all sequential technique and a support vector machine, this research takes a tiny step towards the early detection of sleep disorders such as Sleep Apnea, Insomnia, Parasomnia, and Snoring based on physiological and psychological symptoms. An individual can self-diagnose against any sleep condition based on previous detection, allowing for the right action to be done to prevent the disorder from having any further impacts on other sections of the human body. Following data generation, a MATLAB-based SVM system was constructed utilising an OVA-coded design. SVM's primary drawback is that it can only use binary classification to sort the outcomes into two categories. One of the classical approaches, OVA, was utilised to get around this problem by individually running the structure of SVM on each disorder. One class with an appropriate positive group number and another with a negative value comparable to the other classes are considered for this purpose. SVM is a supervised learning method that uses an established dataset and user feedback to build a predictor model that can accurately anticipate how new data will be processed.

4. Result and Discussion:

This paper is grounded in the practical application of the suggested computing method ANFUS, an amalgamation of three intelligent computing approaches (ANN-FCM, SVM-OVA). Although this research only makes use of a small subset of the intelligent computing approaches available, the performance characteristics attained using those techniques are detailed in Table I. Sensitivity, specificity, and accuracy are the metrics used.

Accuracy (ACC) is the proportion of samples that were properly identified relative to the total number of samples, while sensitivity (SN) stands for True Positive Rate (TPR) and specificity (SP) stands for True Negative Rate (TNR). Following evaluation parameters are used to evaluate the performance of the proposed algorithm.

$$Senstivity = \frac{TP}{TP+FN}\ X100 \tag{1}$$

$$\text{Specificity} = \frac{TN}{TN+FP}\ X100 \tag{2}$$

$$\text{Accuracy} = \frac{TN+TP}{Total\ data\ Sample}\ X100 \tag{3}$$

Table I: Comparison of different implemented techniques.

Approaches	Accuracy	Sensitivity	Specificity
ANFIS	90.8	90.2	84.6
SVM-OVA	91.2	90.8	85.7
ANFUS	95.6	94.1	94.2

With regards to precision, sensitivity, and specificity, the ANFUS method outperforms the other individual and combined methods. As compared to ANN's performance, ANFUS fares the best in terms of accuracy (95.6%), sensitivity (94.1%), and specificity (94.2%).

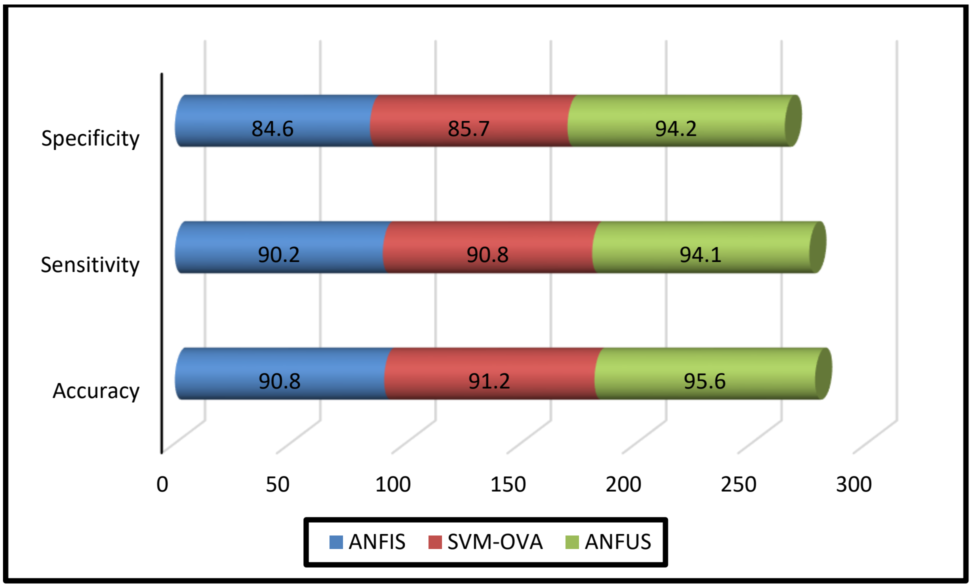

Fig V: Comparison of different implemented techniques.

It has all the elements that are utilised to offer better outcomes than the other decision-making systems, and so it may be the best way for early detection of sleep problems. After that, a number of alternative methodologies used by other researchers have been implemented and compared to ANFUS's results. Based on these three metrics, Table I demonstrates that the proposed system ANFUS outperforms the other currently-used computing methods. As a result, it can be useful for newcomers who find their way here from study in other areas of medicine. Three performance metrics, Ac, Se, and Sp, were used by different researchers to compare the results of their methods for identifying sleep disorders, as shown in Figure V.

5. Conclusion:

This worldwide epidemic of sleep problems is a huge public health concern. As a result, it has risen to become the epidemic that affects the majority of people. The number of people who are diagnosed and treated for sleep disorders is unknown. This illness is escalating the mortality toll not just in India but everywhere. Moreover, the data indicates that sleep disturbances may be particularly prevalent and difficult to detect among the elderly living in poverty. These findings further illustrate how widespread sleep disturbances have become as a growing public health concern. Hence, a patient- and hospital-friendly intelligent computing approach (ANFUS) has been developed for the management of sleep disorders.

The ANFUS system combines ANN, FCM, and SVM-OVA into a single intelligent computing framework. The proposed computational approach was developed for the diagnosis of sleep disorders such sleep apnea, insomnia, parasomnia, and snoring by taking into account ECG signals and the symptomatic guidelines of the patients who are suffering from these conditions. For the proposed technique, ANN is first merged with FCM, and then with SVM-OVA. Accuracy, sensitivity, and specificity have all been calculated using the aforementioned formulas and used to evaluate the system's overall performance. ANFUS has a 94.4% accuracy rate, a 93.44% sensitivity, and a 95% specificity. As a result, ANFUS has the potential to serve both as a better answer for the diagnosis of sleep problems and as a useful tool for novices who may emerge from their studies in other medical areas.

Conflict of Interests:

The authors declare that there is no conflict of interests regarding the publication of this paper.

Ethical approval:

This article does not contain any studies with human participants or animals performed by any of the authors.

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