JOURNAL OF NORTHEASTERN UNIVERSITY

Volume 25 Issue 04, 2022 ISSN: 1005-3026 https://dbdxxb.cn/ Original Research Paper

PREDICTION MODEL DESIGN AND DEVELOPMENT FOR SEIZURE DETECTION

Swati Varshney
Research Scholar Maharishi University of Information Technology Lucknow Email: swati181190@gmail.com

Prof. Chitranjan Gaur
Professor Maharishi University of information Technology Lucknow

Abstract:
Because of advancements in computing and processing capacity, EEG signal analysis has become more reliable and accurate in recent years. It has progressed into an important diagnostic tool for neurological problems, with applications in both the medical and physiological fields. The overlapping manifestations of normal and aberrant signals make epileptic seizure diagnosis and prediction challenging even for the most seasoned neurologist. Consequently, it would be ideal to have a fully automated Computer Aided Diagnostic (CAD) system that can use EEG signals to categorise the severity of epileptic seizures. This motivates the current study's objective of developing a computerised prediction model for interpreting EEG data and making a diagnosis of epilepsy. This chapter presents a computer-aided design (CAD) system that may identify abnormalities in the brain before and during the start of seizures.
Keywords: Prediction Model, Seizure Activity etc

INTRODUCTION

Additionally, the potential for designing CAD systems using two alternative neural network algorithms was studied. Additionally, this paper evaluates the efficacy of various classifiers for two-class seizure classification. For seizure categorization, a novel approach based on a hierarchical CAD system is proposed.

Two critical factors to consider when constructing any prediction model for detection or classification are the type and nature of features to be taken from the EEG input signal and the analysis techniques to be used on these extracted features [169]. Previous research has addressed feature selection, multiple domains of feature selection, and artefact handling, and has concluded with an optimal set of features composing SFV that may be used for classification. Extracted features from the SFV are used as input data for the learning process, and the same set is used for prediction. The chosen collection of features is straightforward but robust in terms of the morphology of the EEG data required for categorization.

DESIGN OF THE PROPOSED CAD SYSTEM

Figure 4.1 depicts the block diagram of the suggested CAD system design for two- and three-class seizure categorization utilising statistical features. The development of an automated soft computing diagnostic system is based on statistical parameters reflecting the shape of EEG data. Chapter 3 details the quantitative and statistical analysis of the selected attributes and

Submitted: 17/10/2022 **Accepted**: 10/11/2022

illustrates the approach using the same data set. All 300 signals are represented as a vector with thirteen odd characteristics, denoted by the symbol SFVj, where I = 1 to 100 and j = 1 to 3.

(a) WORKFLOW INVESTIGATIONS

Extensive experimentation has been conducted to design and evaluate the suggested CAD system's performance. The recommended design is carried out through a series of trials (detailed in Table 4.1).

Table 4.1: Description of experiments carried out for design of CAD system for seizure classification.

Experiment 1	Exhaustive experiments are carried out to develop the architecture of prediction model by varying the number of neurons in the hidden layer and signal feature vector length for deciding the best network topology and ascertain the CAD system with highest overall classification accuracy.
Experiment 2	For evaluating the performance of the proposed CAD system design, rigorous experimentation has been carried out for comparison with other available classifier for the same architecture.
Experiment 3	This experiment deals with two class classification problems with proposed topology and with available binary classifiers to recognize an optimal soft computing paradigm for seizure classification.
Experiment 4	In this work, the focus is on modeling the seizure classification by a hierarchical framework, a variation of the classifier system; HCAD system is proposed.

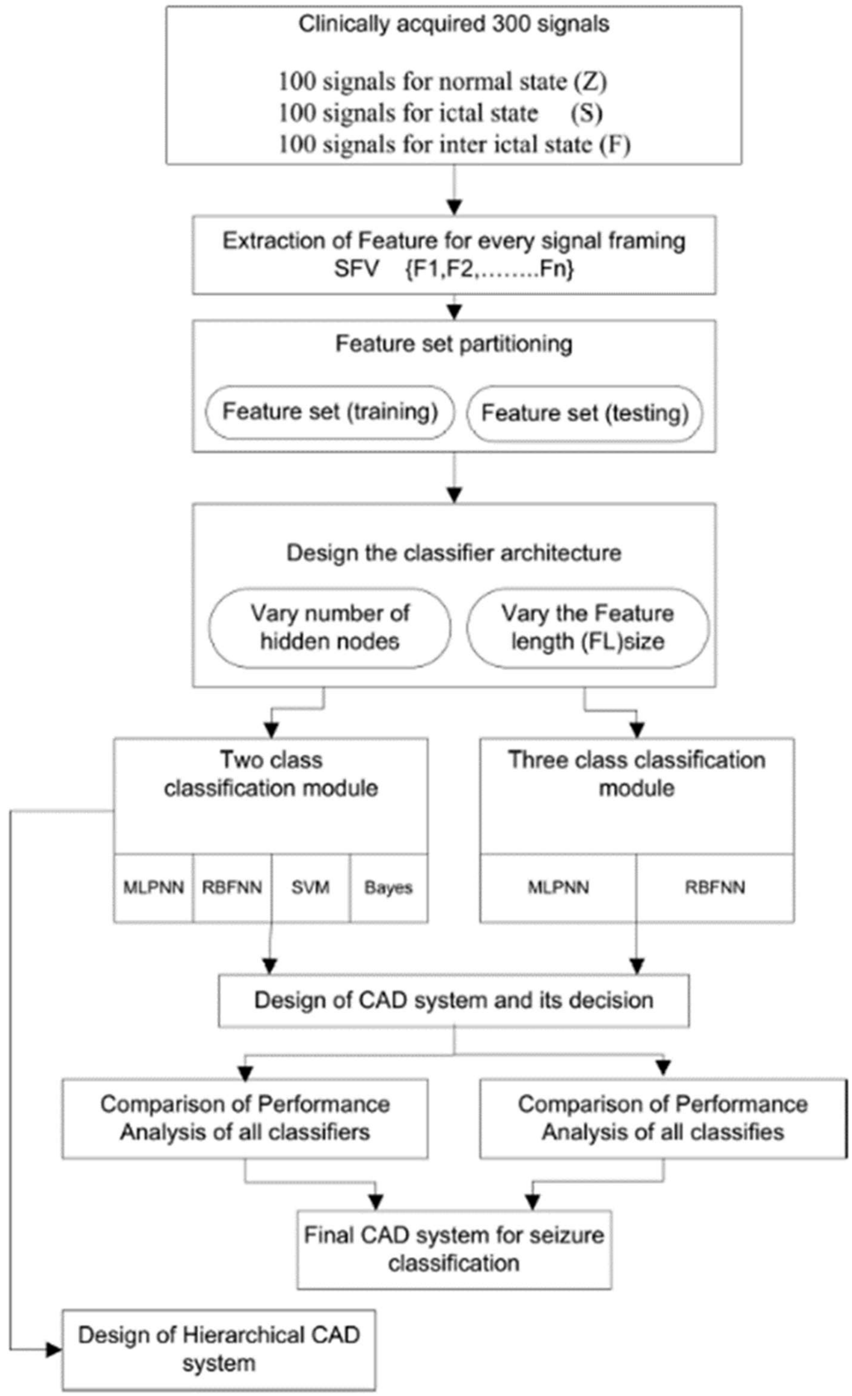

Figure 4.1. Proposed CAD system design using statistical features for two-class and three-class seizure classification

(b) Experiment 1:

To design the prediction model architecture in such a way that the CAD system achieves the maximum overall classification accuracy possible.

(i) System Architecture Design

To improve the accuracy and precision of EEG signal analysis, several computational techniques such as neural networks, support vector machines, and Bayes classifiers may be beneficial. However, due to their high degree of generalisation and predictive capability, neural networks have been effectively used to analyse EEG signals [26]. Due to the enormous number of training samples and relatively large number of synaptic weights, there is always a risk that the network's free parameters will adapt to the unique characteristics of the training data.

This strategy employs the feed-forward multi-layered perceptron Neural Network (MLPNN) algorithm to construct a predictive model, as this classifier exhibits high generalisation performance even without feature space dimension reduction and is less prone to overfitting [170]. To handle this challenge, a multi-layer Perceptron network is employed since it provides explanations for weights and activation functions and adheres to convergent theory by providing a single solution to execute a problem. The performance of an ANN is determined by the network's structure, which includes the number of layers, the number of neurons in the hidden layer, their connections, and the neurons in the output layer. While any number of levels can be employed in a multi-layer perception network, Kolmogrov According to the theorem, a three-layered perception network is capable of separating any type of space and can be utilised to build neural networks. The input layer's number of neurons corresponds to the number of characteristics supplied to the network, followed by a hidden layer of neurons that changes the input into nonlinear combinations and delivers the signals to the output layer. The selected characteristics SFV represent thirteen neurons in the input layer in the proposed design. Due to the fact that this is a three-classification problem, the output layer has three neurons for classifying ictal (S), interictal (F), and normal (Z) categories. The number of neurons in the neural network's hidden layer has a substantial effect on the network's performance [24]. Increased computing is required for additional neurons in the hidden layer; decreased computation results in a high training error and a high generalisation error owing to underfitting. Numerous optimization strategies have been applied to the concealed nodes. These approaches can be classified into two groups. The first category generates a network with a modest number of hidden nodes and gradually increases the number of nodes until the maximum accuracy is obtained. This is referred to as the constructive method. While the second group of methods involves first creating a network with a large number of hidden nodes and gradually decreasing it until the maximum accuracy is achieved; this is referred to as the destructive method. The current work is constructive in nature. Starting with five neurons in the hidden layer, the number of neurons was increased and decreased until the network attained its maximum classification accuracy. Each design with a different number of hidden neurons is trained, tested, and validated, and the performance accuracy of all tested models is shown in Figure 4.2.

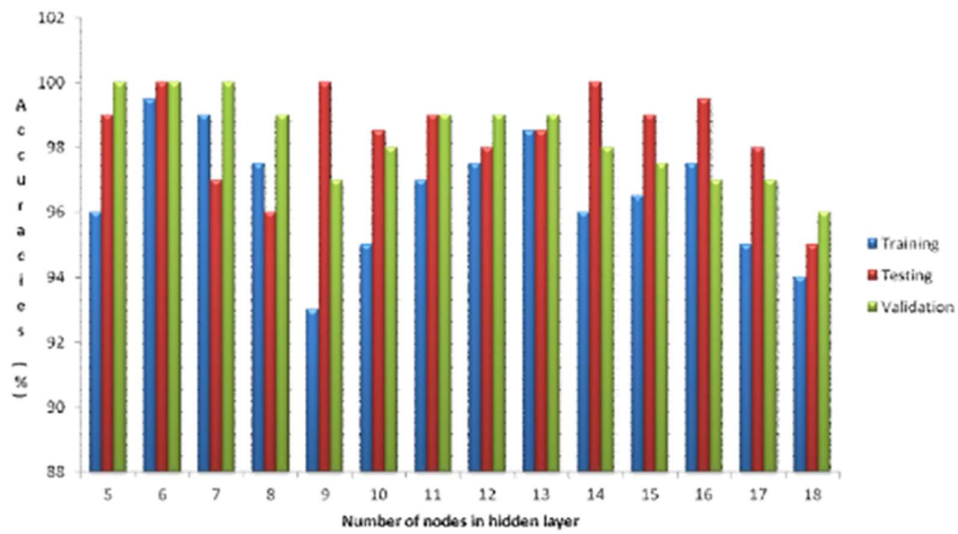

Figure 4.2. Performance accuracies of proposed model in terms of training, testing and validating accuracies; with varying number of neurons in hidden layer.

The highest classification accuracy was recorded when six neurons in the hidden layer were used. It is 100 percent accurate during testing and validation and 99.5 percent accurate throughout training. This network performs substantially better and requires less training iterations. The training efficiency diminishes as the number of nodes increases. Even when the validation and testing efficiencies are good, as in the case of 9 or 13 hidden nodes, the training efficiencies are low in some cases. Keeping these three efficiencies in mind, the number of concealed nodes is set to six. Six hidden nodes will be examined for further experimentation.

Additionally, extensive investigation was conducted to determine the amount of input characteristics or the Feature Length (FL). Two approaches of feature selection are used, namely Sequential Forward Search (SFS) and Sequential Backward Search (SBS). Two feature subset selection approaches are used to produce the optimal combination of predefined selected features by utilising class separability criteria such as FDR, divergence, and others outlined in Chapter 3. In the SFS technique, the most discriminatory feature is chosen from all available characteristics based on a permanently chosen class separability criterion. Additionally, its combination with all remaining traits is evaluated, and the best pair is chosen again according to the adopted class separability criterion. This selection process is repeated until the desired number of characteristics is obtained.

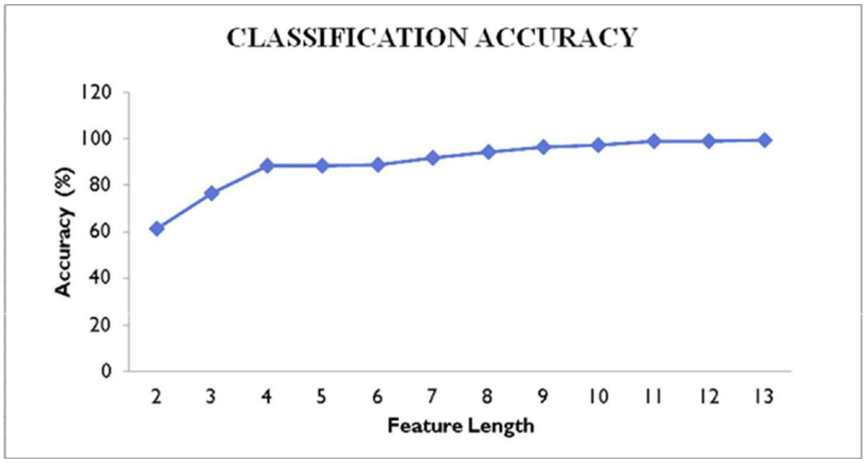

Figure 4.3. Performance analysis of NNs with varied feature lengths in terms of classification efficiency.

Subsets of features were employed to train the network and categorise the signals in this approach, starting with the feature length of two prime features. This procedure was repeated until all retrieved features had been utilised. After tenfold cross validation, the suggested architecture was used to test the prediction model for categorization. [171].

The performance of each of the developed classifier models was evaluated in terms of training, testing, and validating efficiency. The classification accuracy for various FLs is recorded in Table 4.2 and summarised in Figure 4.3 via a graph.

Table 4.2: Classification summary for the CAD system with varying number of features.

Features	FV	Tr. Effi.	Tst. Effi.	Vald. Effi.	CA
Mean-std	200	61.43	71.11	68.88	61.42
Mean-std-eng	300	84.28	82.22	86.66	76.65
Me-std-eng-ent	400	88.15	88.64	88.64	88.29
Me-std-eng-ent-Sk	500	88.32	86.66	88.95	88.94
Me-std-eng-ent-Sk-ku	600	88.63	86.36	90.91	88.68
Me-std-eng-ent-Sk-ku-sn	700	93.36	88.64	86.36	91.63
Me-std-eng-ent-Sk-ku-sn-cov	800	93.84	95.45	95.45	94.31
Me-std-eng-ent-Sk-ku-sn-cov-med	900	95.32	99.55	100	96.72
Me-std-eng-ent-Sk-ku-sn-cov-med-mod	1000	96.21	100	100	97.32
Me-std-eng-ent-Sk-ku-sn-cov med-mod-max	1100	98.58	100	100	98.99
Me-std-eng-ent-Sk-ku-sn-cov med-mod –max-min	1200	98.88	100	100	99.01
All	1300	99.80	100	100	99.3

Note: *Tr. Effi: Training Efficiency, Tst. Effi: Testing Efficiency, Vald. Effi: Validation Efficiency, FV: Feature vector, CA: Classification Accuracy, All efficiencies are in %*

As illustrated in Table 4.2, a NN classifier with a feature vector of length 13 demonstrated superior classification capacity for epileptic seizure detection when compared to feature vectors of lengths 2, 3, 4, and so on. Although testing and validation efficiencies grow greatly to 100% after nine features, classification accuracy does not improve significantly. The discrepancy in classification accuracy between thirteen features and ten, eleven, and twelve features is quite large. The primary goal of the challenge at hand is to achieve high classification accuracy and training efficiency, and so the model with the highest values for these two parameters should be favoured over the others. As a result, 13 features extracted from the EEG signal are considered for further analysis, with preset nodes in the hidden layer and needed nodes in the NN's output layer. Thus, the final design of the neural network will consist of thirteen input nodes, six hidden nodes, and three output nodes, as seen in Figure 4.4 with a fully linked architecture.

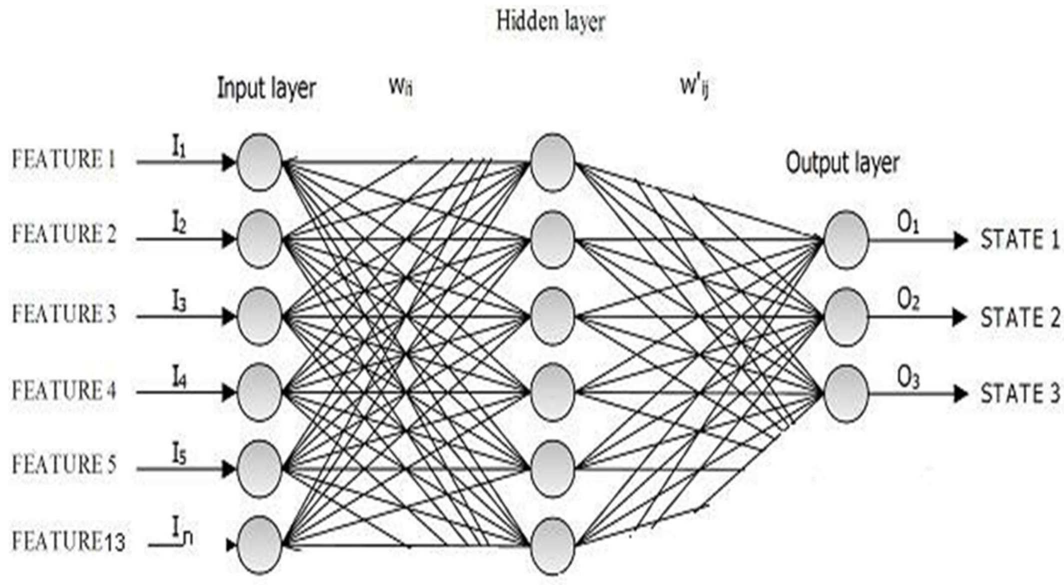

Figure 4.4. The proposed neural network architecture is as follows: thirteen nodes in the input layer, six neurons in the hidden layer, and three neurons in the output layer.

The overall classification system is composed of three layers of artificial neural networks with tan-hyperbolic and softmax activation functions for the hidden and output layers, respectively, with Cross Entropy serving as the error function and BFGS (Broyden-Fletcher-Goldfarb-Shanno) serving as the training technique[170]. To minimise the bias in the training and testing data sets, bootstrapping and tenfold cross-validation are preferred. These strategies provide insight into the classification model's ability to work effectively on new data streams. 70% of the data set is used for training, 15% for testing, and 15% for validation in this work. The bootstrapping method with 1000 seed points is used to effectively train the network (primarily to avoid overfitting), to evaluate the method's average predictive ability, and to improve prediction accuracy.

(ii) Findings and discussion

The most critical characteristic of a prediction method is its accuracy. Sensitivity, specificity, classification accuracy, and receiver operating characteristic curves are performance indicators for classifying and validating any classifier (discussed in Chapter 1). The confusion matrix and classification summary are both valuable tools for assessing a classification network's effectiveness.

After conducting rigorous trials, the proposed architecture was used to evaluate the prediction model for classification. The model's confusion matrix and classification summary are shown in Tables 4.3 and 4.4. Individual Classification Accuracy (ICA) should also be high for medical applications, while Overall Classification Accuracy (OCA) and Individual Misclassification Accuracy (IMA) should be as low as possible. For clinical applications, a diagnosis system should have a high sensitivity and specificity but also nearly no false positive or negative events [138].

Table 4.3: Classification summary for three class classification using proposed architecture

	Interictal	Ictal	Normal	OCA
Total	99	100	100	299
Correct	98	99	100	297
Incorrect	1	1	0	2
ICA(%)	98.98	99	100	99.33(%)
IMA (%)	1.01	1	0	0.67(%)

Note: *IMA- Individual Misclassification Accuracy, ICA-Individual Classification Accuracy.*

From a strategic standpoint, we developed a fully automated neural network model capable of classifying seizure activity into ictal, interictal, and normal states with an accuracy of 99.3 percent and a misclassification error of 0.67 percent. The ICA for ictal conditions is 99 percent and the IMA is 1%; for normal conditions, the ICA is 100 percent and the IMA is 0%; and for interictal conditions, the ICA is 98.9 percent and the IMA is 1.01 percent.

Table 4.4: Confusion Matrix for the selected prediction model for three class classification using designed network architecture.

	Inter-ictal	Ictal	Normal	OCA	Sen(Ictal)
Inter-ictal	98	0	0		
Ictal	0	99	0	99.33%	99%
Normal	1	1	100		

Note: *OCA – Overall Classification Accuracy, Sen- Sensitivity*

The accuracy of proper categorization is 99.3 percent, while the accuracy of misclassification is 0.67 percent. For a given set of parameters and optimal number of neurons in the hidden layer, the ANN model demonstrated a superior model for classifying. This network performs substantially better and requires less training iterations. The encouraging results demonstrate the efficiency and utility of systems designed for categorization and prediction of epileptic patients' normal, ictal, and interictal states.

(c) EXPERIMENT 2

Comparison of Machine Learning Techniques for Epilepsy Prediction

(i) METHODOLOGY

The potential of two alternative neural network techniques (back propagation and radial basis function) for categorization of EEG signals was studied in this approach. Classification is performed using quantitative characteristics extracted from the neurophysiologic signals used to train the networks, and the networks' performance is examined to ensure their efficacy. To identify participants according to their condition of epilepsy using EEG signals and to construct an effective model workflow, as illustrated in Figure 4.5.

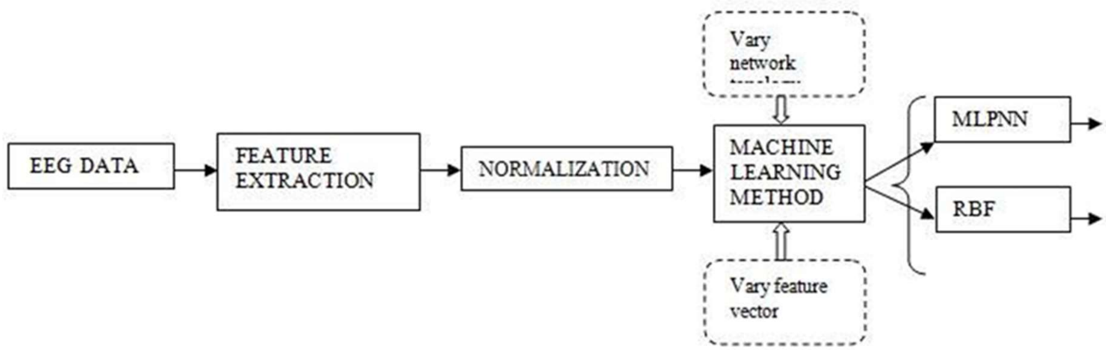

Figure 4.5. illustrates the process of comparing two machine learning approaches for the classification of three classes.

The comparative analysis is based on differences in the topology of the networks and the feature vectors used to train the networks. The approach of determining the feature length is customised in a methodical manner by enumerating all possible feature vector combinations. The number of neurons in the input layer was set to thirteen to correlate to the FL, and the number of neurons in the output layer was set to three to classify three distinct classes. The number of hidden nodes was tested between 5 and 25 in order to determine the design that provided the best performance with the highest accuracy. To validate a predictive model with good generalisation performance, the dataset is randomly divided into 70% for training the network, 15% for validation, and 15% for testing the model's predictive performance. Around 20 networks were trained for each sequence in the training and testing sets, and the best five networks were averaged to provide the performance characteristics.

(ii) Results and Discussions

The performance of both networks was analysed for various architectures by altering the number of nodes in the hidden layer. Different designs were trained using nodes ranging from five to twenty-five in the hidden layer, and their performance and results are displayed in Figure 4.6. With two distinct types of networks with distinct topologies, significant difference in accuracy was seen during training, testing, and validation. It is noteworthy to observe that as the number of nodes increases, the efficiency of RBF increases from 50% to roughly 95%, whereas the efficiency of MLPNN does not alter significantly as the number of nodes increases. Following that, the discrimination ability of various feature sets is examined. The effectiveness and sensitivity of classification techniques are determined by altering the FL. The comparison of the two techniques in terms of sensitivity is shown in Figure 4.7, using different lengths of FL and varied numbers of concealed nodes. It is noticed that a composite FL comprised of all aspects has a higher degree of efficiency and discrimination capability. As illustrated in Figure 4.6, the maximum and minimum sensitivities obtained are 99.3 percent and 61.4 percent for MLPNN, and 96.9 percent and 59.9 percent for RBF, respectively. All of the results obtained utilised the discrimination capacity of all of the 300 signals' specified attributes.

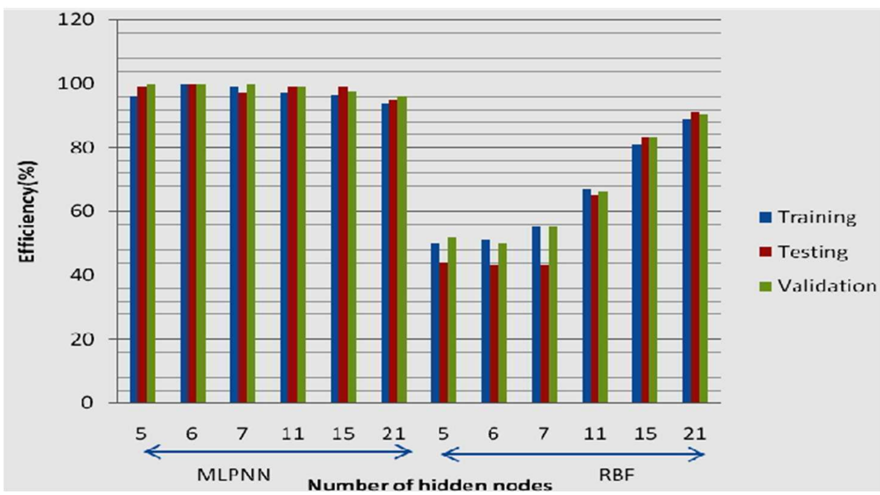

Figure 4.6. Comparative performance comparison of two machine learning algorithms for classifying seizure activity into three categories

As previously demonstrated, MLPNN outperforms RBF in this classification task; so, another comparative performance analysis was conducted. The models were constructed and their efficiency determined by altering the number of features but keeping the number of hidden nodes constant. Figure 4.7 summarises the various comparisons for altering FL in terms of prediction sensitivity.

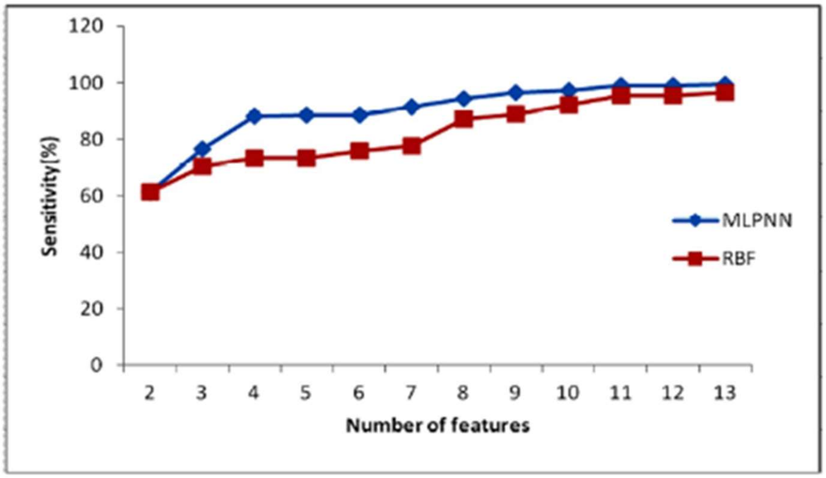

Figure 4.7.Performance Analysis of MLPNN and RBF in terms of sensitivity with same network topology and varying feature index.

The results of subsets of feature vector sets utilised for classification are depicted in Figure 4.8. Figure 4.8 (a) compares two models with the same number of hidden nodes and two features; similarly, Figures 4.8 (b-d) compare models with different FL. As illustrated in the graph, training accuracy is always higher with MLPNN than with RBF, but there is little fluctuation in testing and validation efficiency accuracy once training is complete.

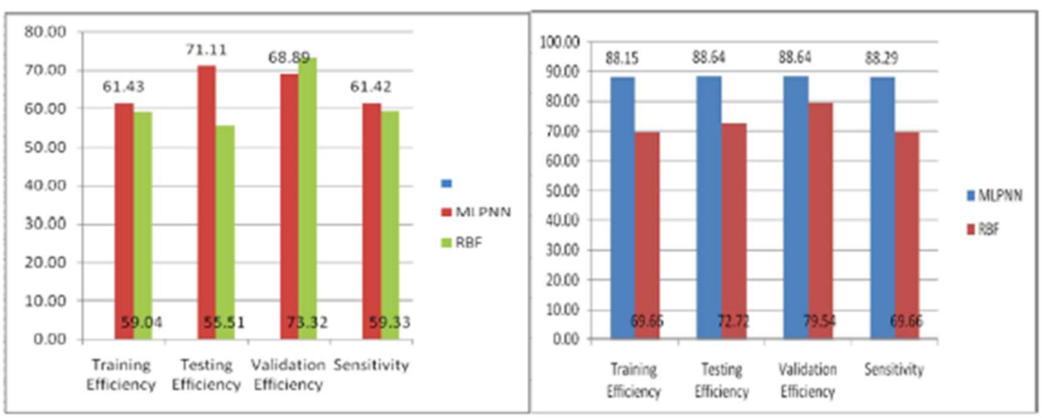

Figure 4.8. Classification Efficiency Analysis of MLPNN and RBF (*a*) Two features with same number of hidden nodes (FL:2) (*b*) Four features (FL:4)

A comparison of the two models for seizure classification using the CAD system is performed. The effectiveness of the best two models in terms of training, testing, and classification is depicted in Figure 4.9. The network design of these networks indicated that the number of hidden nodes varies between the two strategies.

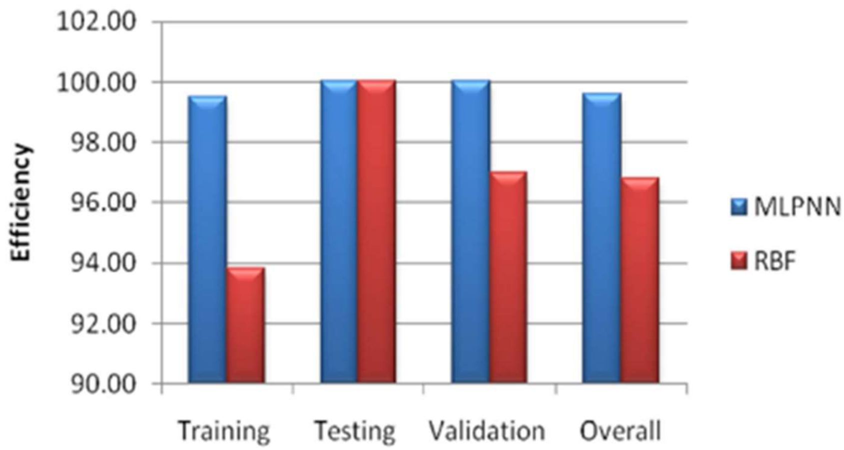

Figure 4.9. Classification Efficiency (in %) for MLPNN and RBF for the final network topology.

The current work compares two machine learning algorithms for classifying epileptic patients' ictal, inter-ictal, and normal states. Even as prototypes, both ANNs demonstrated practical effectiveness, demonstrating the efficacy of machine learning approaches.

Table 4.5: Classification Summary for prediction model with RBFNN providing highest accuracy with topology of 13-30-3

	Normal(Z)	Intict(F)	Ict(S)	Sen Z	Sen F	Sen S	OCA
Normal	97	3	0	97			
INTICT	4	93	2		93.9		96.9
ICT	0	0	100			100	

Note: *Sensitivity, OCA values in %.*

We proved the capability of selecting the number of classification features and found that MLPNN was the superior model in terms of efficiency and number of hidden nodes.

Table 4.6: Confusion Matrix for RBF network with proposed topology

	Normal	Intict	Ict
Total	100	99	100
Correct	97	93	100
Incorrect	3	6	0
ICA (%)	97	93.9	100
IMA(%)	3	6	9

MLPNN may be an excellent contender for achieving 99.3 percent efficiency, compared to 96.9 percent attained by RBF, with a smaller number of hidden nodes, resulting in a simpler design. The results of this study indicate that a classification system based on ANNs can assist in automating the analysis of neurophysiologic signals, and that the quantity and kind of parameters used as feature set determine the type of network to utilise for maximum system efficiency. In all experiments, RBF provided comparable accuracies. The evaluation parameters for RBF that provide the highest classification accuracy are listed in Table 4.5, and the finalised model's confusion matrix is presented in Table 4.6. Classification accuracy of 96.8 percent was achieved with 30 hidden nodes including a greater number of hidden neurons. Classification techniques' performance is quantified in terms of classification accuracy and misclassification. Individual classification accuracy is 97 percent, 93.9 percent, and 100 percent for normal, interictal, and ictal classes, respectively, with a misclassification rate of 3%, 6%, and 9%. The inter-ictal condition has a sensitivity of 93.9 percent, whereas the ictal condition has a sensitivity of 100 percent. The normal condition has a sensitivity of 97 percent. The overall classification accuracy for the three-class classification problem is 96.9 percent.

(d) EXPERIMENT 3

This experiment examines two classification problems, proposing a topology and evaluating known binary classifiers for seizure classification.

(i) Methodology

Advanced signal and data processing techniques, combined with increased computing power, result in improved computing tools for recording and analysing EEG signals. The new techniques provide an in-depth understanding of brain mechanisms; computationally sophisticated signal processing techniques have increased the accuracy and precision of signal analysis. The current methodology is used to a bi-class problem in order to demonstrate the generalizability of the soft computing paradigm technique. The techniques could be utilised to obtain more detailed information about the EEG linked with epilepsy occurrences in an automated manner. Thirteen statistical features collected and selected from raw signals are examined in this paper to determine their suitability for discriminating between two classes of epileptic subjects. The findings of various classifiers are shown, along with their classification results.

Support Vector Machine (SVM) as classifier

SVMs are generally used for classification tasks because they can handle several continuous and categorical variables by creating hyperplanes in a multidimensional space to distinguish between distinct instances of different class labels [31]. It first attempts to map the input feature vector into a high-dimensional feature space, either linearly or via methods dependent on the kernel type used, with the goal of minimising error over the training dataset. A division that is optimal is one in which two classes are separated by the greatest possible margin. It enables users to select from a variety of accessible kernel modes and functions. We predominantly used Gaussian RBF and polynomial kernel functions in our work because to their localised and finite responses over the full real x-axis range. The cut-off number for prediction in our case is 0, which means that a query vector is considered a member of the positive dataset if its score is larger than 0 and a member of the negative dataset if its score is less than 0 [172]. The number of support vectors was determined to be 91 for a polynomial kernel with degree=3.000 and gamma=0.077 (84 bounded). The number of support vectors was determined to be 26 for SVMs with radial basis functions as kernels and gamma=0.077. Three critical parameters are evaluated while evaluating the classifier's performance and validity: Sensitivity, Selectivity, and Accuracy are all measured using the confusion matrix shown in Table 4.7.

Table 4.7 Classification performance with SFV using SVM classifier for two-class seizure classification

Feature vector	Classifier		CM		Acc.	Sen.	Spec.	Miss rate
			NOR	ICT				
SFV	SVM	NOR	97	3	98.0%	97.0%	99.0%	0.02
		ICT	1	99				

Note: *CM: Confusion Matrix, Acc. Accuracy for binary classification, Sen: Sensitivity, Spec: Specificity expressed in percentage.*

Each confusion matrix is evaluated by computing the SVM efficiency parameters for each kernel. In light of the challenge at hand, the highest result for seizure classification was found using SVM with RBF kernels with a classification accuracy of 98.0 percent. When the CM of SVM is analysed, the other two notable results are a sensitivity of 97 percent and a specificity of 99 percent. Only 2% of cases depart from the established categorisation.

Naive Bayes as classifier

Naive Bayes models are simple to use and interpret, and they are powerful classification tools because they incorporate a number of methods for modelling the conditional distributions of the inputs, such as normal, lognormal, gamma, and Poisson. As shown in Table 4.8, 97.5 percent of individuals are correctly classified into three classes with a sensitivity of 97 percent and a specificity of 98 percent. Only 2.5% of patients are misclassified, resulting in unclear data.

Table 4.8: Classification performance with SFV using Naive Bayes classifier for two-class seizure classification

Feature vector	Classifier		CM		Acc.	Sen.	Spec.	Miss rate
			NOR	ICT				
SFV	Naive Bayes	NOR	98	2	97.5%	97.0%	98.0%	2.5%
		ICT	3	97				

Note: *SFV: Signal Feature Vcetor, CM: Confusion Matrix for classification.*

Radial Basis Function neural network (RBFNN) as classifier

The Gaussian function and the least squares (LS) criterion are used as the activation function and goal function, respectively, in this study for RBFNN. The network's inputs are routed to the middle layer kernels, which are followed by the output layer. The amount of hidden neurons is determined by extensive training and testing. Seizures are classified accurately 95.5 percent of the time. As shown in Table 4.9, the true positive rate is 96 percent and the true negative rate is 95.0 percent.

Table 4.9: Classification performance with SFV using RBF classifier for two-class seizure classification

Feature vector	Classifier		CM		Acc.	Sen.	Spec.	Miss rate
			NOR	ICT				
SFV	RBF	NOR	95	5	95.5%	96.0%	95.0%	4.5%
		ICT	4	96				

CONCLUSION

The purpose of this objective is to construct an automated, robust, and efficient predictive model for diagnosing an epileptic patient's status using EEG signals. Classification is performed using quantitative characteristics extracted from neurophysiologic signals that are utilised to train the networks, and the networks' performance is examined to ensure their efficacy. The comparative analysis is based on differences in the topology of the networks and the feature vectors used to train the networks. From a strategic standpoint, we developed a fully automated neural network model capable of classifying seizure activity into ictal, interictal, and normal states with an accuracy of 99.3 percent and a misclassification error of 0.67 percent. Additionally, the comparison of two machine learning approaches (MLM) for epilepsy prediction using the same dataset is emphasised. For classification purposes, perceptron neural networks and radial basis function neural networks excel in the field of mathematical modelling. Both algorithms are tried and evaluated in this research work for two-class and three-class classification, and comparison findings are analysed comprehensively.

Accurate classification of features within two classes is also critical for improving the detector's performance. As such, this objective also attempts to establish a computer-assisted diagnostic system for binary classification of electroencephalogram (EEG) signals. Numerous approaches for monitoring an epileptic patient that could be implemented in hardware are examined. The classifier chosen should be capable of establishing a nonlinear decision boundary between seizure and non-seizure feature vectors. The effectiveness of approaches is determined by their performance metrics, sensitivity, specificity, and accuracy. In comparison to other soft computing paradigms, it has been discovered that artificial neural networks and support vector machines with radial basis function kernel are more successful.

The findings of this research clearly suggest that a classification system based on ANNs should be used to automate the interpretation of neurophysiologic signals. The amount and type of parameters utilised in the feature set determine the network topology that will be employed to maximise the system's efficiency. The positive findings produced by the proposed SVM-based HCAD system in the presence of a diverse dataset suggest that it might be employed in a clinical setting to assist neurologist in diagnosing epileptic seizures during ordinary clinical practise. By progressing sequentially from the general classification problem of normal versus abnormal EEG signal to the more specific classification challenge of exact abnormality diagnosis, CAD system designs with hierarchically positioned classifiers improve performance. The encouraging results demonstrate the efficiency and utility of systems designed for categorization and prediction of epileptic patients' normal, ictal, and interictal states.

REFERENCES:

[1] Atlas: Epilepsy Care in the World. World Health Organization, 2018.

[2] J.Gotman, “Automatic recognition of epileptic seizures in the EEG”, Electroen Clin Neuro., vol.54, pp.530–540, 2002.

[3] H.Gastaut, "Dictionary of Epilepsy. Part I: Definitions", World Health Organization. 2003.

[4] C. Logar, B. Walzl, and H. Lechner, “Role of long-term EEG monitoring in diagnosis and treatment of epilepsy”, European Neurology, vol. 34, pp.29-30, 2004.

[5] J.C. Rajapakse, A. Cichocki and V.D. Sanchez, “Independent component analysis and beyond in brain imaging: EEG, MEG, fMRI, and PET”, In Proc. of IEEE Conf. on Neural Information Processing, vol.1, pp. 404-412, 2010

[6] S. Sanei and J.A. Chambers, EEG signal processing. Wiley-Interscience, 2012.

[7] J Gotman, "Automatic seizure detection: Improvements and evaluation", Electroencephalogr. Clin. Neurophysiol., vol.76, pp.317–324,2002.

[8] Merlet, I, Garcia-Larrea, et al., “Simplified projection of EEG dipole sources onto human brain anatomy”, Neurophysiol Clin., vol.29 (1), pp. 9-52, 2009.

[9] N. R. Carlson, “Structure and Functions of the Nervous System”, Foundations of physiological psychology, vol. 5(3), 2012b.

[10] E. Callaway, P.R. Harris, "Coupling between cortical potentials from different areas", Science vol.183 (4127), pp. 873–875, 2004.

[11] W. Chaovalitwongse, P. Pardalos, L. D. Iasemidis, D. S. Shiau, and J. C. Sackellares, “Dynamical Qualitative and Quantitative Evaluation of EEG Signals in Epileptic Seizure Recognition”, MECS I.J. Intelligent Systems and Applications, vol. 06, pp. 41-46, 2016.

[12] W.J.R. Dunseath, E. F. Kelly, "Multichannel PC-based data-acquisition system for high-resolution EEG", IEEE Transactions on Biomedical Engineering, vol.42 (12), pp.1212-1217, 2005.

[13] Ali Bulent Usakli, “Improvement of EEG Signal Acquisition: An Electrical Aspect for State of the Art of Front End”, Computational Intelligence and Neuroscience, vol. 2010, Article ID 630649, 7 pages, 2012.
[14] I. Ulbert, E. Halgren, G, Heit, G. Karmos, " Multiple Microelectrode-recording System for Human Intracortical Applications, Journal of Neuroscience Methods, and vol.106 (1): pp.69-79, 2011.
[15] Teplan, “Fundamentals of EEG Measurement,” Measurement Science Review, vol. 2, pp.1-11, 2012.
[16] Andrzejak, K. Lehnertz, F. Mormann, C.Rieke, P. David, and C. Elger, “Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state”, Phys. Rev. E., vol.4 (6), 2011.
[17] R. Palaniappan, “Brain computer interface design using band powers extracted during mental tasks”, In Proceedings of the 2nd International IEEE EMBS Conference on Neural Engineering, 2015.
[18] U.R. Acharya, Sree S. Vinitha, G. Swapna, R. Joy Martis, J.S.Suri., “Automated EEG analysis of epilepsy: A review”, Knowledge based systems, vol.45, pp.147–165, 2018.
[19] Kannathal, U. R. Acharya, C. M. Lim, and P. K. Sadasivan, “Characterization of EEG—A comparative study”, Computer Methods and Programs in Biomedicine, vol. 80(1), pp. 17– 23, 2015.
[20] J. Arnhold, K. Lehnertz, P. Grassberger, C.E. Elger, “A robust method for detecting interdependences: application to intracranially recorded EEG”, Physica D, vol.134 (4), pp.419–430, 2009.
[21] Epilepsy: Mechanisms, Models, and Translational Perspectives edited by Jong Rho, Raman Sankar, Carl E. Stafstrom.
[22] Fabien Lotte, Marco Congedo, Anatole L´ecuyer, Fabrice Lamarche, Bruno Arnaldi, “A review of classification algorithms for EEG-based brain–computer interfaces", Journal of Neural Engineering, Institute of Physics: Hybrid Open Access, vol. 4, pp.24. 2015.
[23] N. Friedman, D. Geiger, and M. Goldszmidt, “Bayesian network classifiers: Machine Learning”, vol.29, pp.131–163, 2007.
[24] H. Adeli, S.L.Hung, "Machine Learning – Neural Networks, Genetic Algorithms, and Fuzzy Sets", New York: Wiley, 2005.
[25] Claude Roberta, Jean-Franc¸ois Gaudyb,and Aime Limogea, “Electroencephalogram processing using neural networks”, Clinical Neurophysiology, vol.113, pp.694–701, 2012.
[26] S. Haykin, "Neural networks: A comprehensive foundation”, New York: Macmillan, 2004.
[27] Dr.R. Sukanesh, and R.Harikumar, “A Patient Specific Neural Networks (MLP) for Optimization of Fuzzy Outputs in Classification of Epilepsy Risk Levels from EEG Signals”, Engineering Letters, vol. 13(2), pp.50-56, 2016.
[28] C Lee, P Chung, J Tsai, and C Chang, “Robust radial basis function neural networks”, IEEE Trans. Syst. Man Cybern.,Part B, Cybern., vol.29, pp.674– 685, 2009.

[29] K. Z. Mao, K.-C. Tan, and W. Ser, “Probabilistic Neural- Network Structure Determination for Pattern Classification”, IEEE Transactions on neural networks, vol. 1(4), pp. 1009-1016, 2010.
[30] A Lima, AI. Coelho, and M Eisencraft, “Tackling EEG signal classification with least squares support vector machines: a sensitivity analysis study”, Comput. BioI. Med, vol 40(8) pp, 705-714, 2015.