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Identification of Brain Tumor Using Projection Pursuit Bivariate Multilayer Perceptred Classification

Renjeni P.S.[1*], B. Mukunthan[2]

[1]Research Scholar, Jairams Arts and Science College, Karur - 639003 Tamil Nadu, India
[2]Research Supervisor and Assistant Professor, Department of Computer Science
Jairams Arts and Science College, Karur. - 639003, Tamil Nadu, India

**Corresponding Author: renjenips@gmail.com*

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Abstract- The method of identifying the disease with person's symptoms and signs is medical diagnosis. Brain tumour is the stimulating disorder that has to be identified at early stage for treatment. Many classification techniques have been introduced for performing brain tumour identification. However, the brain tumour identification accuracy level was not enhanced and time consumption was not lessened. In order to address these problems, Projection Pursuit Feature Selective Bivariate Multilayer Perceptred Classification (PPFSBMPC) Method is introduced. PPFSBMPC Method comprises two processes, namely feature selection and classification for brain tumour identification. To select the relevant features from the input database, Projection Pursuit Feature Selection process is carried out in PPFSBMPC Method. After performing the feature selection, Bivariate Multilayer Perceptred Classification process is accomplished for brain tumor identification. In addition, the classification process comprised multiple layers to categorize the input data as normal data or tumour diseased data. By this way, PPFSBMPC Method increases the brain tumor identification performance with higher accuracy and lesser time consumption. Experimental evaluation of PPFSBMPC Method is carried out with Epileptic Seizure Recognition Dataset on factors such as brain tumour identification accuracy, execution time, and error rate with respect to number of patient data. The experimental result demonstrates that the PPFSBMPC Method enhances the brain tumour identification accuracy and reduces the execution time when compared to state-of-the-art-works.

Keywords- Medical diagnosis, brain tumour, classification, feature selection, classification process, identification, seizure.

1. INTRODUCTION

The diagnosis of Brain tumor comprises of series of test to determine the patient indications and neurological functions. Many research works have been designed for feature selection and classification techniques to perform brain tumor disease identification. But, the accuracy level and time consumption performance was not improved. In order to solve the issues, the PPFSBMPC Method is introduced to improve the accuracy of brain tumor identification.

An ANOVA based feature selection and fuzzy classifier model was introduced to find seizure state of EEG signal with time and frequency features as in [1]. The state of EEG signal was classified by fuzzy classifier for forecasting the capture. But, the accuracy level was not enhanced. Complex-valued classifiers were introduced for epilepsy diagnosis from electroencephalography (EEG) signals depending on classifiers as mentioned in [2]. The feature of EEG data was extracted by dual-tree complex wavelet transformation at different granularity levels for size reduction. But, the execution time was not minimized by complex-valued classifiers.

Naïve Bayes classification and decision tree algorithm was introduced to perform accurate brain tumor prophesy [3]. The designed algorithm performed prediction by decision tree algorithm and Naïve Bayes algorithm. Long Short-Term Memory (LSTM) networks were introduced for epileptic seizure prediction using convolutional neural networks (CNN) with EEG signals in respect of [4]. A pre-analysis was carried out to identify optimal architecture of LSTM network through testing different modules and memory unit layers. But, the computational cost was not minimized by LSTM.

An automated detection system was designed to substitute the neurologist contribution for time and speed treatment process as shown in [5]. An important feature for epileptic seizure recognition was a matrix determinant of EEG. But, the accuracy level was not improved by automated detection system. A three-class classification system depending on discrete wavelet transform (DWT) and the nonlinear sparse extreme learning machine (SELM) was introduced for epilepsy and epileptic seizure identification as in [6]. However, the time consumption was not minimized by this method.

A statistical analysis of EEG signal was carried out for identifying the epileptic seizure with high accuracy for different age of epilepsy [7]. But, the computational complexity was not minimized by statistical analysis. An

automated seizure detection method was introduced depending on statistical and spectral features of maximum normalized intrinsic mode functions by ensemble empirical mode decomposition with adaptive noise technique as in [8]. Even after, accuracy level was not improved by automated seizure detection method

The epileptic disorder was identified by performing EEG signal analysis through joining best attributes of Artificial Bee Colony (ABC) and radial basis function networks (RBFNNs) as in [9]. But, the feature selection was not carried out in precise manner. A fast and objective diagnosis was carried out with genetic variant of oligodendroglia through feature selection and ensemble-based classification as mentioned in [10]. But, the diagnosis time was not minimized by ensemble-based classification.

The above mentioned problems in the brain tumor disease identification from the existing works are lesser brain tumor disease identification accuracy, more execution time consumption, higher error rate, higher computational complexity, high computational cost, and so on. These kinds of problems were addressed by introducing a new method called PPFSBMPC Method.
The contribution of PPFSBMPC Method is summarized as follows.

- To improve the performance of brain tumour disease identification, PPFSBMPC method is introduced. This method comprises of two processes, namely feature selection and classification for brain tumour disease identification.
- To select the relevant features from the input database, Projection Pursuit Feature Selection process is used in PPFSBMPC Method. This helps to minimize the execution time during brain tumour disease identification.
- To categorize the input data as normal data or tumour diseased data, Bivariate Multilayer Perceptred Classification process is carried out with multiple layers for brain tumor disease identification.

The rest of the paper is organized into five different sections. Section 2 describes the related works in brain tumor disease identification. In Section 3, the proposed PPFSBMPC Method is described with the neat architecture diagram. In Section 4, experimental evaluation is carried out with EEG dataset. The results are discussed with different parameters in Section 5.The conclusion is presented in Section 6.

2. RELATED WORKS

Brain tumor takes place when cells in brain grow out of the control and transfer to nearby tissues. A new gauss-newton representation based algorithm (GNRBA) was introduced for performing breast cancer classification in [11]. However, the tumor classification accuracy was not improved by GNRBA. Ensemble learning and data mining techniques were designed to rank the risk factors and diagnose the recurrence of ovarian cancer [12]. But, the diagnosis time consumption was not minimized by designed method.

The machine learning and matrix factorization method was introduced to determine the risk factors for increasing the disease risk assessment [13]. The designed framework comprised data pre-processing, risk factor optimization and risk assessment. A large quantity of data was provided using magnetic resonance imaging technique to find the brain tumor [14]. The data mining classification techniques were introduced to attain high accuracy. An efficient feature extraction method termed Local Neighbour Descriptive Pattern (LNDP) and One-dimensional Local Gradient Pattern (1D-LGP) was designed to categorize the epileptic EEG signals[15].A convolutional neural network (CNN) was introduced depending on EEG signals to differentiate the ictal, preictal, and interictal segments for epileptic seizure detection[16]. The seizure and non-seizure classification method was carried out depending on bandwidth features of EEG signals as in [17]. The designed method partitioned signal into eight Intrinsic Mode Functions (IMFs).

A new method was designed depending on weighted visibility graph entropy (WVGE) to recognize the seizure from EEG signals [18]. Single channel EEG signals were mapped onto WVGs and WVGEs.

A new approach was introduced for automated identification of seizure EEG signal as in [19]. The designed method decomposed the EEG signal into collection of sub-band signals through tunable-Q wavelet transform (TQWT) based filter-bank. A tunable-Q wavelet transform (TQWT) framework was introduced to decompose the EEG signals into sub bands [20]. The nonlinearity of EEG signals was assessed through computing cantered correntropy (CCE) from sub bands.

3. PROJECTION PURSUIT FEATURE SELECTIVE BIVARIATE MULTILAYER PERCEPTRED CLASSIFICATION (PPFSBMPC) METHOD

To classify the patient data with higher accuracy and minimum time consumption, Projection Pursuit Feature Selective Bivariate Multilayer Perceptred Classification (PPFSBMPC) Method is introduced .This method comprises the two processes, namely feature selection and Classification with data points. In feature selection process, the relevant features are selected from the dataset. Projection Pursuit is a kind of statistical method employed for choosing the relevant features from dataset. After that, the data classification is carried out by using Bivariate Multilayer Perceptred Classification with the selected features for achieving higher accuracy. The architecture diagram of the PPFSBMPC Method is illustrated in figure 1 (a).

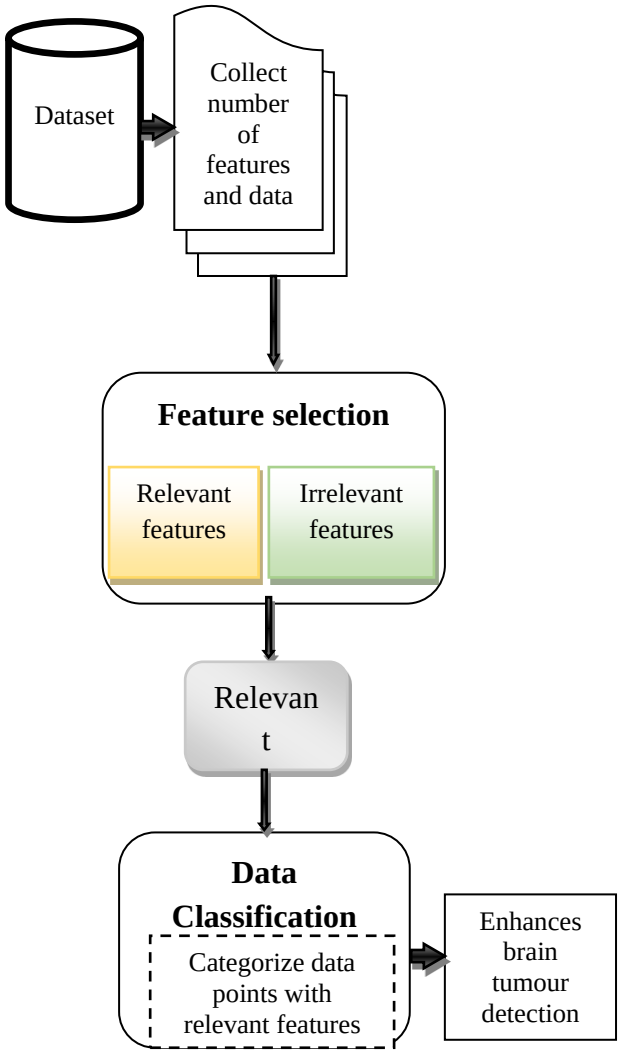

Figure 1(a). Architecture diagram of the proposed PPFSBMPC Method

Figure 1 depicts an architecture diagram of PPFSBMPC method with feature selection and data classification. Initially, the number of features and data are collected from the dataset. PPFSBMPC method selects the relevant features and removes the irrelevant features before performing the classification process. This process minimizes the time consumption for performing brain tumour identification. In second step, classification is carried out using bivariate multilayer perceptred classification to categorize the data points as normal or tumour diseased data. The detailed explanation of PPFSBMPC method is briefly described in the following subsections.

3.1 Projection Pursuit Feature Selection

The initial step of PPFSBMPC Method is the feature selection. The main aim is to select the relevant features from the large database. PPFSBMPC Method uses Projection Pursuit Analysis for feature selection process. Projection Pursuit Analysis is a kind of the statistical technique employed to interactively find out the relevant features from the multidimensional space. The dataset has number of features '$sfe_1, sfe_2, sfe_3, \ldots . sfe_n$' in multidimensional space. Projection Pursuit is a mapping of features set into two subsets (i.e., relevant or irrelevant).

Let us take, 'S' is a $n * k$ matrix that explains 'n' features of 'k' dimensions and 'Q' is a $n * l$ matrix that explains the 'l' dimensional target view of features. The projection matrix 'M' identifies the similarity between target and the features in dataset. Sørensen–dice indexed coefficient is employed for determining the similarity between the target and features in matrix 'S'.

$$\delta = \frac{2|T \cap sfe_i|}{|T| + |sfe_i|} \quad (1)$$

From (1), 'δ' represents the sørensen–dice indexed coefficient, 'T' denotes the target, 'sfe_i' represents the input features. '$T \cap sfe_i$' represent the mutual dependence between target and feature. The sørensen – dice indexed coefficient (δ) provides the similarity value ranges from 0 to 1. Depending on the similarity value, the projection matrix projects the relevant features into subset. The projection matrix reduces size of difference between feature and target when similarity is high. The projection matrix employs the steepest gradient descent to reduce the variation and it is given as,

$$sgdf(x) = arg\min \|Q - S.M\| \quad (2)$$

From (2), '$sgdf(x)$' denotes the steepest gradient descent function and '$arg\ min$' denotes the argument of minimum. Steepest gradient descent function projects the similar features into two-dimensional space. The less similarity features with higher variation between target and feature projection termed as irrelevant features and it is eliminated from dataset. The algorithmic process of the Projection Pursuit Analysis based feature selection is described as follows,

// **Algorithm 1:** Projection Pursuit Analysis based Feature Selection
Input: Dataset D_t, number of features $sfe_1, sfe_2, sfe_3, \ldots . sfe_n$
Output: Select relevant features

Begin

1. **For** each feature $sfe_1 D_t$
2. Construct feature matrix S', target matrix Q, projection matrix $'M'$
3. Determine the correlation between the features and target 'ρ'
4. **if** $(\delta = +1)$ **then**
5. It is considered as relevant feature
6. Projection matrix project the high similarity features into two-dimensional space
7. Reduce the difference between projection of feature and the target $arg\min \|Q - S.M\|$
8. Select relevant features

9. else
10. Remove irrelevant features
11. End if
12. End for
End

Algorithm 1 Projection Pursuit Analysis based Feature Selection

Algorithm 1 illustrates the feature selection using projection pursuit analysis. Initially, the numbers of features are considered as input from dataset. After that, the correlation between the target and features in the matrix are determined to identify the high and low similarity features. The projection matrix project high similarity features into two-dimensional space. The high similarity feature projection reduces the difference between projection of feature and target. Subsequently, the high similarity features are chosen for brain tumour identification and the low similarity features are removed. The feature selection process in PPFSBMPC Method reduces the time complexity for brain tumour identification.

3.2 Bivariate Multilayer Perceptred Classification

A multilayer perceptron is the machine learning system along with set of feature vector. Bivariate analysis is the quantitative analysis for determining the relationship between them. The multilayer perceptron is a feed-forward neural network with two or more layers like one input layer and one output layer with one hidden layer of activating nodes. Then, an input region and the features are fed into input layer. In hidden layer, support vector regression is used to categorize the patient data into two classes with help of selected features through separating hyper planes. Finally, the results are transmitted to the output layer.

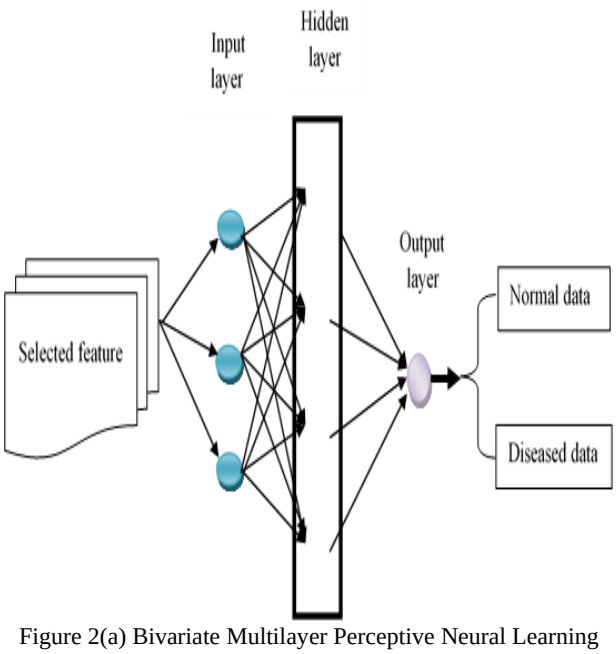

Figure 2(a) Bivariate Multilayer Perceptive Neural Learning

Figure 2(a) illustrates the multilayer perceptive neural learning for brain tumor identification. As illustrated in figure 2, neurons like nodes in one layer are fully linked with the other layer to form entire network with help of arrow symbol. The input layer collects the number of features into the network at time 't' denoted by '$I(t)$'. The node in one layer links to another layer through dynamic weights. It is given by,

$$I(t) = \sum_{i=1}^{n} sfe_i * w_1 + b \quad (3)$$

From (3), 'sfe_i' represent the selected features with adjustable initial weight 'w_1' between input and hidden layer. 'b' denotes the bias. After that, the input is fed into the hidden layer where the support vector regression is used for data classification. The regression is a statistical process used for classifying the data according to the feature values. The support vector regression uses separating hyperplane to analyze and categorize the data. The two marginal hyperplanes are created on both sides of hyperplane. The hyperplane act as the threshold between the output classes. A separating hyperplane (H_s) is defined as,

$$H_s \rightarrow \overrightarrow{We}.(dp) + \vec{B} = 0 \quad (4)$$

From (4), $\overrightarrow{We}$ represents the weight vector to hyperplane, 'dp' denotes the data points and $\vec{B}$ symbolizes the bias. When the feature value of the patient data is greater than the threshold value, then the data points are classified by constructing two marginal planes and it is given below as,

$$MH_1 = \overrightarrow{We}.(dp) + \vec{B} > 0 \rightarrow \text{tumour diseased data} \quad (5)$$

$$MH_2 = \overrightarrow{We}.(dp) + \vec{B} < 0 \rightarrow \text{normal data} \quad (6)$$

From (5) and (6), $MH_1$and MH_2 denotes two marginal hyperplanes (i.e., above and below the hyperplane). The data point values higher than the threshold is classified above the hyperplane. The data point values lesser than the threshold is classified below the hyperplane. The support vector regression categorizes the data points into normal or diseased based on either side of the hyperplane. The output of hidden layer at the time *'t'* is given as follows,

$$L(t) = I(t) * w_2 \quad (7)$$

From (7), '$L(t)$' represents the output of hidden layer at time 't'. 'w_2' denotes the weight between input layer and hidden layer. Finally, the results are displayed at the output layer.

$$O(t) = w_3 * L(t) \quad (8)$$

From (8), O(t) represents the output at time instant't'. 'w_3' denotes the weight between the hidden and output layer, $L(t)$ denotes an output of the hidden layer. As a result, the proposed classifier exactly identifies the brain tumour disease with higher accuracy and lesser time consumption. The algorithmic process of Bivariate Multilayer Perceptred Classification is described as given below,

// Algorithm 2: Bivariate Multilayer Perceptred Classification

Input: Number of selected features $sfe_1, sfe_2, sfe_3 \ldots\ldots sfe_n$
Output: Improves brain tumor identification accuracy

Begin
Step 1: Number of features at the input layer
Step 2: For each data with selected features sfe_i
Step 3: Construct hyper plane 'β_h'
Step4: Find two marginal hyper plane MH_1, MH_2
Step 5:If $(MH_1 > 0)$ **then**
Step 6: Data point is classified as $tumour\ diseased$
Step 7: else if $(MH_2 < 0)$
Step 8: Data point is classified as $normal$
Step 9: End if
Step 10: **Return "**normal data or diseased data" at the output layer
Step 11: end for
End

Algorithm 2 given above explains the step by step process of bivariate multilayer perceptred classification. Initially, the number of features is selected from the input database and given as input. After that, input is transferred into the hidden layer. In that layer, the support vector regression classifies the patient data into normal or diseased based on either side of the hyper plane. As a result, the patient data is classified with higher accuracy and lesser time consumption.

4. EXPERIMENTAL SETTINGS

In order to evaluate the performance, the PPFSBMPC Method is implemented in with Epileptic Seizure Recognition Dataset. The Epileptic Seizure Recognition Dataset is taken from UCI Machine Learning Repository for conducting the experiments. Epileptic Seizure Recognition Dataset comprises 5 folders. Every folder has 100 files. Every file has patient data (i.e. brain activity of patient for 23.6 seconds). PPFSBMPC Method considers different number of patient data in the range of 50-500 from Epileptic Seizure Recognition Dataset. The performance of the PPFSBMPC Method is measured in terms of brain tumour identification accuracy, execution time and error rate as well as compared with existing ANOVA based feature selection and fuzzy classifier model [1] and Complex-valued classifiers [2]. The experiments of PPFSBMPC Method are conducted for several instances with different number of patient data.

5. RESULT AND DISCUSSIONS

The performance result of PPFSBMPC Method is discussed in this section. The efficiency of the PPFSBMPC Method is measured with help of table and graph using the below parameters such as brain tumour identification accuracy, execution time, and error rate.

5.1 Impact on Brain Tumour Identification Accuracy

Brain tumour identification accuracy (BTIA) is defined as the ratio of number of patient data accurately classified as normal or diseased to the total number of patient data. Brain tumour identification accuracy is determined as,

BTIA= (Number of patient that are accurately categorized as normal or abnormal)/n*100 (9)

From equation (9), the brain tumour identification accuracy is determined. 'n' denotes the total number of patient data taken. The brain tumour identification accuracy is measured in terms of percentages (%).

Table 1 Number of patient data versus Brain Tumor Identification Accuracy

Number of patient data	Brain Tumor Identification Accuracy (%)		
	ANOVA based feature selection and fuzzy classifier model	Complex-valued classifiers	PPFSBMPC Method
100	89	86	94
200	88	80	92
300	85	80	92
400	86	85	96
500	91	84	94
600	89	87	94
700	89	88	97
800	91	88	96
900	90	88	97
1000	91	89	98

Table 1 explains the experimental results of brain tumour identification accuracy with respect to different number of patient data. For the experimental purpose, number of patient data taken ranges from 100 to 1000. Let us consider the number of patient data is 800, brain tumour identification accuracy of proposed PPFSBMPC Method is 96% whereas the brain tumour identification accuracy of two existing ANOVA based feature selection and fuzzy classifier model [1] and Complex-valued classifiers [2] are 91% and 88%. Likewise the various brain tumour identification accuracy results are shown in figure 3.

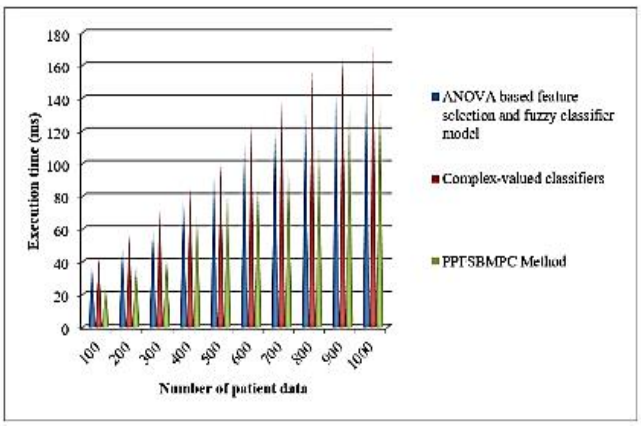

Figure 4 Performance results of Execution Time

Figure 3 explains that proposed PPFSBMPC Method increases the brain tumour identification accuracy than existing methods. This is due to application of projection pursuit feature selection and bivariate multilayer perceptred classification for brain tumor disease identification. Projection pursuit feature selection chooses the related features and removes the unrelated features before performing the classification process. Subsequently, bivariate multilayer perceptred classification categorizes the data points as normal or tumour diseased data points. The average of ten results illustrates that the brain tumor tumour identification accuracy of PPFSBMPC method is increased by 7% when compared to ANOVA based feature selection and fuzzy classifier model [1]. In addition, the brain tumor tumour identification accuracy of PPFSBMPC method is considerably improved by 11% when compared to Complex-valued classifiers [2].

5.2 Impact on Execution Time

Execution Time '(ET)' computes the time consumed to identify the existence and absence of brain tumor disease. The execution time is determined as,

$$ET = n * t_S \quad (10)$$

From equation (10), the execution time of brain tumor disease is attained. 'n' denotes the number of patient data. 't_S' symbolizes the time consumed to categorize the presence and absence of brain tumor disease of one patient data. The execution time is measured in terms of millisecond (ms). The performance result analysis of execution time is shown in the Table 2.

Table 2

Number of patient data	Execution Time (ms)		
	ANOVA based feature selection and fuzzy classifier model	Complex-valued classifiers	PPFSBMPC Method
100	36	42	25
200	48	56	38
300	61	72	45
400	79	85	68
500	92	99	81
600	112	124	92
700	129	139	101
800	135	157	112
900	142	165	135
1000	152	172	145

The PPFSBMPC Method is implemented in Java Language through considering the dissimilar number of patient data in the range of 100-1000 from Epileptic Seizure Recognition Dataset for identifying the execution time involved during brain tumor disease identification. The experimental result of execution time using the PPFSBMPC Method is compared with conventional ANOVA based feature selection and fuzzy classifier model [1] and Complex-valued classifiers [2]. When considering the number of patient data as 700 from Epileptic Seizure Recognition Dataset to perform experimental work, PPFSBMPC Method consumed takes 101ms execution time whereas ANOVA based feature selection and fuzzy classifier model [1] and Complex-valued classifiers [2] consumes 129ms and 139ms respectively. Consequently, PPFSBMPC Method consumed minimum execution time for brain tumor identification when compared to other state-of-the-art methods [1] and [2].

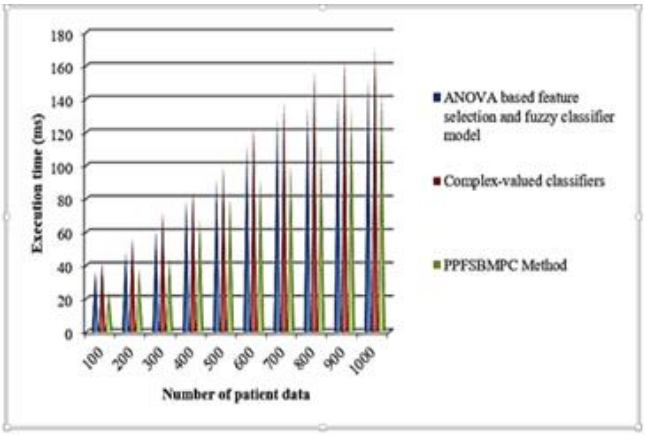

Figure 4 Performance results of Execution Time

The above figure 4 explained that PPFSBMPC Method minimizes the execution time for brain tumor disease identification than conventional techniques. This is because of applying the projection pursuit feature selection and bivariate multilayer perceptred classification for brain tumor disease identification. Projection pursuit feature selection in PPFSBMPC method chooses relevant features and eliminates the irrelevant features before classification process. This in turn helps to minimize the execution time during brain tumor disease identification. After that, bivariate multilayer perceptred classification categorizes the data points as normal or tumour diseased data with lesser time consumption. The average of ten results show that the execution time of PPFSBMPC method is reduced by 17% when compared to ANOVA based feature selection and fuzzy classifier model [1]. In addition, the execution time of PPFSBMPC method is significantly reduced by 26% when compared to Complex-valued classifiers [2].

5.3 Impact on Error rate

Error Rate '(ER)' is defined as the ratio of number of patient data that are incorrectly classified as normal or abnormal to the total number of patient data. The error rate is formulated as,

ER=(Patient that are wrongly classified as normal or abnormal)/n*100 (11)

From equation (11), the error rate of brain tumor disease identification is determined. The error rate is evaluated in terms of percentages (%).The experimental result analysis of the error rate is demonstrated in below Table 3.

Table 3 Number of patient data versus Error rate

Number of patient data	Error rate (%)		
	ANOVA based feature selection and fuzzy classifier model	Complex-valued classifiers	PPFSBMPC Method
100	11	14	6
200	25	40	17
300	45	60	24
400	58	62	16
500	47	79	31
600	65	79	35
700	79	100	22
800	75	99	30
900	86	105	24
1000	91	110	20

PPFSBMPC Method is executed in Java Language with different number of patient data in range of 50-500 from input dataset to estimate the error rate of brain tumor disease identification. The experimental result of error rate using PPFSBMPC Method is compared with ANOVA based feature selection and fuzzy classifier model [1] and Complex-valued classifiers [2]. When number of patient data is considered as 500 from Epileptic Seizure Recognition Dataset to accomplishing experimental evaluation, PPFSBMPC Method attains 31% error rate whereas ANOVA based feature selection and fuzzy classifier model [1] and Complex-valued classifiers [2] attains 47% and 79% respectively. Therefore, the proposed PPFSBMPC Method attained minimal error rate for tumor disease identification as compared to other existing methods [1] and [2].

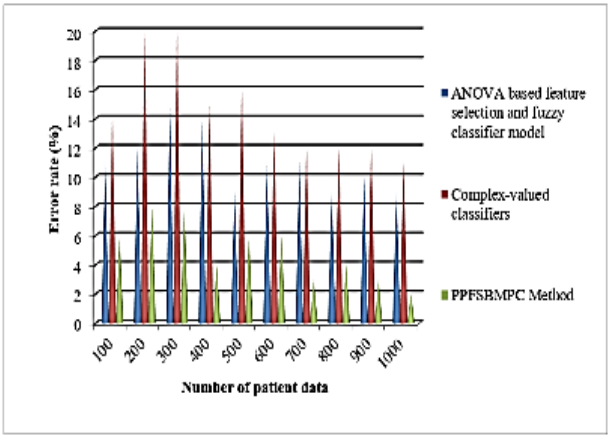

Figure 5 Performance results of Error Rate

The above figure 5 illustrates that PPFSBMPC Method reduces the error rate in brain tumor disease identification. This is due to the application of projection pursuit feature selection and bivariate multilayer perceptred classification for performing tumor disease identification. Projection pursuit feature selection in PPFSBMPC method selects relevant features and removes the irrelevant features before performing the classification process. The bivariate multilayer perceptred classification classifies the data points as normal or tumour diseased data. This helps to reduce the error rate during brain tumor disease identification. The average of ten results illustrates that the error rate of PPFSBMPC method is minimized by 55% when compared to ANOVA based feature selection and fuzzy classifier model [1]. In addition, the error rate of PPFSBMPC method is significantly reduced by 67% when compared to Complex-valued classifiers [2].

6. CONCLUSION

An efficient method termed PPFSBMPC method is introduced for improving the performance of brain tumor disease identification with minimal execution time. PPFSBMPC method collects the patient data from input dataset. The relevant feature selection and irrelevant feature elimination is carried out by applying projection pursuit. The projection matrix identifies the similarity between target and the features. The feature selection of PPFSBMPC method is to reduce the execution time in the brain tumor disease identification. Finally, the data classification is performed using bivariate multilayer perceptred classification to classify the data points as normal or tumour diseased data. By this way, the error rate during brain tumor disease identification gets reduced. The experimental evaluation performed with different metrics such as brain tumour identification accuracy, execution time, and error rate. The observed result demonstrates that the PPFSBMPC method enhances the disease diagnosing accuracy and minimizes the execution time as well as error rate when compared to existing classification methods.

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AUTHORS' PROFILE

P.S. Renjeni received B.Sc Chemistry from Sree Devi Kumari College for women, Manonmaniam Sundaranar University, India and obtained MCA from Noorul Islam College of Engineering, Manonmaniam Sundaranar University, India. Presently, she is doing Ph.D in Bharathidasan University, Trichy, India. She has 16 years of teaching experience and working as Assistant Professor in the Department of Computer Science , V T M College of Arts and Science, Arumanai, Tamil Nadu, India. Her research interest is in Data Mining.

B. Mukunthan pursed Bachelor of Science in Computer Science from Bharathiar University, India in 2004 and Master of Computer Applications from Bharathiar University in year 2007 and Ph.D from Anna University - Chennai in 2013. He is currently working as Research Advisor in Department of Computer Science, Jairams Arts & Science College, Affiliated to Bharathidasan University, Tiruchirapalli since 2016. He is a member of IEEE & IEEE computer society since 2009, a life member of the MISTE since 2010. He has published more than 25 research papers in reputed international journals. He is also Microsoft Certified Solution Developer. His main research work focuses on Algorithms, Bioinformatics, Big Data Analytics, Data Mining, IOT and Neural Networks. He also invented a Novel and Efficient online Bioinformatics Tool and filed for patent. He has 12 years of teaching experience and 10 years of Research Experience.

