

Integrating Brain-Computer Interface (BCI) for Assessing Olfactory Perceptual-Ability of Human Subjects using TSK-Induced Interval Type-2 Fuzzy Classifier

Abik Saha¹, Aritra Majumdar², Debjit Base³, Hrishav Manna⁴, Sattwik Bhattacharjee⁵ and Mousumi Laha⁶
¹⁻⁶Institute of engineering & Management (IEM), University of Engineering & Management, Kolkata
Email: abikblg@gmail.com, aritra13.majumdar@gmail.com, debjit1608@gmail.com, hrishav.manna7492@gmail.com, sattwikb22@gmail.com, lahamou@gmail.com

Abstract— Olfactory perceptual-ability in human subjects refers to the process of recognizing aromas at varying concentration levels. The aim of the paper is to introduce a novel approach that helps to evaluate perceptual-ability of human subjects with various odor concentration levels using Brain-Computer Interface (BCI) techniques. The most important non-invasive method for brain data acquisition is the Electroencephalogram (EEG). EEG signals can be used to identify brain activation regions and neural pathways involved in processing different odor stimuli. Due to the non-stationary characteristics of brain signals, the Takagi-Sugeno-Kang (TSK) induced Interval Type-2 Fuzzy logic is suitable for decoding brain signals to assess the perceptual-ability of human subjects. Three different concentration levels (High, Medium and Low) of five odor stimulus are utilized for the experiments. The analysis of the acquired brain signals using e-LORETA software confirms the involvement of the prefrontal and frontal cortex in the specified cognitive task. The experimental results demonstrate that the proposed method significantly enhance the precision of olfactory assessments compared to traditional subjective methods. A Friedman statistical test confirms that the proposed classification algorithm is superior to other classification algorithms. Moreover, in real time scenario, the recognition of olfactory stimulus and olfactory perceptual-ability assessment of human subjects is applicable for the bio-marker/ early diagnosis of Alzheimer disease and neuro-degenerative disorder.

Keywords—Olfactory perceptual-ability, Brain-Computer-Interface (BCI), Electroencephalogram (EEG), Interval Type-2 Fuzzy logic, Alzheimer disease.

I. INTRODUCTION

Brain-Computer Interfacing (BCI) technology is a popular innovative approach which bridging human brain with the external devices. BCIs allow a person's movement inhibition to be circumvented through mechanical devices in order to capture motion of the brain and computers [1]. Therefore, it is an encouraging technology and promises applications in the field of medicine, neuro rehabilitation, and cognitive studies. Olfactory perceptual-ability or the ability to smell is useful for human beings for performing different functions ranging from warning about threats such as smoke or expired food to helping with memory, emotion, and socialization [2].

Compared to other sensory systems, the sense of smell remains the least examined to date, especially when it comes to the use of BCIs for the study of olfactory perception. There are endeavors to develop new diagnostic tests that utilize the discrimination of visual and olfactory stimuli in humans to assess their brain functioning, cognitive skills, and even neurobiological psychopathology. In this context, the paper aims at to assess the olfactory perceptual-ability of healthy and neuronal diseased subjects through the use of brain electrical activity recording i.e. electroencephalograms (EEG) [3].

EEG is an important non-invasive modality that captures electrical activity of the brain, serving as an effective tool for capturing neural responses to olfactory stimuli. By analyzing the brain's electrical patterns in response to different smells, the study seeks to identify distinct neural markers that correlate with olfactory perception [4]. The integration of EEG data with advanced computational models, such as the TSK-induced Interval Type-2 Fuzzy Classifier [5], enables the classification of olfactory perceptual ability with a high degree of accuracy. This approach not only provides insight into how the brain processes olfactory information but also holds potential for diagnosing olfactory dysfunctions in patients with neurodegenerative diseases or brain injuries.

Recent researches on Brain-Computer Interface (BCI) applications for olfactory perception have explored the way in which the electrical responses of the brain activity, in particular EEG signals, occur due to the alterations of the stimulus of odor [6], [7]. One of the most important studies that appeared in 2023 [8] proposed that alterations in the activity of brainwaves concerning theta rhythms of frontal cortex could be tracked by using EEG-based BCIs in olfactory tasks, such as in odor perception and discrimination. Another research [9] illustrates that subjects could sustain effective odor discrimination over long periods; particular EEG components, such as the P200, were affected by olfactory stimulation. The above two studies inspired the authors to assess the olfactory perceptual ability of human subjects by analyzing the brain's electrical responses, specifically focusing on signals obtained from the frontal and prefrontal regions.

The study is undertaken using Cyton + Daisy Bio-sensing Boards manufactured by Open BCI systems are placed over the respective position of the scalp of the subjects. The acquired brain signals are filtered and pass through the e-LORETA technique for the identification of the highly activated brain locations associated for olfactory perception. The recorded EEG signals from the brain often include intra- subjective noise because of other processes occurring simultaneously in the thinking activity of the subject, artifacts from eye-blinking, and also involuntary motor actions carried out by the subject. Type-2 Fuzzy set is more effective tools for handling the inter- and intra- subjective uncertainty in the brain signals.

Although any conventional classification model can be used to train classifiers with the generated training instances, Type-2 Fuzzy classifier is more appropriate option to minimize the intra- and inter subjective uncertainty. Thus, this paper proposed a novel TSK-induced Interval Type-2 Fuzzy (IT2F) Classifier to rectify the problem. The TSK model with respect to the Mamdani approach is more advantageous at the certain level of the fuzzy rules' structure. The consequent parts of both models differ although their antecedent components are the same. In the case of the Mamdani model, the consequent is formed by a fuzzy propositional logic for the output variable, while in the case of the TSK model, a linearity function of the antecedent variables is used in the consequent [10]. This allows the output to be directly generated from the TSK model, which bypasses the additional steps of defuzzification and type-reduction process.

Moreover, the proposed TSK-induced Interval Type-2 Fuzzy Classifier is compared against the traditional and existing approaches in terms of computational cost and runtime complexity. Statistical analyses demonstrate that the proposed TSK- induced IT2Fs Classifier model significantly outperforms traditional methods, confirming its superiority in both efficiency and effectiveness.

The paper is organized in to six parts. Section 2 illustrates the schematic representation of the approach proposed for olfactory perceptual-ability assessment. Section 3, describes the proposed TSK-induced Interval type-2 fuzzy classification algorithm used in the perceptual-ability assessment. The experimental procedures are demonstrated in Section 4. Section 5 gives a performance analysis of the proposed method. Finally, conclusions based on experimental findings are summarized in Section 6.

II. SYSTEM OVERVIEW

This section illustrates all techniques employed to categorize three concentration levels of five odor samples accomplished by an individuals from their response. Fig. 1, describes the block diagram of the entire system. First, EEG signals are recorded from the scalp of the subjects using gold-cup electrodes of the Cyton and Daisy board. These signals are then processed through Exact Low Resolution Electromagnetic Topographic Analysis (e-LORETA) [11] software for identification of the active regions associated with olfactory perception during the experiment. This allows for precise localization of neural activity relevant to the perceptual task. The raw

EEG signals are passed through a 10th-order elliptical band-pass filter having a cutoff frequency range of 0.1 to 13 Hz. A band-pass filter is employed due to its effective eliminating power of artifacts and physiological noise [12]. After filtering, the signals undergo Independent Component Analysis (ICA) software [13] to separate 16 independent components from 16 separated channels. To extract the necessary feature sets, the feature extraction process is carried out in different domains. The features are obtained in the frequency domain using Power Spectral Density (PSD) analysis while Discrete Wavelet Transform (DWT) is used to extract time-frequency correlated features [14]. Therefore, the dual approach supports the successful fulfillment of having the maximum representation of features in both space and time domain with respect to the classification and analysis of signals. In this experiment, a total of 513 PSD features were extracted using the Welch method. Besides, 1,278 f DWC features were obtained following Fourth-level decomposition. Hence, a total of 1,791 features were extracted from one trial of the subject. For each subject, a total of 53,730 features were generated based on the formula: number of subjects $\times$ 6 trials per session $\times$ 5 sessions per stimulus. To streamline the feature set and reduce computational complexity, Principal Component Analysis (PCA) [15] has been applied as the feature selection method, allowing for the elimination of redundant features. Ultimately, 100 optimal features were selected and fed into the proposed classifier module to categorize the three types of odor concentration of five different odor stimuli.

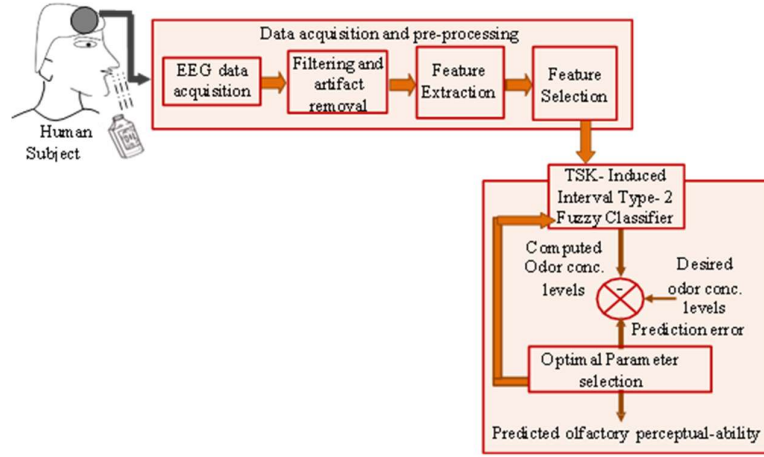


Fig. 1. Block Diagram of the Proposed Olfactory Perceptual-Ability Assessment

III. TSK- INDUCED IT2FS CLASSIFIER FOR PERCEPTUAL-ABILITY ASSESSMENT

Let,

$f_1, f_2, \dots, f_n$ be n features extracted from the corresponding channel placed over the subject's brain during the performance of the experiment. The experiment is conducted over five sessions in a day with each session comprising of ten experimental trials. Now, one common TSK Induced Interval type-2 Fuzzy Classifier of Rule j is given by

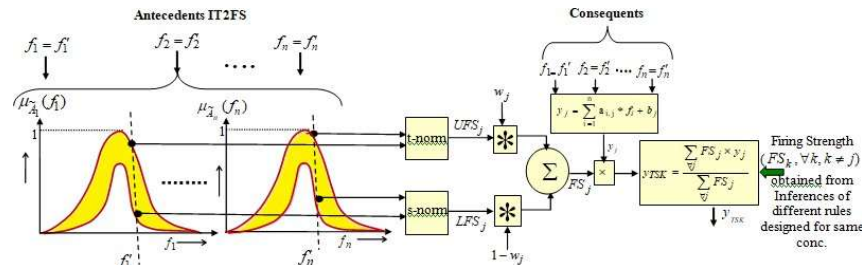


Fig. 2. Architecture of the proposed TSK-Induced Interval Type-2 Fuzzy Classifier

$$\text{If } f_1 \text{ is } A_{1,j}, f_2 \text{ is } A_{2,j}, \dots, f_n \text{ is } A_{n,j}, \text{ Then } y_j = \sum_{i=1}^n a_{i,j} * f_i + b_j.$$

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Here, f_i is $A_{i,j}$, be the Fuzzy antecedent propositions for $i=1$ to n of j -th rule obtained from multiple assessment of the experiments, whereas, y_j represents the signal strength of the Superior Frontal region to classify five olfactory classes. The co-efficient $a_{i,j}$ and b_j are determined by classical least min-square technique. Now consider, $f_{i,h,s,j}$ be i -th feature extracted on session s in trial h of rule j . The mean and the variance of the feature i over a session s of that rule are respectively given by

$$\bar{f}_{i,s,j} = \left(\sum_{h=1}^5 f_{i,h,s,j} \right) / 5 \quad (2)$$

$$\sigma^2_{i,s,j} = \frac{1}{5} \sum_{h=1}^5 (f_{i,h,s,j} - \bar{f}_{i,s,j})^2 \quad (3)$$

Now, a type-1 Gaussian MF $G(f_{i,s,j}, \sigma^2_{i,s,j})$ is constructed to model the intra-session variation of i -th feature obtained from rule j . To accommodate the sessional variation of the experimental trials, such Gaussian Membership function (MF) has been constructed. Finally, the Upper Membership Function (UMF) and the Lower Membership Function (LMF), are obtained by taking maximum and minimum of these Type-1 Gaussian MFs respectively, which produces the Footprint of Uncertainty (FOU) of the IT2Fs. Formally, the UMF and LMF are represented as

$$UMF = \text{Max}_{\forall s} (\mu_{A_{1,s}}(f_1), \mu_{A_{2,s}}(f_2), \dots, \mu_{A_{n,s}}(f_n)) = \mu_{A_{i,s}}(f_i) \quad (4)$$

$$LMF = \text{Min}_{\forall s} (\mu_{A_{1,s}}(f_1), \mu_{A_{2,s}}(f_2), \dots, \mu_{A_{n,s}}(f_n)) = \mu_{A_{i,s}}(f_i) \quad (5)$$

To meet the convexity norm of the obtained membership functions (MFs), the curved peaks are connected by a horizontal straight line (slope = 0), creating a flat-top approximated type-2 fuzzy set (T2FS).

Now, consider the following steps of the proposed TSK-induced IT2Fs model.

- Evaluate the Upper Firing Strength (UFS) and the Lower Firing Strength (LFS) for rule j at the selected measurement point $f_1 = f'_1, f_2 = f'_2, \dots, f_n = f'_n$ are provided by eq. (6) and (7) respectively.

$$UFS_j = \min_{\forall s} [\mu_{A_{1,s}}(f_1), \mu_{A_{2,s}}(f_2), \dots, \mu_{A_{n,s}}(f_n)] \quad (6)$$

$$LFS_j = \max_{\forall s} [\mu_{A_{1,s}}(f_1), \mu_{A_{2,s}}(f_2), \dots, \mu_{A_{n,s}}(f_n)] \quad (7)$$

- Next, the firing strength (FS_j) of rule j is calculated by calculating the multiplication of the weighted sum of the upper and lower firing strengths,

UFS_j and LFS_j . The weights lie within the range [0, 1], where one weight is w_j and the other is $1 - w_j$. Therefore, the firing strength (FS) for rule j is given by:

$$FS_j = w_j \cdot UFS_j + (1 - w_j) \cdot LFS_j. \quad (8)$$

- Finally, Principal Component Analysis (PCA) has been adopted for optimal selection of the weights. The resulting response of the TSK-based type-2 fuzzy classifier model is computed by

$$y_{TSK} = \frac{\sum_{\forall j} FS_j \times y_j}{\sum_{\forall j} FS_j}, \quad (9)$$

where FS_j is the firing strength of the j -th rule.

Now, to classify 5 concentrations of odors from the measure of y_{TSK} , we divide the interval $[0, y_{TSK}^{\max}]$ into 5 non-overlapped portions. The detailed architecture of the proposed model is presented in Fig. 2.

IV. EXPERIMENTS AND RESULTS

This section describes the experimental procedures and the results of the olfactory perceptual-ability assessment using EEG device.

A. EEG data acquisition and experimental framework

The experiment was conducted at the Innovation and Entrepreneurship Development Centre (IEDC) of the Institute of Engineering & Management (IEM), and University of Engineering & Management (UEM), Kolkata, India. The whole-brain Electroencephalogram (EEG) device is used in this study to capture the electrical responses from the brain. A Cyton + Daisy bio-sensing chip manufactured by Open BCI system has been utilized in this experiment. This is a 16-channel bio-amplifier and an Arduino-compatible 32-bit processor. The Cyton + Daisy Board acquires raw EEG signals from all 16 channels at a rate of 125 Hz/ seconds. In this research work, five various odor stimuli at three levels of concentration (high, medium, and low) were applied to assess the olfactory perceptual-ability of subjects. Cyton board consists of 8 channels (1 to 8 channels) and Daisy board consists of (8 to 16 Channels) altogether form a 16 EEG channels are placed on the respective position of the brain such as Pre-frontal lobe (FP1 and FP2), Frontal lobe (F3, F7, F4, F8), Motor cortex (C3 and C4), Paraital Lobe (P3 and P4), Temporal Lobe (T3 T4, T7 T8) and Occipital Lobe (O1 and O2). Fig. 3 represents the whole Open BCI system with the respective electrode positions. Fig. 3 (a) depicts the experimental setup of olfactory perceptual-ability assessment along with the Cyton and Daisy board in fig.3. (b), scalp map and electrode position in fig.3. (c) and the raw EEG signals in fig.3. (d). Thirty volunteers had participated in the experiment aged between 20 and 45. Of these participants, 20 were male, while 10 were female. In order to reduce artifacts, participants had previously been informed to sit comfortably with their arms resting on the armrests so that movement, and consequently potentially external factors during testing, does not influence the data collection process

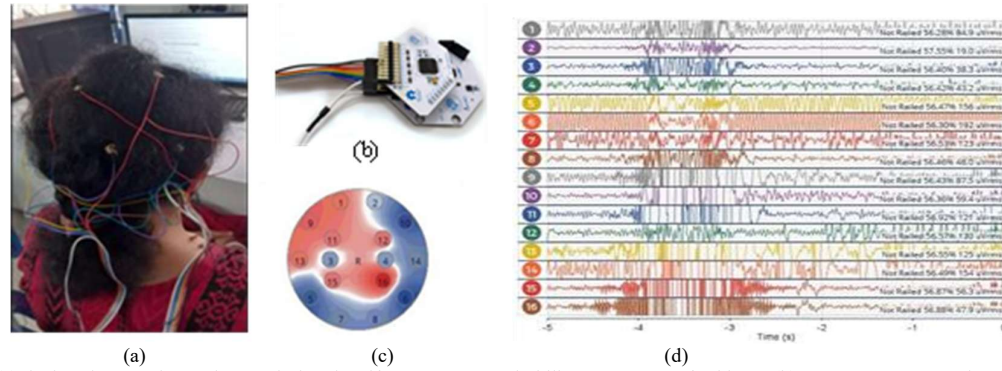


Fig. 3 (a) depicts the experimental setup during the olfactory Perceptual-ability assessment of subjects, (b) Open BCI Cyton and Daisy board, (c) scalp map and electrode position of the system, (d) 16 channels raw EEG signals acquired during the experiment

B. Stimulus Presentation and Preparation

The format of the stimulus used in this experiment is illustrated in Fig. 4. The procedure begins with a 3-second interval to allow the subject to focus on the cognitive task. Following this, a 10-second time interval is given to displays an instruction set informing the subject about the specific task to be performed. Then, for the next 15 seconds, a particular odor sample with a fixed concentration is placed on the subject's nose, during which the subject mentally evaluates whether the concentration of the odor stimulus is high, moderate/tolerable and Low/pleasant. After making this mental decision, the subject communicates their judgment to the experimenter. Five different types of olfactory stimuli such as detol, rose water, eucalyptous oil, ammonia, Acitic Acid are used, each presented at varying concentration levels.

C. Experiment 2: Identification of active brain regions using e-LORETA software

The experiment aims at to identify the active brain regions associated with olfactory perception using e-LORETA software.

The Exact Low Resolution Brain Electromagnetic Tomography (eLORETA) technique has been employed to examine the distribution of electrical activity within the brain's cortical regions. A significant observation has been found that the Superior Frontal cortex showed maximum degree of activation during the high concentration level of the odor stimulus, as illustrated in Fig.5.

This cortex, located in Broadmann area 10 at the Superior Frontal Gyrus of the Frontal lobe, was notably engaged. Additionally, activation in the pre-frontal lobe was accompanied by the involvement of the anterior cingulate cortex, particularly the dorsal part, which is situated in the prefrontal and frontal lobes. These findings are consistent with previous studies [16] that also support the results observed through the e-LORETA software.

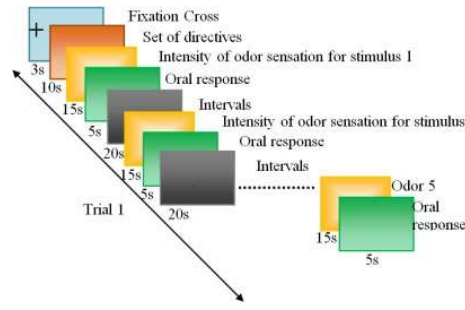


Fig. 4 Presentation of a single trial for subjective assessment of olfactory sensation

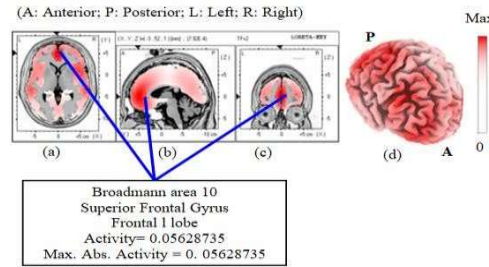


Fig. 5 (a) e-LORETA results obtained during high concentration level of odor stimulus (detol) (a) axial view (b) sagittal view (c) coronal view (d) 3D view of activation map

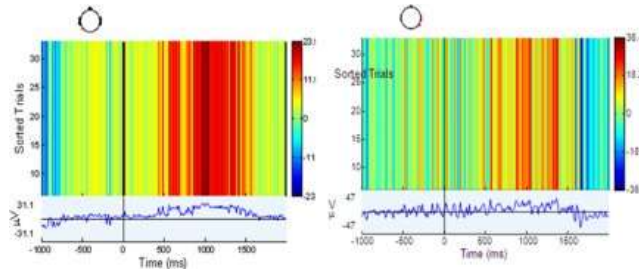


Fig.6. Activation of F3 and F4 electrodes in presence of high concentration level of olfactory stimulus

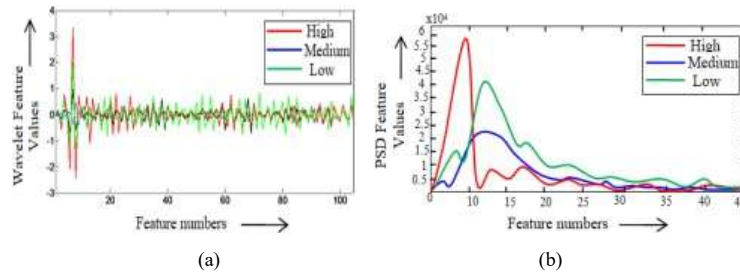


Fig.7 (a), (b) Represent the PSD and DWT feature maps of F3 electrode for three concentration levels of olfactory stimulus

D. Experiment 3: Filtering and Feature Extraction

This experiment discusses the technique used for artifact removal and feature extraction on the EEG signals. It is noticed, from the experimental results, that the band power at the lower alpha band (8-13Hz), upper Theta (4-8Hz) bands are increased substantially with time after stimulation. The noise and other artifacts were removed using a band-pass filter with a pass-band of 0.5-13Hz. A 10th-order elliptical filter has been selected for filtering due to its better roll-off and stop band attenuation. To remove the physiological artifacts and noise, Independent Component Analysis (ICA) was utilized further to recover 16 independent components from 16 individual electrodes of the EEG signals. Fig. 6 shows the activation in the Frontal area (F3 and F4) occurs while the subject is experienced high concentration of the odor stimulus represents red color for highest activation and blue for lowest activation.

Next to extract certain features from the filtered EEG signals acquired from the active brain regions, PSD and DWT are suitable for extracting critical set of features in frequency and time –frequency co-related domain respectively. Fig. 7 (a) and 7 (b) represent the PSD and DWT feature maps of F3 electrode for three concentration levels of olfactory stimulus. It is observed from the figure that there are some overlapped features in High and Moderate concentration levels for wavelet coefficients. To overcome the miss-classification, both PSD and DWT features have been considered as extracting features. Finally, the Principal Component Analysis (PCA) has been used to select 100 optimal features to increase the efficiency and accuracy of the classifier.

TABLE I. COMPARATIVE STUDY (STANDARD DEVIATION) OF PROPOSED CLASSIFIER WITH OTHER CLASSIFIERS

Classifier Algorithm	Classification accuracy and F1 Score (in %) of the three concentration levels						Average Rank for Friedman Statistical Test
	High		Medium		Low		
	CA	F1 Score	CA	F1 Score	CA	F1 Score	
LSVM [17]	75.89	76.32	77.25	78.12	76.56	77.12	9
KSVM-Gaussian Kernel [18]	77.02	78.56	78.96	78.33	78.32	79.36	7
KSVM-polynomial Kernel [19]	78.69	78.05	80.12	81.02	79.98	79.52	6
SOFNN [20]	83.75	82.99	82.56	82.98	83.12	84.25	6.66
BPNN [21]	86.88	87.52	85.32	86.45	85.95	86.78	5
Type-I fuzzy[22]	88.10	88.45	89.01	89.97	88.10	88.03	4.33
IT2FS [23]	90.12	90.07	90.96	91.04	91.02	92.78	3.66
TSK based Fuzzy [24]	93.56	93.78	92.63	92.55	93.66	93.98	2.33
Proposed GT2FS	95.45	95.63	94.71	94.85	95.78	96.02	1

V. CLASSIFIER PERFORMANCE AND STATISTICAL VALIDATION

To verify the performance of the proposed classifier, five metrics were utilized: Classification Accuracy (CA), Sensitivity (SEN), Specificity (SPE), and F1-score, defined with equations.

$$CA = \frac{TP + TN}{TP + TN + FP + FN}, \quad SEN = \frac{TP}{TP + FN}, \quad SPE = \frac{TN}{TN + FP}, \quad F1 \text{ score} = \frac{2TP}{2TP + FP + FN}.$$

The relevant metrics are computed with regards to true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). A comparison, reflected in Table II, is drawn between a proposed classifier and other traditional classifiers. It is observed from the table that the proposed classifier enhances the accuracy of classification and reduces computational complexity compared to traditional methods. Table-I provides the relative performance analysis of the proposed classifier with respect to the traditional ones. Additionally, to validate the superiority of the proposed classifier, the well-known Friedman Statistical Test [25] has been performed. The average rank of the proposed TSK-Induced IT2FS classifier is presented in Table-I. The rank of the proposed classifier is 1 which confirms the superiority of the algorithm against other algorithm.

VI. CONCLUSION

The paper has proposed a new approach toward the olfactory perceptual ability of human subjects by integrating BCI technology with a TSK-based Interval Type-2 Fuzzy Classifier. It included capturing EEG signals emanating from the brains of the subjects when they perceived olfactory stimuli and using advanced signal processing techniques such as Power Spectral Density and Wavelet Transforms to actually extract relevant features.

Thus, experimental results confirm that the proposed system is efficient for distinguishing between different smells using EEG data when compared with a traditional classifier in terms of accuracy and computational efficiency.

Applying fuzzy logic, especially the Interval Type-2 Fuzzy System (IT2FS), effectively addresses the inherent uncertainties found in EEG signals for reliable classification. The results are believed to bring into the future potential in BCI-related research in olfactory sensing as well as open new avenues of application in diagnostics of Alzheimer disease, cognitive assessment, and even neurobiological studies related to olfactory dysfunctions.

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REFERENCES

- [1] D. Kim, & S. W. Lee, (2018, October). "Model-based BCI: A novel brain-computer interface framework for reading out learning strategies underlying choices," In 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 480-484, october 2018, IEEE.
- [2] J. Kum et al, "Neural dynamics of olfactory perception: low-and high-frequency modulations of local field potential spectra in mice revealed by an oddball stimulus," *Frontiers in neuroscience*, vol. 13, pp. 478, 2019.
- [3] R. Abiri, S. Borhani, E. W. Sellers, Y. Jiang, X. Zhao, "A comprehensive review of EEG-based brain- computer interface paradigms," *Journal of neural engineering*, vol. 16, no. 1, pp. 011001, 2019.
- [4] M. Laha, L. Ghosh, S. Parui, S. Ghosh, A. Konar, "Evaluation of density based odor classification by general type-2 fuzzy set induced pattern classifier," In 2018 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), pp. 1-6, 2018, IEEE.
- [5] N. N. Karnik, J. M. Mendel, and Q. Liang, "Type-2 fuzzy logic systems," *IEEE trans. on Fuzzy Systems*, vol. 7, no.6, pp. 643-658, 1999.
- [6] G. A. Wright and B. H. Smith, "Variation in complex olfactory stimuli and its influence on odour recognition. Proceedings of the Royal Society of London," *Series B: Biological Sciences*, vol. 271, no.1535, pp. 147-152, 2004.
- [7] S. R. Jaeger, J. F. McRae, C. M. Bava, M. K. Beresford, D. Hunter, Y. Jia, and K. R. Atkinson, "A Mendelian trait for olfactory sensitivity affects odor experience and food selection," *Current Biology*, vol. 23, no.16, pp. 1601-1605, 2013.
- [8] M. Morozova, A. Bikhavova, V. Bulanov, M. A. Lebedev, "An olfactory-based Brain-Computer Interface: electroencephalography changes during odor perception and discrimination," *Frontiers in Behavioral Neuroscience*, vol. 17, pp. 1122849, 2023.
- [9] I. Ninenko, D. F. Kleevea, N. Bukreev, M. A. Lebedev, "An experimental paradigm for studying EEG correlates of olfactory discrimination," *Frontiers in Human Neuroscience*, vol. 17, pp. 1117801, 2023.
- [10] S. Ahmed, N. Shakev, A. Topalov, K. Shiev, and O. Kaynak, "Sliding mode incremental learning algorithm for interval type-2 Takagi–Sugeno–Kang fuzzy neural networks," *Evolving Systems*, vol. 3, no. 3, pp. 179-188, 2012.
- [11] M. Laha, A. Konar, P. Rakshit, and A. K. Nagar, "Exploration of Subjective Color Perceptual-Ability by EEG-Induced Type-2 Fuzzy Classifiers," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 12, no. 3, pp. 618-635, 2019.
- [12] M. Laha, A. Konar, P. Rakshit, A. K. Nagar, "Hemodynamic analysis for olfactory perceptual degradation assessment using generalized type-2 fuzzy regression," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 14, no. 3, pp. 1217-1231, 2021.
- [13] A. Kachenoura, L. Albera, L. Senhadji, and P. Comon, "ICA: a potential tool for BCI systems," *IEEE Signal Processing Mag.*, vol. 25, no. 1, pp. 57-68, 2008
- [14] M. Laha, A. Konar, M. Das, C. Debnath, N. Sengupta, and A. K. Nagar, "P200 and N400 induced aesthetic quality assessment of an actor using type-2 fuzzy reasoning," In 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) (pp. 1-8). IEEE, July, 2020.
- [15] A. De, M. Laha, A. Konar, and A. K. Nagar, "Classification of Relative Object Size from Parietooccipital Hemodynamics Using Type-2 Fuzzy Sets," In 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) (pp. 1-8). IEEE, July, 2020.
- [16] M. R. Woodward et al., "Validation of olfactory deficit as a biomarker of Alzheimer disease," *Neurology: Clinical Practice*, vol. 7, no. 1, pp. 5-14, 2017.
- [17] W. Al-Salman, Y. Li, and P. Wen, "Detection of EEG K-complexes using fractal dimension of time frequency images technique coupled with undirected graph features," *Frontiers in Neuroinformatics*, vol. 13, pp. 45, 2019.
- [18] W. Wang, Z. Xu, W. Lu, and X. Zhang, "Determination of the spread parameter in the Gaussian kernel for classification and regression," *Neurocomputing*, vol. 55, no. 3,4, pp. 643-663, 2003.
- [19] C. L. Goodale, J. D. Aber and S. V. Ollinger. "Mapping monthly precipitation, temperature, and solar radiation for Ireland with polynomial regression and a digital elevation model," *Climate Research*, vol. 1, pp: 35-49, 1998.
- [20] V. N. Dao, and V. R. Vemuri, "A performance comparison of different back propagation neural networks methods in computer network intrusion detection," *Differential equations and dynamical systems*, vol. 10, no. 1&2, pp. 201-214, 2002.
- [21] D. Bhattacharya, A. Konar, A., and P. Das, "Secondary factor induced stock index time-series prediction using self-adaptive interval type-2 fuzzy sets," *Neurocomputing*, vol. 171, pp. 551-568, 2016.
- [22] D. Basu, S. Bhattacharyya, D. Sardar, A. Konar, D. N. Tibarewala, and A. K. Nagar, "A differential evolution based adaptive neural Type-2 Fuzzy inference system for classification of motor imagery EEG signals," *FUZZ-IEEE*, pp. 1253-1260, 2014.
- [23] M. Laha, A. Konar, A. K. Nagar, "Olfactory Perceptual-Ability Assessment by Near-Infrared Spectroscopy Using Vertical-Slice Based Fuzzy Reasoning," *IEEE Access*, vol. 11, pp. 17779-17792, 2023.

- [24] M. Laha, D. Bose, A. Konar, “TSK-Based Type-2 Fuzzy Analysis of Infrared Spectroscopic Data for Classification of Touch-Induced Affection,” In *Intelligent Systems and Human Machine Collaboration: Select Proceedings of ICISHMC 2022*, pp. 147-162. Singapore: Springer Nature Singapore, 2023
- [25] J. Demsar, “Statistical comparisons of classifiers over multiple data sets,” *J. Mach. Learn. Res.*, vol. 7, pp. 1–30, Dec. 2006.