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A New Fractal Pattern Feature Generation Function based Emotion Recognition Method using EEG

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Abstract: Electroencephalogram (EEG) signal analysis is one of the mostly studied research areas in biomedical signal processing, and machine learning. Emotion recognition through machine intelligence plays critical role in understanding the brain activities as well as in developing decision-making systems. In this research, an automated EEG based emotion recognition method with a novel fractal pattern feature extraction approach is presented. The presented fractal pattern is inspired by Firat University Logo and named fractal Firat pattern (FFP). By using FFP and Tunable Q-factor Wavelet Transform (TQWT) signal decomposition technique, a multilevel feature generator is presented. In the feature selection phase, an improved iterative selector is utilized. The shallow classifiers have been considered to denote the success of the presented TQWT and FFP based feature generation. This model has been tested on emotional EEG signals with 14 channels using linear discriminant (LDA), k-nearest neighborhood (k-NN), support vector machine (SVM). The proposed framework achieved 99.82% with SVM classifier.

Keywords: Emotion Recognition; EEG signal classification; Fractal Firat Pattern (FFP); Iterative Chi-square selector; Artificial intelligence; Machine learning.

1. Introduction

1.1. Background

Emotion is an important part of the human life that affects people's physical and behavioral state [1]. Emotion recognition is a process of identifying human emotions. Emotion recognition systems have been created with the emotions used in the communication channel [2, 3]. With the advancement of technology, these systems are widely used in real-time applications in different fields such as smart drive systems [4], medical services [5], voice assistants [6], robotics [7]. It is possible to describe human emotions as a conscious experience marked by human brain activity [8]. It is possible to identify emotions through physiological activities, body posture, speech, facial expressions, etc. EEG signals are widely used in the analysis of inner emotions [9-11]. In various aspects, such as human communication, decision-making, our emotions play a critical role. Recently, emotion analysis has been utilized in different fields, for instance the design of video games, health care facilities, treatment, etc. [12]. Cognition that is an important branch of artificial intelligence (AI) is another essential aspect of emotion. Typically, emotions are complicated and challenging to describe. Despite the fact that it is another normal behavior, human emotions are not given much consideration for a significant period of time. With the advent of Human Machine Interaction (HCI), however, situation changed entirely. The reason for the immediate interest is the need for computers to function like human beings. In such a scenario, the computer should perceive the different levels of emotions exhibited by human beings [8]. Hence, in the field of AI, the notion of emotion recognition has happen extremely significant [13]. In order to define emotional states, different models have been presented. The six main emotional states, namely fear, surprise, anger, disgust, sadness, and happiness typically articulate a discrete model [14, 15]. Emotion recognition has obtained a lot of attention from various fields and domains. Mental state of subjects can be monitored via emotion classification, which is crucial in the diagnosis of diseases such as natural depression. In addition, many patients suffering from neurological diseases such as Parkinson's disease, and autism have trouble showing their actual emotions. Advances in applications of AI in emotion identification help specialists identify and manage mental illnesses of patients. In HCI, emotions can be used as a feedback to enhance communication between the robots/computers and human beings. Several researchers are presently attempting to develop robots capable of detecting human emotions. Emotion classification enable computers to have a more effective way of dealing with human beings [12].

EEG signals are also used to determine the emotional state of people. In the literature, computer games have been utilized in different studies to determine the emotional states of people [16-20]. It has been proven that games cause different emotional states for instance sadness, fear, and happiness in the human brain. For this reason, EEG signals obtained by using different types of computer games are used to determine the emotional states of people [21, 22]. In this study, the effective classification of EEG signals from different types of gamers is presented. In the proposed method, an efficient feature extraction scheme was obtained by using the Firat University logo [23], and the performance of the method was presented comparatively.

1.2. Problem statement

In recent years, different technologies such as online shopping, online video games, social media have been widely used in our daily lives. Current HCI systems, however, are inadequate in understanding and interpreting the emotional states and lack of emotional intelligence. They do not describe the emotional states of the subjects and utilize this data for decision-making and intervention. In improved intelligent HCI, managing the communication between humans and machines is crucial. A HCI device that ignores efficient human states could fail to respond appropriately to those states. Machines should be equipped with the ability to understand and interpret human emotional states in order to resolve this issue in HCI. An accurate, precise, robust and adaptable emotion recognition scheme is therefore a prerequisite to develop an intelligent HCI. Several researchers in the AI field have conducted studies of efficient computing and emotion recognition, making them an exciting and emerging research area, with the ultimate objective of supporting machines with emotions. Intelligent emotion-aware systems have recently been employed in different fields, such as e-learning, recommendation systems, e-health, smart city, smart home, and smart communication systems (e.g., chatbot). In numerous intelligent systems, including mental health monitoring, neuro-marketing (feedback evaluation of customers), and online gaming, the utilization of computer-based automated emotion detection has big potential. Researchers are also seeking ways to reliably identify human feelings to establish intervention schemes for mental health, considering the importance of mental health in modern society [24].

According to the research, EEG signals in different emotion states are varying and the brain's response to each mood is different. EEG signals are complicated and nonlinear. For this reason, various methods have been proposed for automatic processing of EEG signals used to describe an emotion state [24-28]. The main purpose of this study is to classify EEG signals correctly. For this purpose, GAMEEMO dataset containing EEG signals collected from individuals playing different categories of video games was processed [12].

1.3. Literature Review

There are several studies in the literature on emotion recognition utilizing facial expression, EEG signal, and voice. Among these studies, the ones based on EEG are presented in Table 1.

Table 1. Literature Review

Year	Studies	Method	Dataset	Evaluation Criteria	Accuracy Result
2017	Zheng et al. method [29]	Extreme learning machine, differential entropy, power spectral density, rational asymmetry, differential asymmetry, differential caudality asymmetry	1. DEAP [30, 31] 2. SEED [32, 33]	Accuracy	1. 69.67% 2. 91.07%
2019	Qing et al. method [34]	Random forest, k-nearest neighbor, decision tree	1. DEAP [30, 31] 2. SEED [32, 33]	Accuracy, time	1. 62.63% 2. 74.85%
2019	Pandey and Seeja method [35]	Variational mode decomposition, deep neural network	DEAP [30, 31]	Accuracy	62.50%
2019	Zhang et al. method [36]	Spatial–temporal recurrent neural network	1. SEED [32, 33] 2. CK + [37]	Accuracy, confusion matrix	1. 89.50% 2. 95.40%
2020	Liu et al. method [38]	Capsule network	1. DEAP [30, 31] 2. DREAMER [39]	Accuracy, time	1. 98.32% 2. 95.26% (for 10-fold cross validation)
2020	Alakus et al. method [16]	Discrete wavelet transform, support vector machines, k-nearest neighbour, multi-layer perceptron neural network	GAMEEMO	Accuracy, error, kappa value	72.73% average value of all channels in MLPNN (for 10-fold cross validation)
2020	Hassouneh et al. method [40]	Deep neural network, long short-term memory, convolutional neural network	Collected data	Accuracy, precision, sensitivity,	99.81%

				specificity, F-score	
2020	Chen at al. method [41]	Empirical mode decomposition,	Collected data	Accuracy	82.63%
2020	Li et al. method [42]	Transfer learning	SEED [32, 33]	Accuracy	88.92
2020	Wei et al. method [41]	Recurrent neural Network, simple recurrent units, dual-tree complex wavelet transform	SEED [32, 33]	Accuracy, confusion matrix, precision, recall, F-score, time	80.02

1.4. Motivation

The primary motivation of this model is to achieve better classification rates by using the GAMEEMO dataset [16]. A new accurate EEG signal classification method is presented using a fractal pattern to achieve this aim. In nature, there are many fractals, and a Firat fractal pattern (FFP) is developed by using the Firat University Logo. There are various local feature generator/extractor in the literature and they have used variable patterns to extract relevant features. Also, fractal geometry has been used to create more complex shapes or graphs. As far as we know, there is no fractal geometry based local feature generator in the literature. Therefore, FFP is proposed for feature extraction from emotional EEG signals. The main objective of the FFP is to denote the feature extraction ability of a fractal geometric pattern and present a new local feature generation methodology. This methodology can be called as fractal geometry based local feature generation. To denote success of the presented FFP, a FFP based EEG emotion recognition method is presented.

A high accurate pattern recognition framework should use effective feature generation and selection methods. A multilevel feature generation function should be used to generate low, medium, and high level features to achieve better performance. The main problem of the multilevel feature generation is the size of the feature vector. An appropriate feature selector should be used in this phase. The feature selectors have two fundamental objectives. These are increasing classification capability and decreasing the execution time of the classifier. Iterative Chi-square selector (IChi2) is employed as a feature selection method in this paper.

1.5. Novelties and contribution

The novelties and contributions of the proposed FFP and TQWT [43, 44] based feature generation and IChi2 based feature selection model are;

- A new fractal-based feature generation function (FFP) is presented. By using FFP, the effect of the fractals for feature generation has been demonstrated.
- The TQWT decomposition model is one of the effective decomposition methods for the one-dimensional signals. The TQWT method is employed as a decomposition/level creation method to create a multilevel feature generation function. The developed FFP generates features from each decomposed signal and the raw EEG signal. The developed TQWT and FFP based feature generation model is a multilevel method, which has feature extraction ability in low, medium, and high levels.
- Chi2 [45] is one of the effective and fast feature selection algorithm. To improve discriminative and relevant features selection capability of this selector, an iterative version of this selector is presented in this research.

2. Dataset

In this study, the GAMEEMO dataset is used. The attributes of the dataset used are presented in Table 2 [16].

Table 2. Attributes of the GAMEEMO dataset

Attributes	Values
Signal type	EEG
Device channel	14-channel EMOTIV EPOC+
EEG electrodes	16 different scalp zones
The sampling rate	2048 Hz
The bandwidth of the signals	0.16 Hz and 43 Hz.
Samples	38.252
EEG data	Each class contains 28 EEG signals with a length of 38252. Then, each EEG signal segment is divided into five equal non-overlapping block and 140 EEG signal instances with a window length of $\left\lfloor\frac{38252}{5}\right\rfloor = 7650$ are generated for each classes. Therefore, 140 x 4 $= 560$ total EEG signal instances are used for the classification.
Game type	4 different games - Funny - Boring

	- Horror - Calm
Game recording time	5 minutes (20 minutes in total for 4 games)
Subject	28
The range of subjects ages	20-27

3. The proposed Firat fractal pattern

A new fractal pattern is developed as a feature generation function, which is called Firat Fractal Pattern because it is inspired from the Firat University Logo, which is shown in Figure 1.

Fig. 1. Firat University Logo.

By using this logo, a new feature generation function is presented. In a fractal, the shapes are repeated. In this pattern, square shapes are repeated. The proposed Firat fractal is presented in Figure 2.

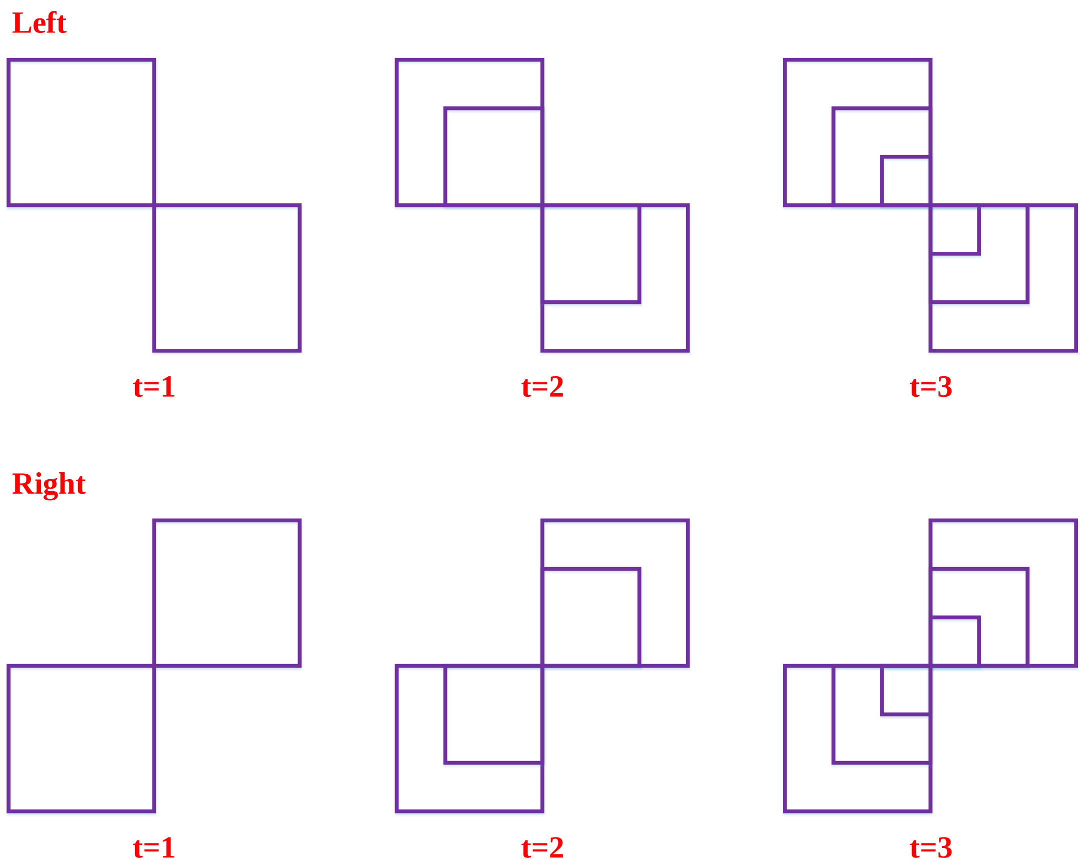
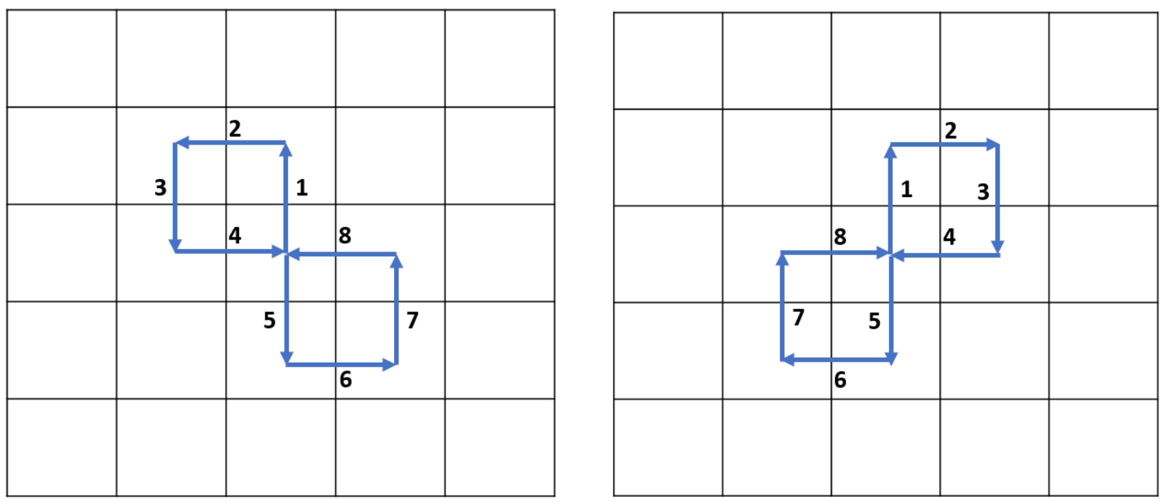


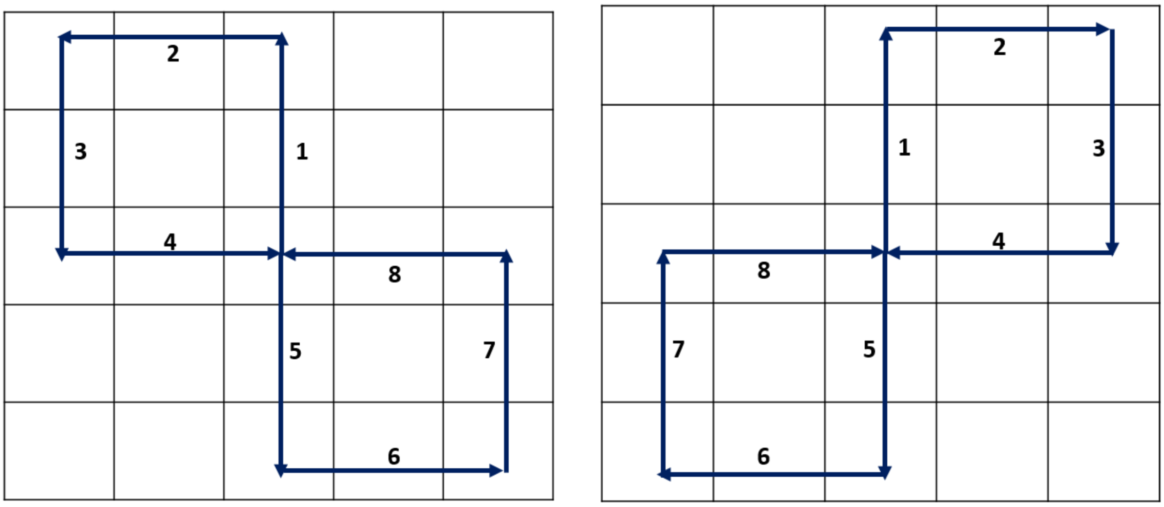
Fig. 2. The proposed Firat fractal. This research uses t=2 fractal to present a new fractal based feature generation model.

This fractal pattern consists of four directed and Hamiltonian graphs [46], and by using each graph, 8-bits are generated. The used graphs are shown in Figure 3 separately.



(a) First graph

(b) Second graph



(c) Third graph (d) Fourth graph

Fig. 3. The used feature generation graphs. As seen in these graphs, the square shape is repeated. Also, the third graph is the mother graph of the first graph, and the fourth graph is the mother graph of the second graph. The path numbers are demonstrated here. Bits are extracted by using these numbers. Each arrow shows the input parameters of the signum function. The start point of an arrow describes the first parameter of the signum function. The endpoint defines the second parameter of the signum function. By using these arrows and signum function, 8-bits are extracted from each graph.

The fundamental binary feature generation function is the signum function. Signum function is a basic comparison function, and the mathematical notation of this function is shown below.

$$S(ip, ep) = \begin{cases} 0, ip - ep < 0 \\ 1, ip - ep \geq 0 \end{cases} \quad (1)$$

where $S(.,.), ip$ and ep express signum function, initial point/first parameter of the signum function, and endpoint/second parameter of the signum function. As shown in Equation 1, signum function is a basic comparison function and this function is used for binary feature generation like local binary pattern (LBP). Step by step definition of the proposed FFP is given below for better representation.

0: Load one-dimensional EEG signal.

1: Divide signal into overlapping blocks with a length of 25. The presented FFP uses 5 x 5 sized matrix. To model this pattern on the one-dimensional signal, 25 sized overlapping block/window division is used.

$$w^i(j) = EEG(i + j - 1), i \in \{1,2, \dots, length(EEG) - 24\}, j \in \{1,2, \dots ,25\} \quad (2)$$

where w^i is ith 25 sized overlapping window, EEG define loaded EEG signal, $length(EEG)$ expresses the length of the loaded EEG signal. i and j are indices.

2: Reshape the obtained windows to 5 x 5 sized matrixes. This step is used for construct 5 x 5 sized matrix to generate features. Equation 3 defines vector to matrix transformation.

$$m^i(k,l) = win^i(j), k \in \{1,2,..,5\}, l \in \{1,2,\dots,5\} \quad (3)$$

3: Apply the defined four graphs and signum function. Generate 8-bits from each graph. As seen from Figure 3, four directed graphs are defined to generate binary features using signum function. To generate bit groups, the Equations 5-8 are used per Figure 3.

$$\begin{bmatrix} bit^1(1) \\ bit^1(2) \\ bit^1(3) \\ bit^1(4) \\ bit^1(5) \\ bit^1(6) \\ bit^1(7) \\ bit^1(8) \end{bmatrix} = \begin{bmatrix} S\left(m^i(3,3), m^i(2,3)\right) \\ S\left(m^i(2,3), m^i(2,2)\right) \\ S\left(m^i(2,2), m^i(3,2)\right) \\ S\left(m^i(3,2), m^i(3,3)\right) \\ S\left(m^i(3,3), m^i(4,3)\right) \\ S\left(m^i(4,3), m^i(4,4)\right) \\ S\left(m^i(4,4), m^i(3,4)\right) \\ S\left(m^i(3,4), m^i(3,3)\right) \end{bmatrix} \quad (5)$$

$$\begin{bmatrix} bit^2(1) \\ bit^2(2) \\ bit^2(3) \\ bit^2(4) \\ bit^2(5) \\ bit^2(6) \\ bit^2(7) \\ bit^2(8) \end{bmatrix} = \begin{bmatrix} S\left(m^i(3,3), m^i(2,3)\right) \\ S\left(m^i(2,3), m^i(2,4)\right) \\ S\left(m^i(2,4), m^i(3,4)\right) \\ S\left(m^i(3,4), m^i(3,3)\right) \\ S\left(m^i(3,3), m^i(4,3)\right) \\ S\left(m^i(4,3), m^i(4,2)\right) \\ S\left(m^i(4,2), m^i(3,2)\right) \\ S\left(m^i(3,2), m^i(3,3)\right) \end{bmatrix} \quad (6)$$

$$\begin{bmatrix} bit^3(1) \\ bit^3(2) \\ bit^3(3) \\ bit^3(4) \\ bit^3(5) \\ bit^3(6) \\ bit^3(7) \\ bit^3(8) \end{bmatrix} = \begin{bmatrix} S\left(m^i(3,3), m^i(1,3)\right) \\ S\left(m^i(1,3), m^i(1,1)\right) \\ S\left(m^i(1,1), m^i(3,1)\right) \\ S\left(m^i(3,1), m^i(3,3)\right) \\ S\left(m^i(3,3), m^i(5,3)\right) \\ S\left(m^i(5,3), m^i(5,5)\right) \\ S\left(m^i(5,5), m^i(3,5)\right) \\ S\left(m^i(3,5), m^i(3,3)\right) \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} bit^4(1) \\ bit^4(2) \\ bit^4(3) \\ bit^4(4) \\ bit^4(5) \\ bit^4(6) \\ bit^4(7) \\ bit^4(8) \end{bmatrix} = \begin{bmatrix} S\left(m^i(3,3), m^i(1,3)\right) \\ S\left(m^i(1,3), m^i(1,5)\right) \\ S\left(m^i(1,5), m^i(3,5)\right) \\ S\left(m^i(3,5), m^i(3,3)\right) \\ S\left(m^i(3,3), m^i(5,3)\right) \\ S\left(m^i(5,3), m^i(5,1)\right) \\ S\left(m^i(5,1), m^i(3,1)\right) \\ S\left(m^i(3,1), m^i(3,3)\right) \end{bmatrix} \tag{8}$$

Equations 5-8 defines the bit generation process for the presented FFP. For exempla, to generate $bit^1(1)$, $S\left(m^i(3,3), m^i(2,3)\right)$ equation is used. In this equation, $m^i(3,3)$ is ip and $m^i(2,3)$ is ep parameters (See Eq. 1).

4: Calculate map values using the generated bits in Step 3.

$$map^1(i) = \sum_{p=1}^{8} bit^1(p) * 2^{p-1} \tag{9}$$

$$map^2(i) = \sum_{p=1}^{8} bit^2(p) * 2^{p-1} \tag{10}$$

$$map^3(i) = \sum_{p=1}^{8} bit^3(p) * 2^{p-1} \tag{11}$$

$$map^4(i) = \sum_{p=1}^{8} bit^4(p) * 2^{p-1} \tag{12}$$

where map^t is t[th] ($t \in \{1,2,3,4\}$)map value, which is generated by using t[th] graph. As seen from Equations 9-12, the generated map values are coded in 8-bits.

5: Repeat steps 3-4 for each window.

6: Generate histograms of each map value. The size of each histogram is calculated as 256.

7: Concatenate all generated histograms and obtain a feature vector with a size of $256 \text{ x } 4 = 1024$.

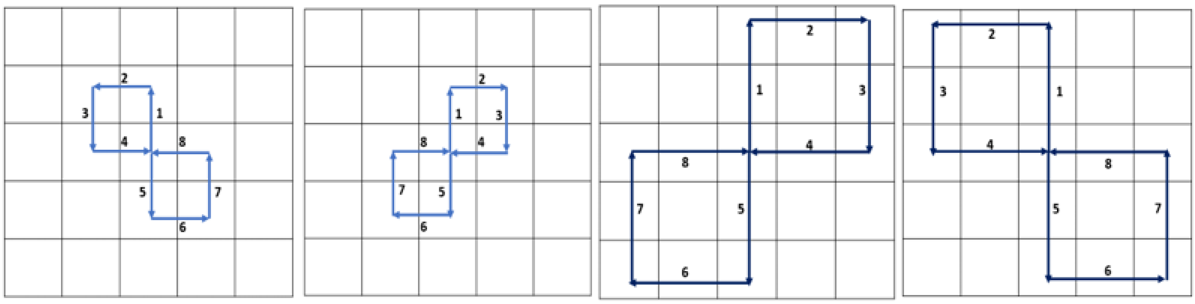
These *seven* steps are defined as the recommended FFP function. $FFP(.)$ function is defined to simplify the proposed TQWT-FFP and IChi2 method. The pseudo code of the $FFP(.)$ function is also given in the Algorithm 1.

Algorithm 1. The pseudocode of the $FFP(.)$ subroutine.

Subroutine name: $FFP(.)$
Input: The used one-dimensional EEG signal (OES) with a size of $Lngth$. **Output:** The generated fractal textural features (ft) with a size of 1024.

01: for j=1 to $Lngth - 24$ do
02: $M = vec2mat(OES(j{:}j + 24), 5 \text{ x } 5)$; // where $vec2mat$ is vector to matrix transformation. The divided/created 25 sized window is converted to 5 x 5 sized matrix.
03: Assign vertex using firat fractal graph which is denoted in the Figure 3.
04: Create binary features using the firat fractal graph and signum function (see Eq. 1). There are four sub-graphs. Therefore, four bit groups are extracted.
05: Calculate four map signals using Eqs. 4-7.
06: end for j
07: Extract histograms of the calculated four map signals.
08: Merge these histograms and obtain 256 x 4=1024 sized feature vector (ft)

A numerical example about the FFP is also shown in Figure 4.



86	70	32	36	79
57	71	53	13	27
22	32	47	99	54
72	46	61	29	42
23	30	97	29	4

Id	Value	Bit
1	47<53	0
2	53<71	0
3	71>32	1
4	32<47	0
5	47<61	0
6	61>29	1
7	29<99	0
8	99>47	1

First map value

$(00100101)_2$=37

Id	Value	Bit
1	47<53	0
2	53>13	1
3	13<99	0
4	99>47	1
5	47<61	0
6	61>46	1
7	46>32	1
8	32<47	0

Second map value

$(01010110)_2$=86

Id	Value	Bit
1	47>32	1
2	32<86	0
3	86>22	1
4	22<47	0
5	47<97	0
6	97>4	1
7	4<54	0
8	54>47	1

Third map value

$(10100101)_2$=165

Id	Value	Bit
1	47>32	1
2	32<79	0
3	79>54	1
4	54>47	1
5	47<97	0
6	97>23	1
7	23>22	1
8	22<47	0

Fourth map value

$(10110110)_2$=182

Fig. 4. A numerical example of the FFP feature generation function. Here, both patterns and a numeric matrix are shown. By applying the fractal patterns, four map values are generated from a 5 x 5 size matrix. These values are coded in 8-bits. Therefore, histogram of each map signal has $2^8 = 256$ values. These histograms are merges and 1024 sized feature vector is created by employing the recommended FFP.

4. The proposed EEG signal classification framework

In this section, the recommended FFP based emotional EEG signal classification framework is presented, and details of this method are given. The recommended classification model has three phases, which are multilevel TQWT and FFP feature generation network, IChi2 selector based feature selection, and classification phases. In this framework the emotional EEG signals are loaded, and TQWT is applied to each EEG signal, and wavelet sub-bands coefficients are obtained. The presented FFP extracts features from raw EEG signal and decomposed signals/sub-bands of the used TQWT. The generated features are combined, and a concatenated feature vector is obtained. The combined features are utilized as the input of the IChi2 feature selector. The optimal number of features is selected according to the problem. Here, 14 channels of the EEG signals are evaluated. Therefore, the results of the 14 items are presented. By applying this evaluation, a comprehensive performance analysis is obtained. A block diagram is given to visualize the proposed method in Figure 5.

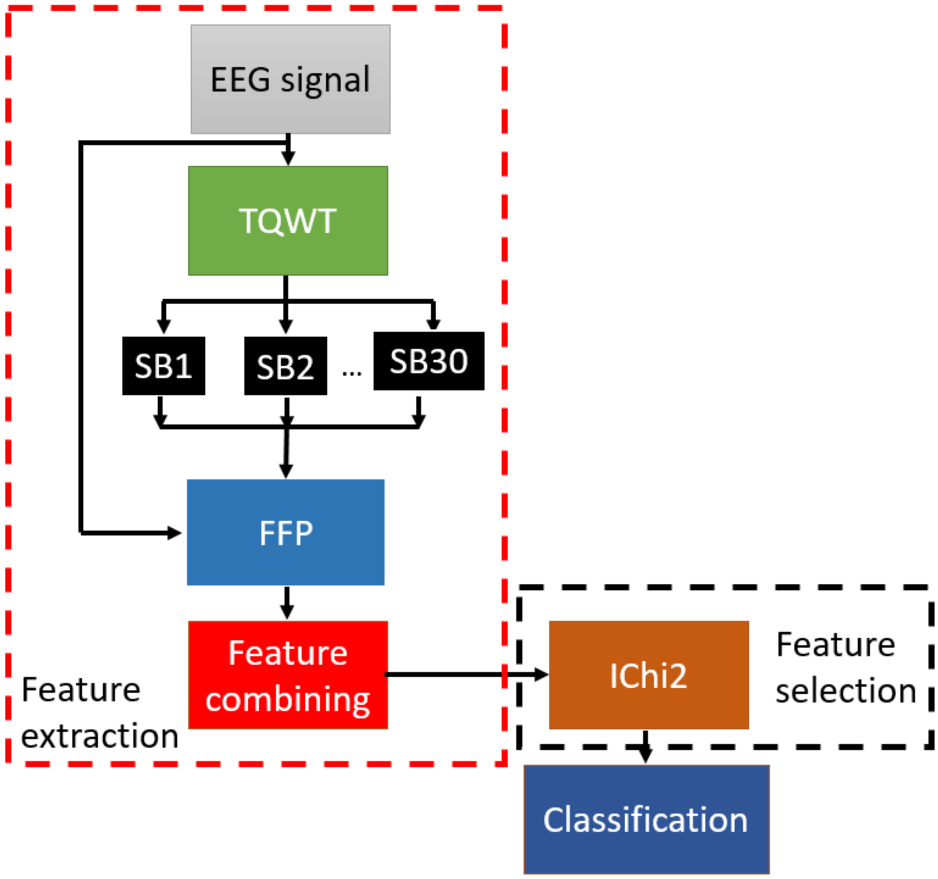


Fig. 5. The graphical summarization of the proposed method.

Also, the steps of the proposed TQWT-FFP and IChi2 based classification model are given below.

Step 1: Apply TQWT to each loaded EEG signal.

Step 2: Employ the proposed FFP to each EEG signal and sub-bands of it. These sub-bands are calculated by employing TQWT decomposition.

Step 3: Concatenate the generated features.

Step 4: Select the most informative features using IChi2. In this feature selector, Quadratic SVM is utilized as an error value calculator.

Step 5: Classify the selected optimum features using shallow classifiers.

The pseudo code of the presented Firat Fractal Pattern and IChi2 based EEG emotion classification method is given in Algorithm 2.

Algorithm 2. Pseudo code of the recommended FFP and IChi2 based method.

Input: EEG signals (EEG)

Output: Validation predictions (vp)

01: **for** k=1 to Dim **do** // Dim is number of EEG signals.

02: Load each EEG signal from dataset.

03: Select channel (Chn)

04: $SB = TQWT(EEG_k, 3.5,3,29)$; // Generate 30 subbands using TQWT.

05: $X(k, 1{:}1024) = FFP(Chn_k)$; // Feature generation from raw EEG channel using the recommended FFP.

06: **for** t=1 to 30 **do**

07: $X(k, t * 1024 + 1{:}(t + 1) * 1024) = FFP(SB_t)$;
// Feature generation and merging step. 1024 features are generated from each sub-band and merge these features.

08: **end for t**

09: **end for k**

10: Select the most informative feature using IChi2 feature selector.

11: Classify the chosen features using a conventional classifier and calculate vp.

The phases of this model are given in the subsections in detail.

4.1. Feature generation using TQWT

A new multilevel feature generation technique is proposed in this paper. The fundamental/primary feature generation function is FFP. Therefore, this method is a naïve method. As stated deep networks, the high classification capability can reach by generating the low-level, mid-level, and high-level features. To yield high performance, TQWT is employed as a decomposition method in this step. By employing TQWT, the EEG signals are decomposed into sub-bands. TQWT is an effective decomposition model and it has generally been used on one-dimensional signals. It is an improved version of the single Q factor wavelet transform.

The users can create variable wavelet transformation using Q-factor (Q is oscillatory value, if Q =1 non oscillatory transformation is performed. If Q>1, oscillatory transformation is performed), redundancy value (r) and number of levels (J) parameters. Q and r parameters are calculated scaling values (λ, ξ) setting and maximum value of J (J_{max}) is depended on the length of used one-dimensional signal (Ln) and scaling values. Parameter calculation using scaling values are given in Equations 13-15.

$$Q = \frac{2-\xi}{\xi}, 0 < \xi \leq 1 \tag{13}$$

$$r = \frac{\xi}{1-\lambda}, 0 < \lambda < 1, \xi + \lambda > 1 \tag{14}$$

$$J_{max} = \frac{\log\left(\frac{\xi Ln}{8}\right)}{\log\left(\frac{1}{\lambda}\right)} \tag{15}$$

Here, the set Q, r, and J parameters are 3.5, 3, and 29, respectively. By deploying these parameters, 30 TQWT sub-bands are obtained. These are tested parameters, and the best results have been obtained by using the chosen parameters. The proposed FFP is applied to the raw EEG signals and the sub-bands coefficients. 31 x 1024 features are generated. This phase is explained below step by step. To simplify this phase, $TQWT(.,.,.,.)$ and $FFP(.)$ are utilized to define TQWT decomposition and FFP function, respectively.

1: Decompose the EEG signals into sub-bands by applying TQWT with 3.5, 3, and 29 Q, r, and J parameters. Here, sub-bands (SB) or levels are calculated. Therefore, this step can be named pre-processing of this model.

$$SB = TQWT(EEG, 3.5,3,29) \tag{16}$$

Here, 30 sub-bands (decomposed bands) are calculated.

2: Generate features from each sub-bands and the raw EEG signal.

$$ftr^1 = FFP(EEG) \tag{17}$$

$$ftr^t = FFP(SB^{t-1}), t \in \{2,3, \dots ,31\} \tag{18}$$

where ftr^t extracted t^{th} feature vector with a size of 1024.

As can be seen from Eqs. 14-15, the prime feature generation function is the FFP. The graphical summarization of the FFP is also given in Figure 6.

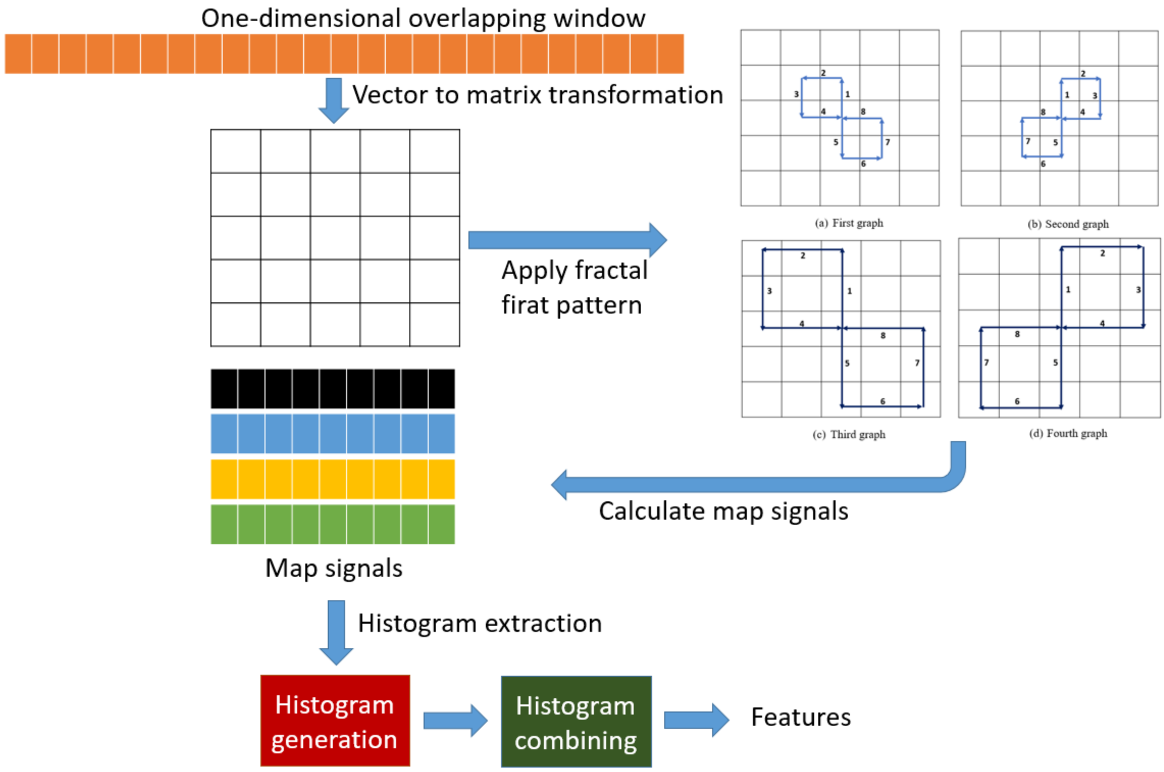


Fig. 6. The implementation process of the recommended FFP. The details and steps of the FFP are also given in the Sect. 3.

3: Concatenate the generated feature vectors from each level and calculate the final vector (X).

$$X((t-1)*1024+i)=ftr^{t}(i), i\in\{1,2,\ldots,1024\}, t\in\{1,2,\ldots,31\} \quad (19)$$

Eq. 11 expresses the feature combining function, and according to this function, the length of the X is calculated as 31 x 1024 = 31744.

These steps denote that the proposed TQWT and FFP feature generation network extracts 31744 features from each EEG signal. This size is very big. A feature selection process should be used to decrease the size of the features and obtain high accuracy.

4.2. Feature Selection using Iterative Chi-square

The second phase of this research is feature selection, and the presented feature selection phase aims to select the optimal number features. Chi2 is a statistical attribute generation function and it is generally used to calculate the expected value in prediction and numerical analysis. By using this attribute of the Chi2, a feature selection model was implemented. The Chi2 [45, 47] feature selection function is selected. Chi2 is one of the effective selectors in the literature. Moreover, time complexity of the Chi2 feature selection is low. Because, it does not use any optimization technique. The Chi2 feature selector has a major problem that can be automated using optimal number of features selection. Therefore, an improved version of the chi2 is presented, and it is named IChi2 since it uses an iterative feature selection process.

Chi2 selector is defined using $chi2(.,.)$ function to simplify the recommend IChi2. In order to select the best vector, a loss value calculator should be used. Here, Cubic SVM is utilized as a loss value calculator with 10-fold cross-validation. The specifications of the IChi2 are given below.

- The implementation of this model is simple. Therefore, it can be used on the real-time applications easily.
- It selects variable-sized features per variable problem.
- It has the optimal feature selection ability.
- Different classifiers can be utilized as an error value generator.

The steps and the flow diagram of the recommend IChi2 are given in Figure 7.

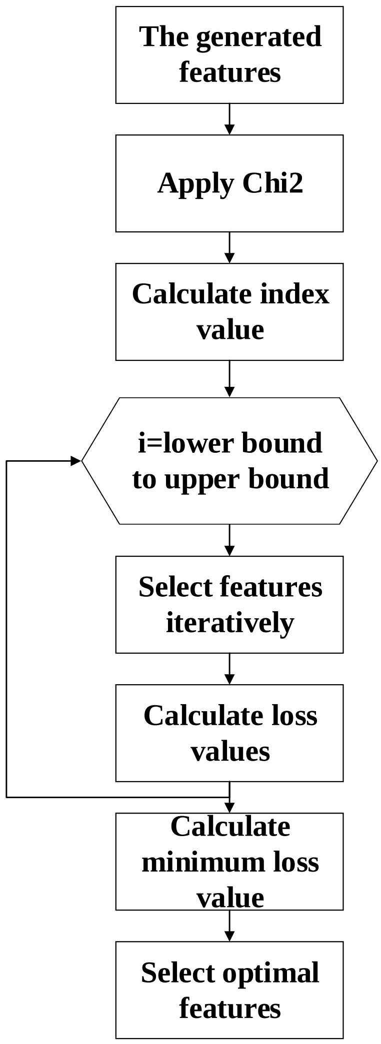


Fig. 7. The flow diagram of the IChi2 selector.

0: Load X with a size of d x 31744, where d defines the number of EEG signals.

1: Normalize features of each EEG signal by deploying min-max normalization.

$$X^{Norm}(:,h) = \frac{X(:,h) - \min(X(:,h))}{\max(X(:,h)) - \min(X(:,h))}, h \in \{1,2,\dots,31744\} \quad (20)$$

where X^{Norm} is normalized features.

2: Calculate the sorted indices (idx) using the Chi2 selector.

$$idx = chi2(X^{Norm}, trgt) \quad (21)$$

where $trgt$ defines actual targets.

3: Define the initial point and endpoint of the iteration. In Figure 5, they are defined as lower and upper bounds. Here, our iteration is from 100 to 1000.

4: Select features by using idx.

$$ftr^i(h,j) = X(h, idx(j)), i \in \{100,101,\dots,1000\}, j \in \{1,2,\dots,i\} \quad (22)$$

where ftr^i is i^{th} selected vector.

5: Generate loss value ($1 - accuracy$) of each selected vector by using the Cubic (3^{rd}-degree polynomial kernel) SVM with 10-fold cross-validation.

$$Loss(i - 99) = CSVM(ftr^i, trgt) \quad (23)$$

where $CSVM(.,.)$ represents Cubic SVM, and $Loss$ is the array of the calculated loss values.

6: Calculate minimum loss value and index of it.

$$[mini, indice] = \min(Loss) \quad (24)$$

$$indice = indice + 99 \quad (25)$$

where $mini, indice$ are minimum loss value and index of it. In Eq. 17, the index is increased as 99 since the initial point is 100.

7: Select the most relevant feature vector ($optimal$) by applying $indice$ and idx from the generated feature vector (X).

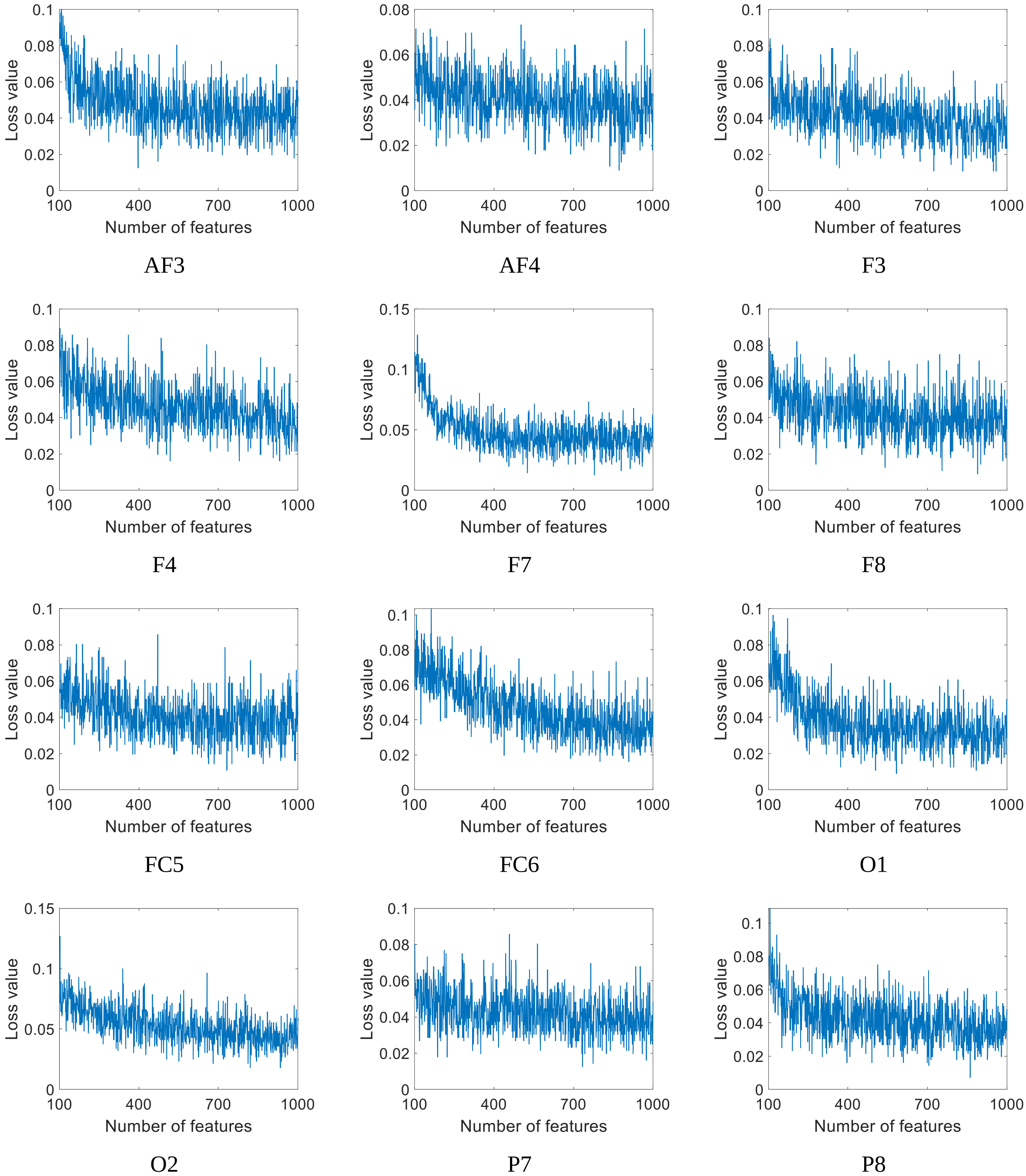
$$optimal(t,j) = X(t, idx(j)), j = \{1,2,\dots,indice\}, t = \{1,2,\dots,d\} \quad (26)$$

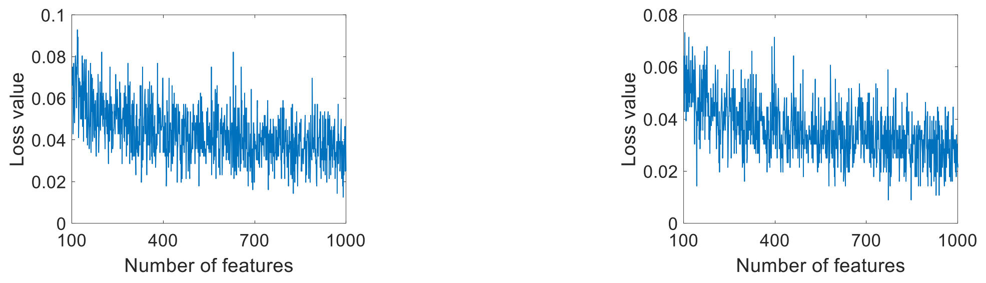
The proposed IChi2 is used for feature selection of the 14 channels of the GAMEEMO dataset, and it selects the various size of features for each channel. The selected $optimal$ is forwarded to the classifier. This phase is implemented in training. In the testing, the calculated idx and $indice$ are utilized. For this problem, the number of selected features by applying the recommended IChi2 for each channel are listed in Table 3.

Table 3. The number of selected features per channel.

Ch	AF3	AF4	F3	F4	F7	F8	FC5	FC6	O1	O2	P7	P8	T7	T8
NoF	396	871	723	517	778	888	731	799	582	819	733	860	990	771

As seen from Table 3, the IChi2 feature selector selected various sized features as *optimal*. The presented IChi2 selects the variable number of features from the EEG signals. In this implementation, there are 19 channels and IChi2 selects different number of features for these channels. IChi2 is an iterative features selector. The feature selection process of this selector is also shown in Figure 8.





T7 T8

Fig. 8. The feature selection process of the used IChi2 for each channel. These plots validate the calculated results. Here, iterative feature selection process is denoted.

Figure 8 shows the calculated loss values in each iteration per channel and it validate the calculated accuracies. Figure 8 also proves Table 3. As seen in Table 3, the optimum features are selected by using Chi2 for different channels with an iteration from 100 to 1000. In each step, loss value of the selected feature vector is calculated in order to select the optimum number of features.

4.3. Classification

Here, the selected features ($optimal$) are utilized as the input of the classifier. The CSVM [48] classifier is used both loss value generator in the feature selection and classification. Moreover, LDA [49] and k-NN [50] classifiers are used. The parameters of these classifiers are given in Table 3. Also, 10-fold cross-validation is utilized as training and testing strategy.

5. Results

To evaluate the success of the proposed TQWT and FFP feature generation and IChi2 feature selector based EEG classification and emotion recognition approach, the GAMEEMO dataset has been used. The used dataset has different EEG signals with 14 channels and it has four classes (see Sect. 2). We evaluated these signals channel by channel. 560 EEG signals instances have been used to obtain comparable (each signal is divided into four frames) results. The used parameters for implementing the proposed method are also listed in Table 4. Table 4 also gives details of the experimental setup.

Table 4. The used parameters in the used FFP and IChi2 based EEG classification method.

Method	Parameter	Value
TQWT [51]	Q	3.5
	r	3
	J	29
FFP	t=2	-

IChi2	The initial point of the iteration	100
	The endpoint of the iteration (maximum number of iterations)	1000
LDA [49]	Covariance Structure	Full
	Discriminant type	Linear
	Gamma	0
SVM [48]	Kernel function	Cubic (3^{rd}-degree polynomial)
	Kernel scale	Auto
	Box Constraint (C)	1
	Coding	One-vs-All
kNN [50]	Distance	Manhattan (L1-Norm)
	k value	1
	Distance weight (voting)	Equal
Validation (For all classifiers)		10-fold cross-validation

The widely used measurements have also been used to evaluate results comprehensively, and mathematical expressions of these metrics are given in Eqs. 19-26. The number of true positives (TP), true negatives (TN), false negatives (FN), and false positives (FP) are used to calculate these parameters [52, 53].

$$Sens = \frac{TP}{FN + TP} \quad (24)$$

$$Spec = \frac{TN}{TN + FP} \quad (25)$$

$$GM = \sqrt{Sens \text{ x } Spec} \quad (26)$$

$$BalAcc = \frac{Sens + Spec}{2} \quad (27)$$

$$Acc = \frac{TN + TP}{FP + FN + TN + TP} \quad (28)$$

$$Prec = \frac{TP}{TP + FP} \quad (29)$$

$$F1 = 2\frac{Prec \text{ x } Sens}{Prec + Sens} \quad (30)$$

$$Rec = \frac{TP}{TP + FN} \quad (31)$$

where $Sens, Spec, GM, BalAcc, Acc, Prec,$ $F1$, and Rec are sensitivity, specificity, geometric mean, balanced accuracy, accuracy, precision, F1-score, and recall, respectively.

These parameters, which are given in Table 5 are calculated. The calculated results (%) for each EEG channel by using k-NN, LDA, SVM classifier were listed in Tables 5-7.

Table 5. The calculated results (%) for each EEG channel by using the k-NN classifier.

Channel	Performance Metrics					
	Accuracy (%)	Balanced Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Geometric Mean (%)
AF3	97.86	97.86	97.88	100.0	98.84	97.85
AF4	98.39	98.39	98.42	100.0	99.20	98.39
F3	98.21	98.21	98.21	100.0	98.75	98.21
F4	98.04	98.04	98.05	100.0	98.67	98.03
F7	98.39	98.39	98.43	100.0	99.11	98.38
F8	98.75	98.75	98.75	100.0	99.02	98.75
FC5	98.04	98.04	98.07	100.0	98.57	98.03
FC6	98.39	98.39	98.43	100.0	98.84	98.39
O1	98.57	98.57	98.61	100.0	99.30	98.56
O2	97.68	97.68	97.68	100.0	98.82	97.67
P7	98.04	98.04	98.09	100.0	98.77	98.03
P8	98.75	98.75	98.75	100.0	99.37	98.74
T7	98.93	98.93	98.93	100.0	99.46	98.92
T8	98.39	98.39	98.41	100.0	99.20	98.39

Table 6. The calculated results (%) for each EEG channel by using the LDA classifier.

Channel	Performance Metrics					
	Accuracy (%)	Balanced Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Geometric Mean (%)
AF3	71.79	71.79	71.66	79.29	75.28	71.46
AF4	95.54	95.54	95.60	97.14	96.20	95.53
F3	88.93	88.93	88.93	92.14	90.33	88.88
F4	60.36	60.36	60.71	67.86	63.09	60.25
F7	80.00	80.00	80.01	88.57	84.07	79.82
F8	91.43	91.43	91.43	95.00	92.84	91.38
FC5	91.07	91.07	91.13	95.71	93.04	91.03

FC6	92.86	92.86	92.88	98.57	95.61	92.82
O1	79.46	79.46	79.67	85.71	82.15	79.42
O2	94.46	94.46	94.46	98.57	95.54	94.46
P7	91.07	91.07	91.20	95.00	92.50	91.06
P8	95.18	95.18	95.21	95.71	94.91	95.14
T7	96.79	96.79	96.82	98.57	97.34	96.78
T8	92.32	92.32	92.30	95.00	93.47	92.27

Table 7. The calculated results (%) for each EEG channel by using the SVM classifier.

Channel	Performance Metrics					
	Accuracy (%)	Balanced Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Geometric Mean (%)
AF3	96.79	96.79	96.80	98.57	97.32	96.78
AF4	99.64	99.64	99.65	100.0	99.82	99.64
F3	99.11	99.11	99.12	100.0	99.20	99.11
F4	98.21	98.21	98.23	100.0	99.01	98.21
F7	97.50	97.50	97.51	98.57	97.68	97.50
F8	99.82	99.82	99.82	100.0	99.91	99.82
FC5	99.29	99.29	99.29	100.0	99.65	99.28
FC6	98.75	98.75	98.76	100.0	99.29	98.75
O1	98.93	98.93	98.96	100.0	99.47	98.93
O2	99.29	99.29	99.29	100.0	99.64	99.28
P7	99.64	99.64	99.65	100.0	99.47	99.64
P8	99.46	99.46	99.47	100.0	99.64	99.46
T7	99.11	99.11	99.11	100.0	99.56	99.10
T8	99.64	99.64	99.65	100.0	99.82	99.64

These tables clearly demonstrate that the performance rate (99.82%) has been obtained from the F8 channel. Overall accuracy mean of all channels is calculated as 98.31%, 86.84%, 98.88 for k-NN, LDA, SVM, respectively. In this study, it was observed that the most successful classifier was SVM.

Also, the time complexity analysis of this method was calculated by using Big O notation. As stated in the Section 4, there are three fundamental phases in this classification model. This analysis is performed to phase by phase, and the calculation results were given below.

Table 8. The time complexity analysis of the presented FFP and IChi2 based model

Phase	Time complexity	Explanation
Feature generation	$O(nlogn)$	The time complexity of the presented FFP is $O(n)$, and the $O(n)$ is the time complexity of the TQWT. This method is multileveled, and TQWT decomposed the EEG signal. Therefore, it is calculated as $O(nlogn)$. where n is the length of the EEG signal.
Feature selection using IChi2	$O(I \text{ x } k^3)$	This model is an iterative selector. This model uses an iteration a feature selector, and a loss value generator. The used loss value generator is CSVM and the average complexity of it $O(k^3)$. Where k is the size of the selected features, and I is iteration numbers.
Classification	$O(kd)$	In the classification phase, CSVM, kNN, LDA are used. These classifiers have various time complexity. Therefore, we used a classification multiplier (d) in here.
Total	$O(nlogn + Ik^3 + kd)$	

6. Discussions

The results have been obtained for 14 channels. For testing, 560 EEG signals instances (we segmented all EEG signal into 7650 samples) have been used for obtaining comparable results. As stated motivation, the main problem of the ML methods is to achieve high performance for EEG emotion dataset. For solving this problem, a new generation model is presented. The presented ML method uses a new feature generator, and the recommended fractal pattern-based method is inspired by Firat University Logo. In order to overcome the decomposition problem, TQWT is used. Moreover, the statistical analysis of these features were calculated by deploying t-test and the calculated minimum p-values were listed in the Table 9. These results revealed the high classification accuracy.

Table 9. The calculated minimum p-values for the channel F8.

Features of classes	p-value
Funny-Boring	3.9389e-39
Funny-Horror	3.8462e-22
Funny-Calm	4.8039e-36
Boring-Horror	1.0071e-39
Boring-Calm	1.3093e-33
Horror-Calm	2.2813e-37

In the informative/relevant feature selection phase, an iterative feature selector is presented, and it is named IChi2. The selected features have been classified by employing the CSVM, k-NN, and LDA classifier. The primary idea of this research is to propose a multilevel and high accurate classification architecture using a fractal-based feature generation function. Since fractals are everywhere, and according to pattern recognition, the appropriate pattern can reach high-performance rates. By using fractals, many patterns can be presented. The effect of the recommended fractal-based method, the calculated results are compared to other state-of-art methods. Table 10 denotes these comparative results.

Table 10. The performance comparison results.

Channel	Alakus et al.'s method + SVM [16]	Alakus et al.'s method + MLPNN [16]	Alakus et al.'s method + kNN [16]	Our method +kNN	Our method +LDA	Our method +SVM
AF3	54	80	42	97.86	71.79	96.79
AF4	50	75	55	98.39	95.54	99.64
F3	40	75	35	98.21	88.93	99.11
F4	54	82	43	98.04	60.36	98.21
F7	70	71	43	98.39	80.00	97.50
F8	69	71	54	98.75	91.43	99.82
FC5	34	75	47	98.04	91.07	99.29
FC6	34	74	36	98.39	92.86	98.75

O1	55	71	43	98.57	79.46	98.93
O2	54	65	38	97.68	94.46	99.29
P7	66	70	41	98.04	91.07	99.64
P8	70	72	40	98.75	95.18	99.46
T7	47	65	38	98.93	96.79	99.11
T8	79	79	45	98.39	92.32	99.64

Table 10 demonstrates that our presented model yielded better accuracy than the best of the state-of-the-art. The yielded lowest accuracy has been calculated as 60.36% for the F4 channel by applying LDA. The best accuracy rate has been calculated as 99.82% for the F8 channel by deploying SVM. Also, the calculated confusion matrix of the best result (99.82%) is shown in Table 10.

Table 11. The calculated confusion matrix for F8 Channel by employing SVM classifier.

True class	Predicted class				
	Funny	Boring	Horror	Calm	Recall (%)
Funny	140	0	0	0	100.0
Boring	0	139	0	1	99.28
Horror	0	0	140	0	100.0
Calm	0	0	0	140	100.0
Precision(%)	100.0	100.0	100.0	99.29	**99.82**

The calculated accuracy denoted using bold font-type. As stated from Table 10, the presented FFP and IChi2 based emotion classification method attained 100.0% performance for Funny, Horror and Calm emotions. The true prediction rate 99.28% for Boring emotion. The number of miscalculation is only *one*. These high performances obviously demonstrate the success of the proposed FFP based EEG classification method. Significant points of this research are given below.

Benefits;

- A new effective feature generation function is presented.
- An improved and successful version of the Chi2 feature selection is presented, and it can be used other learning methods.

- A highly accurate EEG based emotion recognition technique is developed. This technique also has a good success rate. Moreover, the success of this method were tested on 14 different channels, and it yielded high performance for all of them.
- The time complexity of the feature generation is low ($O(nlogn)$). Therefore, the presented feature generation model is both lightweight and effective.

Limitations;

- The presented model must be tested on the bigger datasets.
- The time complexity of the IChi2 is high since it used CSVM as loss value generator.

7. Conclusion and future directions

The automated emotion recognition is a crucial process for artificial intelligence applications. The used game based emotion recognition dataset has been tested by various machine learning methods. Moreover, a new fractal-based emotion recognition is developed in this study. The presented fractal is named as Firat Fractal since it is inspired by the Firat University Logo. By using FFP, TQWT, and the presented IChi2 selector, high performance EEG based emotion recognition model is developed. In the classification phase, CSVM, k-NN, and LDA are utilized as a classifier. Single-channel EEG signals have been used, and the results have been calculated for 14 channels. According to these calculated results, the best accuracy rate has been reached 99.82%. Also, the average accuracy rates were calculated as 98.32%, 87.23% and 98.94% by applying k-NN, LDA and SVM classifiers respectively. The presented method is also compared to the state-of-the-art methods, and it achieved better results.

Our recommended future directions according to the experimental results and findings are given as follows. We developed a new fractal-based EEG signal classification method for emotion recognition, and the high classification rates were achieved. These results obviously denote that the developed fractal pattern is a successful feature generator for EEG based emotion recognition. Therefore, new fractal patterns can be presented in the near future for feature extraction of the biomedical signals. The presented model can be applied to other one-dimensional signals for classification. IChi2 is an improved version of the Chi2 feature selector. We are planning to implement a new intelligent EEG signal monitoring application to help neurosurgery and neurology clinics. Phases of our intended intelligent monitoring application are given as follows. In the first phase, the EEG signals will acquire from patients. These signals will be segmented. By using a trained dataset, abnormalities will be detected. The generated reports (it will give results channel by channel) will be sent to medical professions. This method uses a feed-forward feature generation model. In the near future, a fractal-based deep feature generator can be developed like a convolutional neural network (CNN).

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References

[1] Lu Y, Wang M, Wu W, Han Y, Zhang Q, Chen S. Dynamic entropy-based pattern learning to identify emotions from EEG signals across individuals. Measurement. 2020;150:107003.
[2] Chen T, Ju S, Ren F, Fan M, Gu Y. EEG emotion recognition model based on the LIBSVM classifier. Measurement. 2020:108047.
[3] Dai Y, Wang X, Li X, Tan Y. Sparse EEG compressive sensing for web-enabled person identification. Measurement. 2015;74:11-20.
[4] Nakisa B, Rastgoo MN, Tjondronegoro D, Chandran V. Evolutionary computation algorithms for feature selection of EEG-based emotion recognition using mobile sensors. Expert Systems with Applications. 2018;93:143-55.
[5] Mehmood RM, Du R, Lee HJ. Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors. Ieee Access. 2017;5:14797-806.
[6] Liu Y-J, Yu M, Zhao G, Song J, Ge Y, Shi Y. Real-time movie-induced discrete emotion recognition from EEG signals. IEEE Transactions on Affective Computing. 2017;9:550-62.
[7] Dai Y, Wang X, Zhang P, Zhang W. Wearable biosensor network enabled multimodal daily-life emotion recognition employing reputation-driven imbalanced fuzzy classification. Measurement. 2017;109:408-24.
[8] Izard CE. Human emotions: Springer Science & Business Media; 2013.
[9] Cabanac M. Physiological role of pleasure. Science. 1971;173:1103-7.
[10] Knyazev GG, Slobodskoj-Plusnin JY, Bocharov AV. Gender differences in implicit and explicit processing of emotional facial expressions as revealed by event-related theta synchronization. Emotion. 2010;10:678.
[11] Sharma R, Pachori RB, Sircar P. Automated emotion recognition based on higher order statistics and deep learning algorithm. Biomedical Signal Processing and Control. 2020;58:101867.
[12] Soroush MZ, Maghooli K, Setarehdan SK, Nasrabadi AM. Emotion recognition using EEG phase space dynamics and Poincare intersections. Biomedical Signal Processing and Control. 2020;59:101918.
[13] Hemanth DJ, Anitha J. Brain signal based human emotion analysis by circular back propagation and Deep Kohonen Neural Networks. Computers & Electrical Engineering. 2018;68:170-80.
[14] Ekman P. An argument for basic emotions. Cognition & emotion. 1992;6:169-200.
[15] Zhang Y, Ji X, Zhang S. An approach to EEG-based emotion recognition using combined feature extraction method. Neuroscience letters. 2016;633:152-7.
[16] Alakus TB, Gonen M, Turkoglu I. Database for an emotion recognition system based on EEG signals and various computer games–GAMEEMO. Biomedical Signal Processing and Control. 2020;60:101951.

[17] Dasdemir Y, Yildirim E, Yildirim S. Analysis of functional brain connections for positive–negative emotions using phase locking value. Cognitive neurodynamics. 2017;11:487-500.
[18] Reuderink B, Mühl C, Poel M. Valence, arousal and dominance in the EEG during game play. International journal of autonomous and adaptive communications systems. 2013;6:45-62.
[19] Yoon H, Park S-W, Lee Y-K, Jang J-H. Emotion recognition of serious game players using a simple brain computer interface. 2013 International Conference on ICT Convergence (ICTC): IEEE; 2013. p. 783-6.
[20] Park S, Sim H, Lee W. Dynamic game difficulty control by using EEG-based emotion recognition. Int J Control Autom. 2014;7:267-72.
[21] Kerous B, Skola F, Liarokapis F. EEG-based BCI and video games: a progress report. Virtual Reality. 2018;22:119-35.
[22] Wang L, Liu X, Liang Z, Yang Z, Hu X. Analysis and classification of hybrid BCI based on motor imagery and speech imagery. Measurement. 2019;147:106842.
[23] University F. http://www.firat.edu.tr/tr. 2020.
[24] Zhang J, Yin Z, Chen P, Nichele S. Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review. Information Fusion. 2020;59:103-26.
[25] Petrushin V. Emotion in speech: Recognition and application to call centers. Proceedings of artificial neural networks in engineering1999. p. 22.
[26] Anderson K, McOwan PW. A real-time automated system for the recognition of human facial expressions. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics). 2006;36:96-105.
[27] Pantic M, Rothkrantz LJM. Automatic analysis of facial expressions: The state of the art. IEEE Transactions on pattern analysis and machine intelligence. 2000;22:1424-45.
[28] Yin Z, Zhao M, Wang Y, Yang J, Zhang J. Recognition of emotions using multimodal physiological signals and an ensemble deep learning model. Computer methods and programs in biomedicine. 2017;140:93-110.
[29] Zheng W-L, Zhu J-Y, Lu B-L. Identifying stable patterns over time for emotion recognition from EEG. IEEE Transactions on Affective Computing. 2017.
[30] Koelstra S, Muhl C, Soleymani M, Lee J-S, Yazdani A, Ebrahimi T, et al. Deap: A database for emotion analysis; using physiological signals. IEEE Transactions on Affective Computing. 2011;3:18-31.
[31] Scherer KR. What are emotions? And how can they be measured? Social science information. 2005;44:695-729.
[32] Zheng W-L, Lu B-L. Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. IEEE Transactions on Autonomous Mental Development. 2015;7:162-75.
[33] Zheng W-L, Lu B-L. A multimodal approach to estimating vigilance using EEG and forehead EOG. Journal of neural engineering. 2017;14:026017.
[34] Qing C, Qiao R, Xu X, Cheng Y. Interpretable emotion recognition using EEG signals. Ieee Access. 2019;7:94160-70.
[35] Pandey P, Seeja K. Subject independent emotion recognition from EEG using VMD and deep learning. Journal of King Saud University-Computer and Information Sciences. 2019.
[36] Zhang T, Zheng W, Cui Z, Zong Y, Li Y. Spatial–temporal recurrent neural network for emotion recognition. IEEE transactions on cybernetics. 2018;49:839-47.
[37] Lucey P, Cohn JF, Kanade T, Saragih J, Ambadar Z, Matthews I. The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression. 2010 ieee computer society conference on computer vision and pattern recognition-workshops: IEEE; 2010. p. 94-101.

[38] Liu Y, Ding Y, Li C, Cheng J, Song R, Wan F, et al. Multi-channel EEG-based emotion recognition via a multi-level features guided capsule network. Computers in Biology and Medicine. 2020:103927.
[39] Katsigiannis S, Ramzan N. DREAMER: A database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices. IEEE journal of biomedical and health informatics. 2017;22:98-107.
[40] Hassouneh A, Mutawa A, Murugappan M. Development of a Real-Time Emotion Recognition System Using Facial Expressions and EEG based on machine learning and deep neural network methods. Informatics in Medicine Unlocked. 2020:100372.
[41] Wei C, Chen L-l, Song Z-z, Lou X-g, Li D-d. EEG-based emotion recognition using simple recurrent units network and ensemble learning. Biomedical Signal Processing and Control. 2020;58:101756.
[42] Li J, Qiu S, Shen Y-Y, Liu C-L, He H. Multisource transfer learning for cross-subject EEG emotion recognition. IEEE transactions on cybernetics. 2019.
[43] Ding J, Zhou J, Yin Y. Fault detection and diagnosis of a wheelset-bearing system using a multi-Q-factor and multi-level tunable Q-factor wavelet transform. Measurement. 2019;143:112-24.
[44] Selesnick IW. Sparse signal representations using the tunable Q-factor wavelet transform. Wavelets and Sparsity XIV: International Society for Optics and Photonics; 2011. p. 81381U.
[45] Thaseen IS, Kumar CA. Intrusion detection model using fusion of chi-square feature selection and multi class SVM. Journal of King Saud University-Computer and Information Sciences. 2017;29:462-72.
[46] Llagostera P, López N, Comas C. Network reliability in hamiltonian graphs. arXiv preprint arXiv:200502848. 2020.
[47] Bahassine S, Madani A, Al-Sarem M, Kissi M. Feature selection using an improved Chi-square for Arabic text classification. Journal of King Saud University-Computer and Information Sciences. 2020;32:225-31.
[48] Jain U, Nathani K, Ruban N, Raj ANJ, Zhuang Z, Mahesh VG. Cubic SVM classifier based feature extraction and emotion detection from speech signals. 2018 International Conference on Sensor Networks and Signal Processing (SNSP): IEEE; 2018. p. 386-91.
[49] Zhang Y, Zhou X, Witt RM, Sabatini BL, Adjeroh D, Wong ST. Dendritic spine detection using curvilinear structure detector and LDA classifier. Neuroimage. 2007;36:346-60.
[50] Liao Y, Vemuri VR. Use of k-nearest neighbor classifier for intrusion detection. Computers & security. 2002;21:439-48.
[51] Dogan S, Tuncer T. A novel statistical decimal pattern-based surface electromyogram signal classification method using tunable q-factor wavelet transform. Soft Computing. 2020:1-14.
[52] Tuncer T, Dogan S, Pławiak P, Acharya UR. Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals. Knowledge-Based Systems. 2019;186:104923.
[53] Celik Y, Talo M, Yildirim O, Karabatak M, Acharya UR. Automated invasive ductal carcinoma detection based using deep transfer learning with whole-slide images. Pattern Recognition Letters. 2020.