IMPROVED PSO BASED DRIVER'S DROWSINESS DETECTION USING FUZZY CLASSIFIER

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ABSTRACT

In this drowsiness detection framework two actions including brain and visual features are utilised to distinguish the various levels of drowsiness. These actions are provided by the EEG and EOG signal brain actions. From the EEG and EOG signals the peculiarities like mean, peak, pitch, maximum, minimum, standard deviation are assessed . In these peculiarities we decide on some best attributes - peak and pitch employing an IPSO strategy that picks up the best threshold esteem. These signals are then offered into the STFT which is employed to discover the signal length, producing a STFT network from the intermittent hamming window,the output of which are energy signals alpha and beta. These energy signals are offered into the MCT to get an alpha mean and a beta mean - the most chosen and outstanding attributes. These are then subjected to fuzzy based classification to give a precise result checking over the maximum values in the alpha and the beta series .

Keywords: Drowsiness detection, Electroencephalogram (EEG), Electrooculogram (EOG), Mean Comparison test.

SUBJECT CLASSIFICATION: Bio medical Signal Processing

METHOD/APPROACH: Fuzzy Classification

1. INTRODUCTION

The expression "drowsy" is the same with lethargic, which simply implies a slant to nod off [10]. Drowsiness is the transform between up and awake state and slumber amid which one's capacities to inspect and analyze are emphatically diminished. Drowsiness can be distinguished both in the brain movement which alludes to the ability to practice the information and in eyes action which alludes to the perception limit [7]. To distinguish drowsiness state, a few systems have been recommended, and are by and large grouped into three methodologies. To observe driver's practices related to drowsiness is the introductory methodology. Figuring physiological signal investigation of drivers is the second criteria. To inspect facial image modifications by method for image processing is the third criteria [6]. Physiological signals are respected to be a decent estimate of drowsiness on account of their solid relationship with the driver's exhaustion. EEG is respected to be the most trustworthy technique to recognize drowsiness among all the physiological signals [9]. Three separate procedures are there being utilized via scientists to recognize drowsiness wiz. I) Images Processing based systems II) Artificial neural system based methods III) EEG (electroencephalograph) based strategies [4]. Previously, there are three fundamental classes of drowsiness observing framework recommended via looks into frameworks focused around the term of closure of the eye, frameworks focused around the EEG and frameworks focused around vehicle performance [4].

The strategies focused around EEG utilize alpha (8-11 Hz) and theta (4-7 Hz) actions in the EEG to detect drowsiness [1]. The EEG alpha movement (8-11Hz) will be perceived to be related to drowsiness, developing a sensation referred to as alpha blasts [8]. In slumber studies, Electroencephalography (EEG) is an ordinary system [2]. EEG will be the signal that can before time recognize drowsiness from the brain specifically [6]. Employing electrodes located on the scalp, EEG is a non-intrusive technique to record the electrical action of the brain [9]. Taking into account the self-ruling sources as opposed to the scalp EEG actions Fuzzy Neural Networks were recommended [11]. EEG terminals were commonly joined to a recording framework, and vehicle drivers showed abhorrence to those wires, which controlled flexibility of movement [14]. EEG signals have the profits in making an exact and quantitative assessment of sharpness levels, nearly little data has been held progressively till signal processing routines and machine power are sufficiently fast to take out the related information from the EEG [3]. EEG innovation is sensibly typical and its electronic components are prudent and unsophisticated to create, introducing a fundamentally implementable configuration [12].

Electroencephalography is as often as possible coupled with electrooculography (EOG), as drivers in weakness show modifications in the way their eyes complete a few activities, for example, stirring or twinkling. In drowsy drivers, these activities are known as visual performances and are smoothly clear [2]. For drowsiness distinguishment in drivers, the most incredible base for discovery is based on EOG signals [13]. Electrooculogram (EOG), which is the estimation of the eye electrical muscle movement, has been generally utilized to figure drowsiness. EOG desires no less than three electrodes arranged on the driver's skin [7]. Moreover, Electrooculogram (EOG), which ascertains eye squint an eye

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development, is too usually utilized to distinguish drowsiness. The squint rate in drowsy individual is slower with an eye closure length time quite longer [5]. Employing EOG, peculiarities are accessible to observe drowsiness flickering. It encloses in , merging a decision of flickering peculiarities by method of fuzzy logic on a sliding window [15].

2. LITERATURE REVIEW

A methodology to distinguish driver's drowsiness has been proposed by B.. Lee et al [16] by employing two unique strategies as a part of computer vision and image processing. They have proposed an activity technique that united both machine vision and physiological bio-signals for drowsiness recognition. Unique PPG waveform peculiarities could offer critical changes when a driver consideration level was declining. Undeniably, the proposed framework offers high powerful edge over displayed discretionary drowsiness recognition framework where the driver's wellbeing and mental states could be seen progressively without requirements.

To perceive the driver laziness/exhaustion states, Rami N. Khushaba et al [17] have proposed a novel feature extraction strategy which enhanced to take out the most essential correlated attributes fundamental. This was fulfilled by probing at the related physiological signals from the brain, eye, and heart. Employing another strategy the recommended system evaluates the important MI focused around fuzzy participations showing an exact data content-estimation measure. The test impacts exhibited the imperativeness of FMIWPT in uprooting attributes that exceedingly connect with the different drowsiness levels, accomplishing a characterization exactness of 95%–97% in a normal over all issues.

Under the control of liquor, driver exhaustion is perceived to have associated consequences for driving execution as driving. Through these, drowsiness location frameworks ought to check to be essential in-vehicle protective measures. Stacey Pritchett et al [18] have analyzed the upgraded execution of a hybrid drowsiness detection strategy over its single source partner. It was anticipated that providing hybrid information sources would increase the exactness of such gadgets.

M.J. Flores et al [19] have proposed a non-intrusive driver drowsiness framework to create driver security and were focused around computer vision, artificial intelligence and near-infrared illumination. Continuously that framework consumes propelled advances to inspect and observe the driver's eye state. Additionally, it appraises driver redirection by analyzing the face prologue. To facilitate the analysis work, there were four primary associations: at first, the recognition framework which offers a dynamic vision focused around infrared light and incorporates two LEDs symmetrically situated around the cam.Second, the eye identification module utilizes distinction, angle and FRTS images, making an incredible framework under differing lighting conditions or in its dearth. Third, in light of the position of the eyes and facial anthropometric properties, the face recognition module this incorporates a face model. Finally, the accompanying module for both the face and eyes makes utilization of the CA, neural systems and the difference image. In light of the trial impacts existing in that article amid a nocturnal state of affairs, the recommended strategy for face tracking, eye discovery and eye following is overwhelming and exact under differing lighting, outer enlightenment interference, vibrations, fluctuating background and facial overture.

Fu-Chang Lin et al [20] have proposed a summed up EEG-based Neural Fuzzy framework to conjecture driver's drowsiness. For the security driving issue, driver's drowsiness state performance framework has been included as a causal variable, especially when the driver nodded off or occupied in driving. Then again, the complexities in enhancing such a framework were absence of critical file for distinguishing the driver's drowsy state progressively and the impedance of the complicated noise in a practical and vibrant energetic setting. Fu-Chang Lin et al [20] have proposed a summed up EEG-based Self-sorting out Neural Fuzzy framework to observe and gauge the driver's drowsy state with the occipital zone.

By employing EEG-based power spectrum assessment, Dajeong Kim et al [21] have proposed a technique for drowsiness recognition with eyes open. Issues are picked that focused around ESS (Epworth Drowsiness Scale). In the analysis, all electronic gadgets were turned off to abatement the ancient rarities and quiet ambiance was shaped to cause drowsiness. Drowsy periods were characterized after the EEG trials were finished, by power range changes that incited by the closure of the eyes in a drowsy state. In that paper it was exposed about changes of alpha waves in drowsiness with eyes open. In drowsiness the alpha revealed, for example, descriptive analysis. They demonstrated that alpha expanding turns out before alpha changes by eyes shut and eyes open. Accordingly, the increment of alpha in drowsiness with eyes open like typical drowsiness could be perceived. The drowsiness examples were recognized despite the fact that a subject's eyes were opened for quite a while. In a like manner, recognition of drowsiness with eyes open was possible by utilizing EEG-based power spectrum assessment.

Taking into account driver drowsiness recognition, Weihua Sheng et al [22] have recommended and proposed a structure for programmed exchanging of manual driving and independent driving. Structure demonstrates that discontinuous self-governing driving could be executed as an instrument to maintain a strategic distance from mishaps specifically irregular circumstances. This analysis has four noteworthy elements: an enclosure; an indoor confinement framework; robotized radio controlled (RC) cars; and roadside observing offices. Second, they offer the drowsiness detection strategy which consolidates outward appearance and dashing wheel movement to distinguish driver drowsiness. Third, a manual and self-governing driving exchanging instrument was proposed, which was actuated by the resulting of drowsiness. Finally, investigations were executed on the ITS analyzed to demonstrate the effectiveness of the recommended system.

3. PROBLEM DEFINITION

Now a few measures are talked about drowsiness in vehicle-based measures, behavioral measures and physiological measures. The regular issues in existing drowsiness detection methodologies are specified as follows.

- In EOG dependent visual approaches, abilities can be hampered by scratches on the cornea or by contact lenses. Correspondingly bifocal glasses and hard contact lenses become the origin of these challenging issues.
- The EOG recording strategy requires electrodes to be preset on either side of the eyes,
  It generates some problems definitely. Originally, it needs that a partner is accessible who has to be skilled in such a way to rectify the location of the electrodes.
- Following this, electrodes are preset in the region of the eyes that can be intrusive to the user and disturb his concentration on driving further.
- The key drawback in EOG-based gaze tracking systems based on DC coupled amplifiers is the problem of baseline drift.

These are the chief negative aspects of different works, which stimulate us to perform this research on EEG and EOG signal based drowsiness detection.

4. PROPOSED OPTIMIZATION BASED DRIVER DROWSINESS

Here we propose a methodology in drowsiness recognition employing EEG and EOG signals. The fundamental objective of this paper is recognizing the drowsiness. At first we propose two periods of recognition. In the first stage, the attributes are separated from an EOG signal.The second stage, the varieties of action are measured in a few frequency ranges in EEG channel. Then we use IPSO strategy for discovering best limit esteem in the chosen peculiarities and classification into drowsy and alert states is done using a fuzzy based arrangement . The proposed methodology will be realised in MATLAB environment.

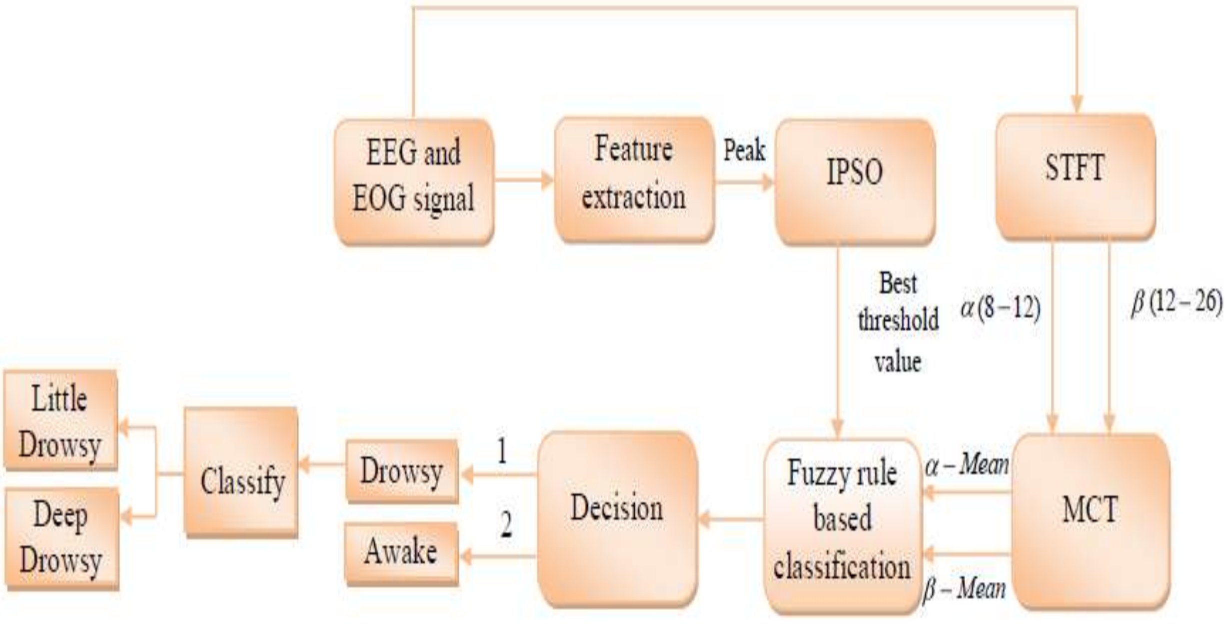


Fig. 1: Proposed drowsiness detection process

4.1. Overview of EEG and EOG signals

The Electrooculography (EOG) is a sort of electrical signal that is used to determine the polarization of the eye ball . Rapid eye movements (REM), and Slow Eye Movements (SEM), transpire when one is “drowsy” and these varieties of actions are recognized by employing the EOG signal. Based on the visual signal we can scrutinize the drowsiness in medical domain where EOG mainly used for detecting and characterising the blinking of eye action.

The Electroencephalogram (EEG) is a confirmation of the electrical motion of the brain from the scalp. The recorded waveforms imitate the cortical electrical motion. Signal intensity: EEG action is rather petite, designed in micro volts (mV). Signal frequency: the chief frequencies of the human EEG waves are:

4.1.1. EEG and EOG Signal drowsiness detection process

The EOG and EEG signals are input motions in this signals from which we take a few peculiarities they are peak and pitch. On the off chance , we are extracting this attribute from the data flags and then employing IPSO improvement strategy for discovering the most excellent threshold esteem. These are then given as input to the STFT that creates alpha and beta and mean values which then are offered into the mean assessment test.At first the signal is checked for artifacts. In the event that they have artifact means we execute the difference correlation test else we execute the mean assessment analysis. Subsequently ,the non artifact signals are specified as input to the mean correlation analysis that produces alpha mean and beta mean. After this they are subjected to the fuzzy procedure to classify the different states.

Input : EEG and EOG signal

Training process contain target value

- Apply IPSO for finding best threshold value
- Apply Short time Fourier transform (STFT)
- Ensue with Mean comparison test (MCT)

Testing process does not contain target values

- Apply IPSO for finding best threshold value
- Apply Short time Fourier transform (STFT)
- Ensue with Mean comparison test (MCT)
- Establish fuzzy for classification

Output: The samples were classified precisely as alert and drowsy instantly.

4.2. Optimal peak selection using IPSO

The IPSO procedure is employed for focusing on the features and discovering the best threshold values. On the off chance the concentrated attributes are mean, peak, pitch, standard deviation, minimum and maximum, and from these concentrated peculiarities we take just the best attributes. They are finally the peak and pitch.

4.2.1. Overview of the Particle Swarm Optimization (PSO)

Population related search algorithm is known to be Particle swarm optimization (PSO). It is created to imagine the conduct of birds in track for food on a cornfield or fish school. The method can proficiently discover optimal or next to optimal resolution in large search spaces. There are two divergent options of description according to PSO. The first one is “individual best” and the second is “global best”.

“Individual best”: It is the individual best range strategy by estimating each individual location of the particle to its own best position $pbest$, only. The data about the other particles is not engaged in this $pbest$.

“Global best”: It is the global preeminent selection algorithm, which gets hold of the worldwide data by building the motion of the particles containing the position of the best particle from the entire swarm. Subsequently, each particle neglects its familiarity with earlier occurrences of its individual best solution.

Every entity particle i has a randomly initialized point $X_i = (x_i^1, x_i^2, \cdots, x_i^D)$ where x_i^d being its position in the d^{th} dimension, velocity, $V_i = (v_i^1, v_i^2, \cdots, v_i^D)$ where v_i^d being the velocity in the d^{th} dimension, $pb_i = (pb_i^1, pb_i^2, \cdots, pb_i^D)$ where pb_i^d being the best position in the dth dimension and $gb = (gb^1, gb^2, \cdots, gb^D)$ where gb^d being the global best position in the dth dimension in the D-dimensional search space. The exciting development of a swarm particle in the search space is explicated as follows:

$$V_i^d = V_i^d + c_1.r_1.(pb_i^d - x_i^d) + c_2.r_2.(gb^d - x_i^d) \tag{1}$$

$$x_i^d = x_i^d + \delta V_i^d \tag{2}$$

In equation (1),

c_1, c_2 - constants with the value of 2.0, with constant inertia weight of 0.7

r_1, r_2 - independent random numbers generated in the range [0-1]

V_i^d - Velocity of ith particle

x_i^d - Current position of the particle i

pb_i^d - Best fitness value of the particle at the current iteration

gb^d - Best fitness value in the swarm.

Demerits of PSO: The search course is not evident and proposes moderate congregation. There is no use by introducing additional data as it didn't take the profit of the extra data.

Thus, Improved Particle Swarm Optimization (IPSO) method is contributing the accurate end result. In the proposed work, the peak and Pitch are optimized by IPSO. The IPSO is utilized for discovering the best threshold esteem.

4.2.2 Peak values to find the best threshold values by using IPSO

- **Swarm initialization**: For a population size u, Randomly generate a solution.
- **Define the fitness function**: Subsequent to the existing solution, the fitness function preferred should to be applied for the constraints.

$$\begin{aligned} Thershold &= par(i) \\ p_k &= pf(x-i,0,ther) \\ f(i,1) &= mean\ p_k \end{aligned} \tag{3}$$

Threshold value – *ther*

Peak value - p_k

Mean value – *mean*

Particle – *par*

Fitness – *f*

Employing the threshold values to locate the peak value and through these outcomes find the mean values simultaneously.

- gb **and** pb **Initialization:**
Initially the fitness value computed for every peak is positioned as the Pbest value of individual particle. Between the Pbest values, the best one is preferred as the gb value.

- **C_1 and C_2** values are calculated using the formula

Assume that $C_{max}=3$, $C_{min}=1$

$$C_1 = \left(\left(C_{\max} / C_{\min}\right) * \left(\left(C_{\min}\left(fit\right) / Mean\left(fit\right)\right) + \left(Min\left(fit\right) / \left(2 * \max\left(fit\right)\right)\right)\right)\right) + C_{\min}$$

$$C_2 = C_1 \tag{4}$$

- **Velocity Computation:** The novel velocity is computed by means of the mentioned equation.

$$V_i^{d+1} = V_i^d + c_1.r_1.(pb_i^d - x_i^d) + c_2.r_2.(gb^d - x_i^d) \tag{5}$$

$$x_i^d = x_i^d + \delta V_i^d \tag{6}$$

In eq. (5),

r_1, r_2 - independent random numbers generated in the range [0-1]

V_i^d - Velocity of i^th particle

x_i^d - Current position of the particle i

pb_i^d - Best fitness value of the particle at the current iteration

gb^d - Best fitness value in the swarm.

- **Swarm Updation:** Exert the fitness function again and revise the pb and gb values. If the latest peak value is superior to the previous one, replace the old by the existing one. Furthermore, opt for the best pb as the gb.

Criterion to stop: Prolong until the solution is excellent enough .

4.3. Short Time Fourier Transform

The short time Fourier tranform (STFT), or generally transient Fourier transform, is a Fourier-related transform connected to discover the sinusoidal frequency and phase content of nearby areas of a signal as it modifies over the delayed instance. For registering the power of the input EEG signal, STFT is implemented. Subsequently, by employing this STFT for estimating signal length, initially it produces an arbitrary framework and from the STFT lattice an intermittent hamming window is created which is splitted and focused around these qualities to figure the time and frequency. Finally, a Mean Comparison Test (MCT) is done to contrast the vitality with a reference level.

4.4. Mean Comparison Test

The MCT is a statistical analysis that assesses two populaces and seeks after a focused diminished typical law. The expectation of this technique is to look at the distinctions of the movement by contrasting the substance of a moving window to an altered reference window. MCT will compute by contrasting the action of the moving window and closed window.

In the beginning, we will ensure the driver position whether the driver is awake or not for this process and the fixed window is estimated initially for this driving session. At first we obtain $\overline{X}_1, \overline{X}_2$, as the mean values, s_1^2, s_2^2, as the standard deviation, $V(i)$ as a variable figured in each second, *i* is denoted as current time in seconds, $\overline{x}_1, \overline{x}_2$, denoted as mean value, n_1, n_2, being the length of the fixed and moving window. By employing this technique they normalize the analysis and a similar threshold can be used for all the variety of drivers.

$$V(i) = \frac{\overline{x}_1 - \overline{x}_2(i)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2(i)}{n_2}}} \tag{7}$$

4.5. Classification based on Fuzzy Logic

A fuzzy standard based classifier is used to figure out if the peak value is a high peak or low peak from the concentrated attributes. The drowsiness detection is made from fuzzy in guideline based strategy. On the off chance that the alpha range is high than the beta range implies a 1 in fuzzy guideline which indicates the driver is drowsy else it is 2 which indicates the driver is in awake state.

4.5.1. Fuzzy Logic

Fuzzy Rule based classification is a technique for producing a mapping from an offered input to an output by employing fuzzy logic. At that point, the mapping provides a premise, from which choices can be created. Enrollment Functions, Logical Operations, and If-Then Rules are employed as a part of the Fuzzy Rule based Process. The phases of Fuzzy are,

1. Fuzzification
2. Fuzzy Rules Generation
3. Defuzzification

4.5.2. Fuzzification

For the fuzzification transform, the data are the best peak attributes, alpha mean and beta mean. Subsequent to that, the minimum and maximum value is ascertained from the input attributes and energy signals. The strategy of fuzzification is processed by applying the accompanying mathematical statements.

$$ML = \min + \left(\frac{\max - \min}{3}\right) \tag{8}$$

$$XL = ML + \left(\frac{\max - \min}{3}\right) \tag{9}$$

where, ML - minimum limit values of the feature M .

XL - maximum limit values of the feature M .

Use these equations (8) and (9), we can calculate the minimum and maximum limit values for energy signals. And also, two conditions are provided to generate the fuzzy values by using these equations.

Conditions

1. The “alpha” values are compared with “Beta“. If alpha value is high and the Beta value is low then those values are set as 1.

2. The “alpha” values are compared with “Beta“. If alpha value is low and the Beta value is high then those values are set as 2.

4.5.3. Fuzzy Rules Generation

According to the fuzzy values for each feature that are generated in the Fuzzification process, the Fuzzy Rules are also generated. The rules are

General form of Fuzzy Rule

“IF A THEN B”

Rules

If the Alpha value is “High” and the Beta value is “Low” Then Drowsy

If the Alpha value is “Low” and the Beta value is “High” Then Awake

The “IF” component of the Fuzzy Rule is denoted as “antecedent” and the “THEN” component of the rule is denoted as “conclusion”.

4.5.4. Defuzzification

The input provided for the Defuzzification methodology is the fuzzy values and the output acquired is a solitary number. The single number output is a value L or H. This estimation of the output indicates whether the given dataset is in the Low series, Medium series or in the High series.

5. RESULTS AND DISCUSSION

The anticipated EEG signal based driver drowsiness detection system is executed in Matlab 2013. The signals are taken from physionet.org. The analysis result and the execution of the proposed drowsiness detection framework are specified beneath in point of interest.

5.1. Experimental Results

Different genuine signals and therapeutic EEG and EOG signals are provided as the input for the proposed drowsiness detection analysis. The signals that are employed have some drowsy and some awake signals. These input signals of the proposed paper are demonstrated in the fig. 2 and fig.3.

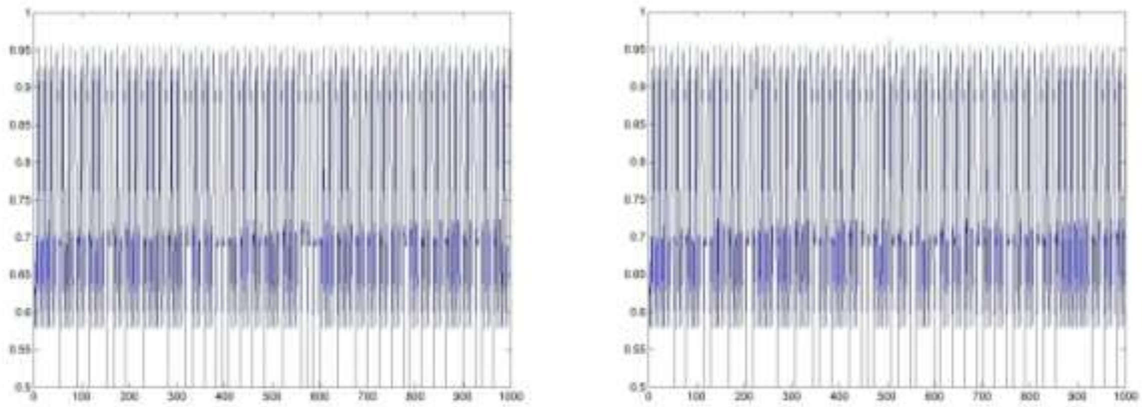


Fig.2. Sample awake signals

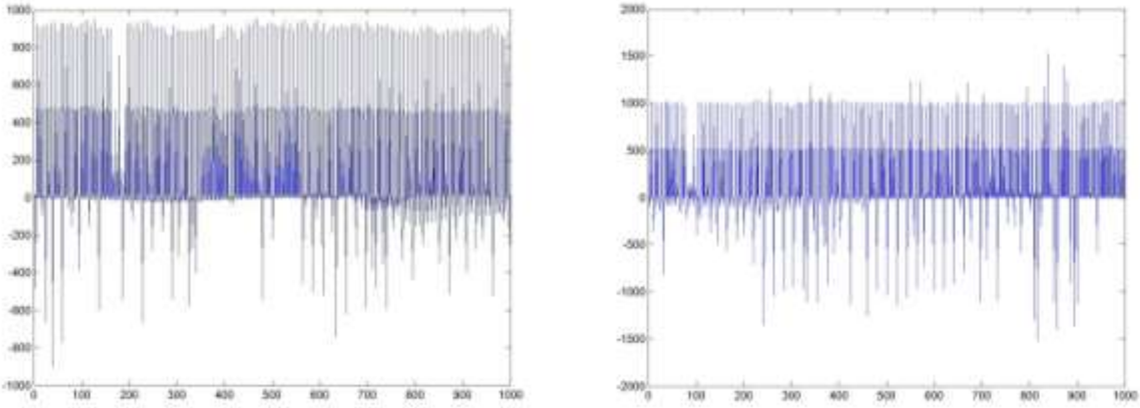
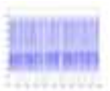
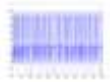
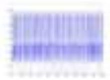
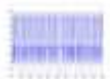
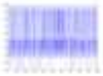
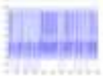


Fig.3. Sample drowsy signals

The set of signals in fig. 2 and fig.3 are given as an input and these signals are used to detect the driver's drowsiness.

Table 1: Values of features extracted from the input signal

Input Signal	Mean	Peak	Pitch Spectrum	Standard Deviation	Minimum	Maximum
	0.750754	493.9741	181.8182	0.135992	0.500313	0.954894
	0.754578	481.1657	181.8182	0.135547	0.500313	0.954894
	0.752132	489.7296	181.8182	0.136047	0.500313	0.962646
	149.135	494.7483	57.14286	317.8571	-445	962
	-1.31449	123.58	400	6.560943	-30	2
	0.753016	489.5248	83.33333	0.137405	0.500313	0.962646
	0.752538	488.2983	181.8182	0.135282	0.500313	0.954894
	0.755413	507.6685	181.8182	0.135294	0.500313	0.954894
	0.745781	506.3033	181.8182	0.136093	0.500313	0.954894
	-529.493	502.5	500	259.31	-659.037	1
	-529.493	502.5	500	259.31	-659.037	1

	-1133.27	820	500	557.7985	-1412.01	2
	-38.4008	572.5	500	18.1152	-47.061	1
	0.755784	503.5625	181.8182	0.137454	0.500313	0.954894
	0.757855	524.7472	200	0.137417	0.500313	0.954894
	0.752442	530.5446	83.33333	0.137928	0.500313	0.962646

The main parameters such as, peak, pitch, mean & standard deviation of the signal and minimum & maximum of the signal is extracted from EEG and EOG signal. The values of the features of five input signals are specified in the Table. 1. The graphical representation of the extracted features are specified in fig. 4

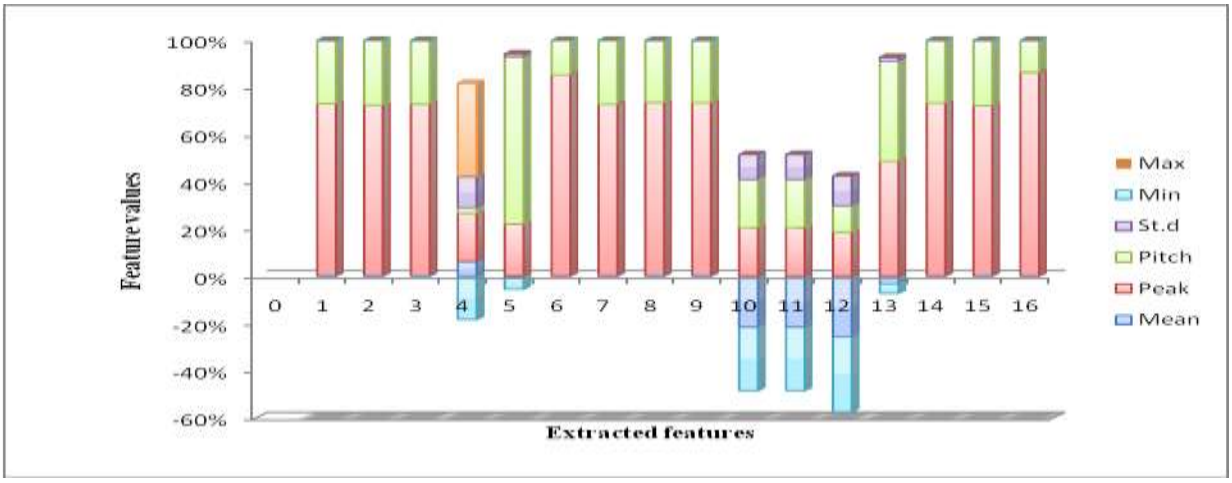


Fig. 4. Plot for extracted features from the input

Convergence graph is used to resolve whether an appraised quantity is converged sufficiently well. The graph that specifies a better convergence of a measure, is the convergence graph as shown in fig.5 .

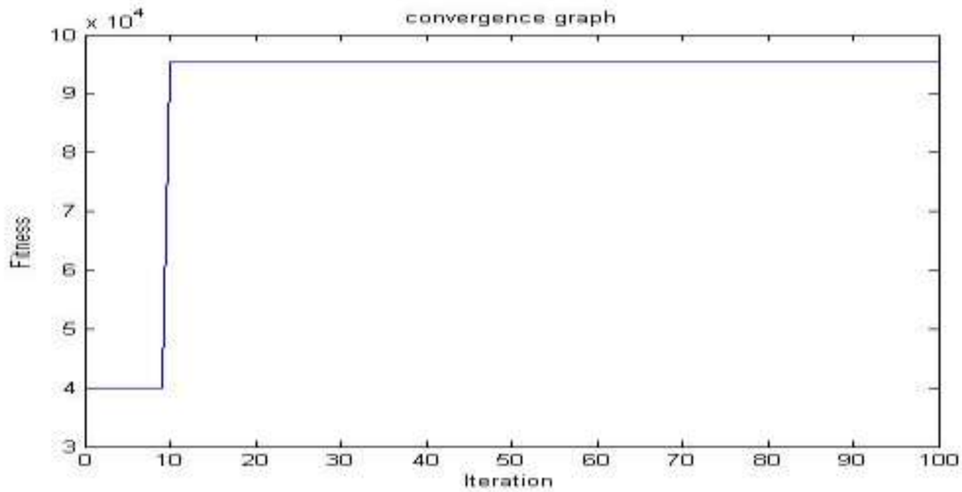


Fig.5. Convergence graph

ROC stands for receiver operating characteristic (ROC).This curve, is a graphical design that shows the execution of a binary classifier framework .The curve is made by plotting the genuine positive rate over the false positive rate at different threshold conditions. The false-positive rate is otherwise called the fall out and can be figured as 1 to specificity. The genuine positive rate is otherwise called sensitivity in biomedicine, or review in machine learning. The ROC curve can be created by plotting the cumulative distribution function area under the probability distribution that ranges from $-\infty to +\infty$ of the detection probability in the y-axis versus the cumulative distribution Function or the false-alarm probability in x-axis. The True positive rate and False positive rate is related in the ROC graph provided in Fig. 6 as follows

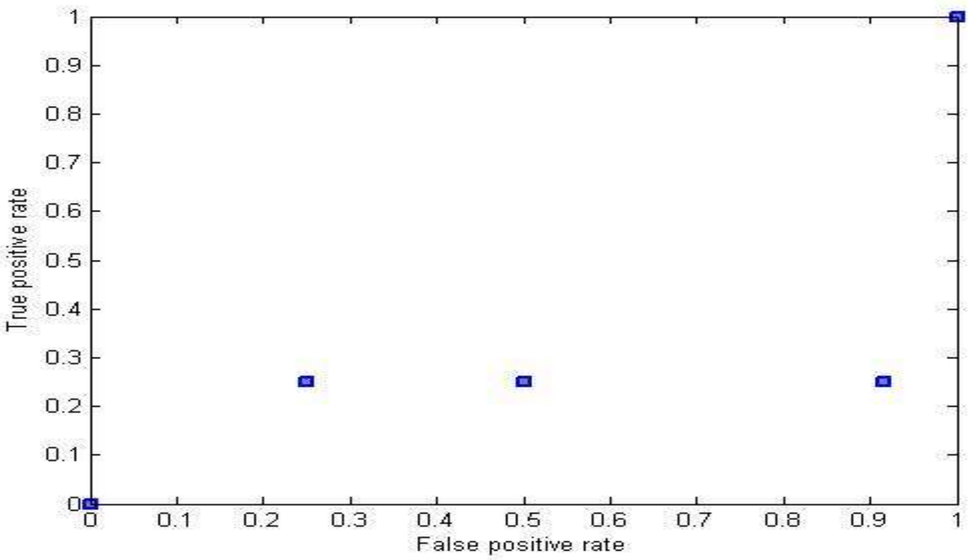


Fig.6. ROC Graph

The drowsiness organization system based on the EEG and EOG analysis attains 90% accurate classification of “drowsy” and “Awake” States .The “Drowsy” state is further classified as “Little drowsy” and “Deep drowsy”.

Table 2: Confusion Matrix based on the EEG and EOG

	True Positive	True Negative	False Positive	False Negative
Drowsy	37.5%	50%	0%	12.5%
Awake	18.75%	75%	6.25%	0%
Little Drowsy	6.25%	75%	12.5%	6.25%
Deep Drowsy	18.75%	81.25%	0%	0%

5.2. Evaluation metrics

A percentage of the measurements that we have picked for our assessment design are True Positive, True Negative, False Positive and False Negative, Specificity, Sensitivity, Accuracy.

Each signal is tested and identified as Drowsy or Awake. The tested signal outcome can be positive (Awake) or negative (Drowsy).

$$True\ Positive\ (TP) = Awake\ people\ correctly\ identified\ as\ Awake$$

$$True\ Negative\ (TN) = Drowsy\ people\ correctly\ identified\ as\ Drowsy.$$

$$False\ Positive\ (FP) = Awake\ people\ incorrectly\ identified\ as\ Drowsy$$

$$False\ Negative\ (FN) = Drowsy\ people\ incorrectl\ y\ identified\ as\ Awake$$

Sensitivity measures the proportion of actual positives which are correctly identified. It relates to the test's ability to identify positive results.

$$Sensitivity = \frac{Number\ of\ true\ positives}{Number\ of\ true\ positives + Number\ of\ false\ negatives}$$

Specificity measures the proportion of negatives which are accurately recognized. It denotes the capability of the analysis to recognize negative results.

$$Specificity = \frac{Number\ of\ true\ negatives}{Number\ of\ true\ negatives + Number\ of\ false\ positives}$$

Through the above results, we can effortlessly obtain the precision value by the following formula,

$$Accuracy = 100 - \frac{[FP/(FP+TN)]\,/\,[FN/(FN+TP)]}{2}$$

False positive rate (FPR) usually refers to the expectancy of the false positive ratio and is defined as,

$$False\ positive\ rate = \frac{FP}{FP+TN}$$

The positive predictive value (PPV) is defined as,

$$PPV = \frac{No\ of\ TP}{No\ of\ TP + No\ of\ FP}$$

The Negative predictive value (NPV) is defined as,

$$NPV = \frac{No\ of\ TN}{No\ of\ TN + No\ of\ FN}$$

The False discovery rate (FDR) is a statistical method used in multiple hypothesis testing to correct for multiple comparisons and is defined as,

$$FDR = 1 - PPV$$

5.3. Performance Analysis comparison of proposed methodology with the existing methods

Table 3 shows the result of the values of the metrics sensitivity, specificity, accuracy, FPR, PPV, NPV, FDR, MCC of the proposed work.

Table 3: Proposed work with perfomance metrics values

Sensitivity	Specificity	Accuracy	FPR	PPV	NPV	FDR	MCC
0.714286	0.888889	0.8125	0.111111	0.833333	0.8	0.166667	0.61807
0.5	0.785714	0.75	0.214286	0.25	0.916667	0.75	0.218218
0.5	0.857143	0.8125	0.142857	0.333333	0.923077	0.666667	0.302614
1	1	1	0	1	1	0	1

From the above table 3, hereby comparing all the values, we assess the values of sensitivity, specificity, accuracy, FPR, PPV, NPV, FDR, and MCC. All cases accomplished a better accuracy which clearly shows the efficiency and reliability of the proposed strategy.

Table 4: Table for comparing the Sen, Spec, Acc,

FPR, PPV, NPV, FDR, MCC

Metrics	Proposed work (Fuzzy) (Avg)	Existing work (Neural network) (Avg)	Existing work (SCG) (Avg)	Existing work (ANFIS) (Avg)
Sensitivity	0.8725	0.6785	0.233333333	0.815
Specificity	0.955	0.8829	0.800378788	0.946439394
Accuracy	0.9062	0.8437	0.6875	0.8975
FPR	0.0549	0.117	0.199621212	0.043560606
PPV	0.8908	0.6041	0.291666667	0.775833333
NPV	0.9507	0.9099	0.778846154	0.939935897
FDR	0.2291	0.3958	0.708333333	0.104166667
MCC	0.8473	0.5347	0.076963425	0.72227631

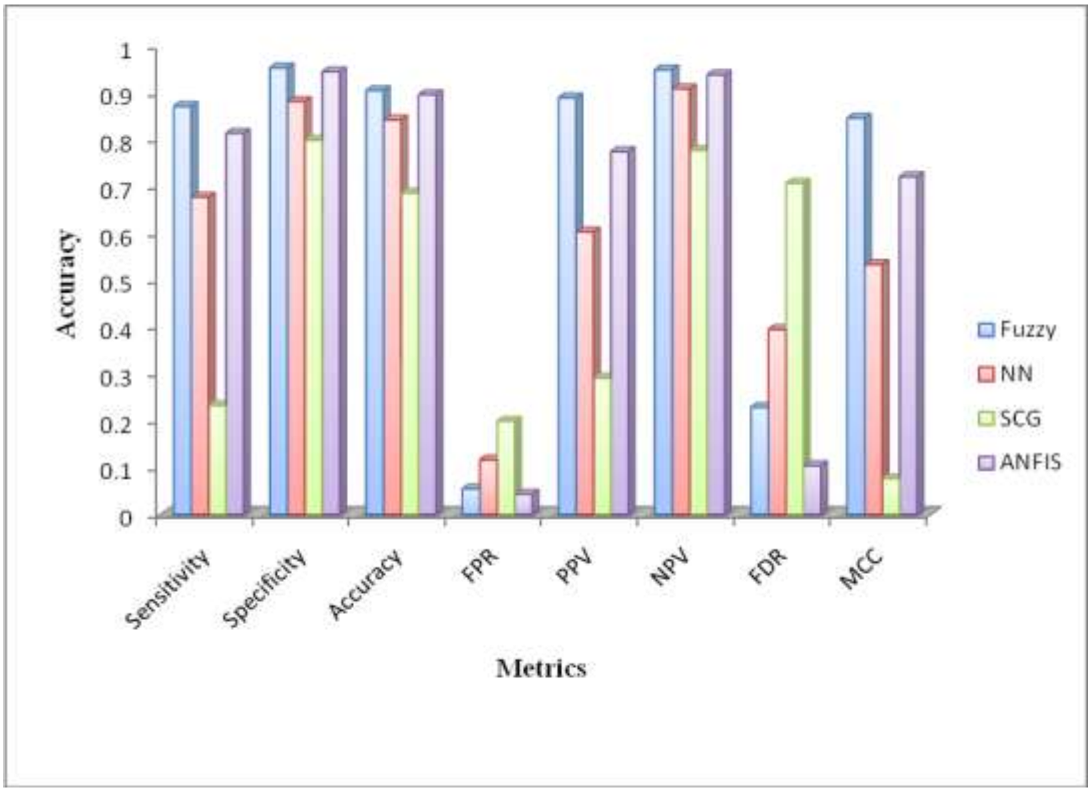


Fig 7: Comparison diagram for the sensitivity, specificity, accuracy, FPR, PPV, NPV, FDR, MCC metrics,

6. CONCLUSION

The vital objective of this study is signal characterization with the help of Fuzzy based EEG and EOG signal. The proposed framework was executed with some EEG signals and EOG signals. The results demonstrate that our proposed drowsiness detection framework employing fuzzy based arrangement has given better results than other different existing methods. Our proposed strategy employing IPSO as a part of Fuzzy puts forward 80% precision. Thus, our proposed Fuzzy based classification has efficiently classified the awake and drowsy state from the input signal.

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