ISSN: 0974-5823 Vol. 7 No. 2 February, 2022

International Journal of Mechanical Engineering

Radial Basis Function Network for the Identification of Dementia

G. Sophana[1] and Dr. V. Joseph Peter[2]

[1]Research Scholar, Research Department of Computer Science, Kamaraj College, Affiliated to Manonmaniam Sundaranar University,Thoothukudi

[2]Associate Professor, Research Department of Computer Science, Kamaraj College, Affiliated to Manonmaniam Sundaranar University, Thoothukudi

Abstract

This research work proposed Radial Basis Function (RBF) Network to identify the patterns of Dementia Symptom and find the Dementia severity class labels. In this, the data present in the Dementia dataset is first resampled using Synthetic Minority Oversampling Technique (SMOTE). This pre-processing helps us to get more reliable and accurate dementia detection performance. The RBF network is performed over these training and testing data to predict targeted dementia severity class labels. These predicted results have been compared with the actual dementia class for evaluating performance. The performance of RBF network over five class labels are calculated using four metrics, namely Accuracy, Precision, Recall and F1-Score. The performance of RBF network achieves higher accuracy than random forest and Naïve Bayes algorithms.

Key Words: Artificial Intelligence, Dementia Detection, Machine Learning, Radial Basis Function (RBF) Network, Synthetic Minority Oversampling Technique (SMOTE).

1. INTRODUCTION

Dementiais a type of infection that influences basic psychologicalcapacitiesfor older folks (Doan et al., 2021). It causes the symptoms related to cognitiveabilitieswhichcontrarilyinfluence language,memory,andthinking (Wilkinson et al., 2018). The symptoms of Dementia are mood changes, confusingday fromthe night, Inabilitytorecognize familiar objects, aloss of abilityfor doing normal tasks, memoryloss, vision loss, loss of coordination, challengesin solving or planning problems, use of inappropriatewords (Walters et al., 2016).

Mostly, the MRI and neuropsychological data are applied on machine learning and Artificial Neural Network (ANN) algorithms to predict dementia severity classes based on Clinical Dementia Rating (CDR) scores. But, an early identification of Dementia from the symptoms of affected patients' is still challenging for the medical practitioners, which will help us to improve the diagnosis and treatment process. Gill et al. (2020) performed prediction on Neuropsychiatric symptoms data using information gain feature selection, and logistic tree classifier. Mathkunti NM and Rangaswamy S (2020) used supervised SVM algorithm for the prediction of Dementia. Bhagya Shree SR and Sheshadri HS (2014) processed patient records to fond whether patient affected by Dementia or not. The ANN based algorithms are providing better performance in medical and healthcare solutions, which performs efficient training and testing process. Altug Y and Zerrin I (2018) applied ANN algorithm to find Dementia and Alzheimer disease. The ANN based RBF network performs better in dementia identification.

The non-linear activation function is used in the layers of RBF network. It learns from given data and translates into class probabilities. It has the advantages of learning ability, strong noise tolerance, good generalization, and easy design. In this work, RBF network is applied over the Dementia dataset to identify the patterns of thirteen early symptoms, like delusion and illusion, indifference about clothing, irritable and suspicious, loss of interest, complex topics, planning, repetitive talking, time consuming, self-meditation, forgetting one of two items, context understanding, and cleaning up.

This work organized into following sections: section 2 reviews existing literatures in dementia detection; section 3 details the RBF network based dementia identification algorithm; section 4 focuses the experimental results and their comparison; section 5 summarizes this chapter.

2. RELATED WORKS

An automated pattern classification approach plays a vital role in Dementia identification at early stage. Most of the authors used machine learning and ANN algorithms for dementia identification problems. Battineni et al. (2020) developed the machine learning based pattern identification methods, like K-Nearest Neighbor (KNN), Logistic Regression, and Support Vector Machine (SVM) algorithms to identify Dementia and Non-Dementia patients from OASIS (Open Access Series of Imaging Studies) dataset. Zhu et al. (2020) applied Ada Boost, LogitBoost, Naïve Bayes, and SVM algorithms to diagnose normal, Dementia, Very Mild Dementia (VMD), and Mild Cognitive Impairment (MCI) dementia classes.

Shanmuga Skandh Vinayak et al. (2020) performed binary classification from OASIS cross-sectional and longitudinal MRI data. In this, the Dementia and Non-Dementia classes are identified using seven machine learning models, like ensemble classification, ensemble gradient boosting, Naïve Bayes, KNN, SVM, ANN, random forest. Nori et al. (2019) used de-identified dataset to identify memory loss disorders, bipolar disorder, mild cognitive impairment, Parkinson's disease. Bin-Hezam, R and Ward, TE (2019) used Neuroimaging Initiative (ADNI) dataset to detect Alzheimer's disease from with 92% of accuracy. Grueso S and Viejo-Sobera R (2021) reviewed various algorithms on the performance of Alzheimer's disease identification from Positron Emission Tomography (PET), and MRI imaging data. Most of the existing Dementia detection algorithms are used neurophysiological and Magnetic Resonance Imaging (MRI) data.

Altug Y and Zerrin I (2018) used Naïve Bayes, Decisiontree, and Random Forest methods for performing this detection task. But these machine learning algorithms is highly depends on the parameter selection by the programmer. The random forest and Naïve Bayes methods produce volatile performance on real-world dementia data. Thus, the random forest based Dementia detection produces F1-score is 0.67, accuracy value is 0.75, recall is 0.75, and precision is 0.63. The Naïve Bayes based Dementia identification algorithm yields F1-score is 0.8, accuracy value is 0.84, recall is 0.85, and precision is 0.87.

Recently, Anuradha G and Najumnissa Jamal (2021) used Feed Forward Artificial Neural Network (FFANN) to diagnose Dementia in Electro Encephalography (EEG) signals. The performance of the FFANN work calculated using Accuracy, Sensitivity, and Specificity values. This research work proposed ANN based Radial Basis Function (RBF) network for dementia identification.

3. PROPOSED METHODOLOGY

This proposed work applied RBF network for dementia identification. It accomplishes four major steps: experimental data, pre-processing, and RBF network based dementia identification, methodology. The process flow architecture of RBF network based dementia identification is visualized in Fig. 1.

Figure 1: The process flow architecture of RBF network based dementia identification

3.1. Experimental Data

This algorithm performs classification in dementia data the collected data from Rengasamy Nursing Home in Thoothukudi District, Tamil Nadu, India of 600 affected patients. The CDR score values are given to the data samples of every dementia patients for thirteen symptoms namely illusion, delusion, indifference about clothing, irritable and suspicious, loss of interest, complex topics, planning, time consuming, self-meditation repetitive talking, forgetting one of two items, cleaning up, and context understanding. Further, the class labels are prepared for RBF network by calculating average CDR values. There are five class labels present in the dataset: Normal; Very Mild; Mild; Moderate; and Severe.

3.2. Resampling of Dementia Data

The numbers of unequal data samples from Dementia dataset are resampled using SMOTE (Chawla et al., 2002) to get balanced samples in five dementia classes. The number of data samples before and after pre-processing in Dementia dataset is mentioned in Table 1. Here, class 2 (Mild Dementia) composed with the maximum amount of data samples is 186, which is called as majority class. The remaining Class 0 (No Dementia), Class 1 (Very Mild Dementia), Class 3 (Moderate Dementia), and Class 4 (Severe Dementia) are called minority classes. The number of samples from these minority classes are synthetically increased using SMOTE (Mukherjee M and Khushi M, 2021). After, all class labels contain equal 186 number of data samples.

Table 1. The number of samples after and before resampling using SMOTE

Dementia Dataset			
S. No	**Class Label Name**	**Actual volume of Samples**	**Rebalanced Number of Samples**
1	**Class 0 (No Dementia)**	75	186
2	**Class 1 (Very Mild Dementia)**	164	186
3	**Class 2 (Mild Dementia)**	186	186
4	**Class 3 (Moderate Dementia)**	152	186
5	**Class 4 (Severe Dementia)**	23	186
Total		**600**	**930**

3.3. RBF Network based Dementia Detection

The pre-processed dementia data samples are divided for testing (25%) and training (75%) processes. Totally, 600 data samples are available in the dementia dataset. After applying SMOTE based pre-processing, the number of data samples increased from 600 into 930 samples. In this, 697 data samples are used for training and remaining 233 samples from pre-processed data are used for testing process. RBF network is processed over training dementia samples to learn the dementia symptoms patterns automatically. It has input hidden and output layers.

The training data samples are trained in input, hidden, and output layers of RBF network. This network used an activation function called radial basis function. During training phase, the network fits a non-linear curve for the data variables, which runs through the stochastic optimization technique. The input layer performs normalization process for input data samples and then forwards their computed results to the upcoming hidden layer. The hidden layer neurons in RBF network are initially trained by backpropagation, which is a curve fitting method. The hidden layer nodes satisfy the non-linearly separable OR functions and performs a set of RBF functions.

For each hidden layer node, this algorithm finds the cluster centers using k-means algorithm and then the radial basis function is centered in these clusters. Here, the distance between cluster center and data points is calculated using the radial basis function. To achieve this, the receptor t is first defined and then the confronted maps have been drawn around this receptor. After, a radial distance r is defined using following Eqn. (1)

$$r = ||x - t|| \qquad (1)$$

where, x is the input, and t is the receptor. The radial function h(x) is calculated based on radial distance is given in Eqn. (2)

$$h(x) = \exp(-r^2/2\sigma^2) \qquad (2)$$

where, σ is called the variance, and $\sigma > 0$. This hidden layer outcome h(j) is passed to the output layer (summation layer). Here, the value of hidden neurons h_j is multiplied with weights w_j and perform weighted average of these multiplications called f(x) function. The formula for calculating the final summation outcome of RBF neural network is defined in Eqn. (3).

$$f(x) = \sum_{j=1}^{m} w_j h_j(\mathrm{x}) \qquad (3)$$

where, j=1,2,3…m, x is the input variable, w_j is the weight value, h_j is the outcome of radial basis function from hidden layer. This summed outcome f(x) is categorically distributed into five dementia severity class labels using sigmoid activation function. The classification process is only done in the output layer. After training, the learned parameters and RBF network model is further used to detect the severity class labels in dementia dataset. This network extracted and classified dementia severity labels automatically. There five dementia class labels are identified by the algorithm. The architecture of RBF network is visualized in Fig. 2. The predicted class labels are compared with original dementia severity labels from dataset for finding performance evaluation using F1-Score, Accuracy, Recall and Precision.

Figure 2: The radial basis function network

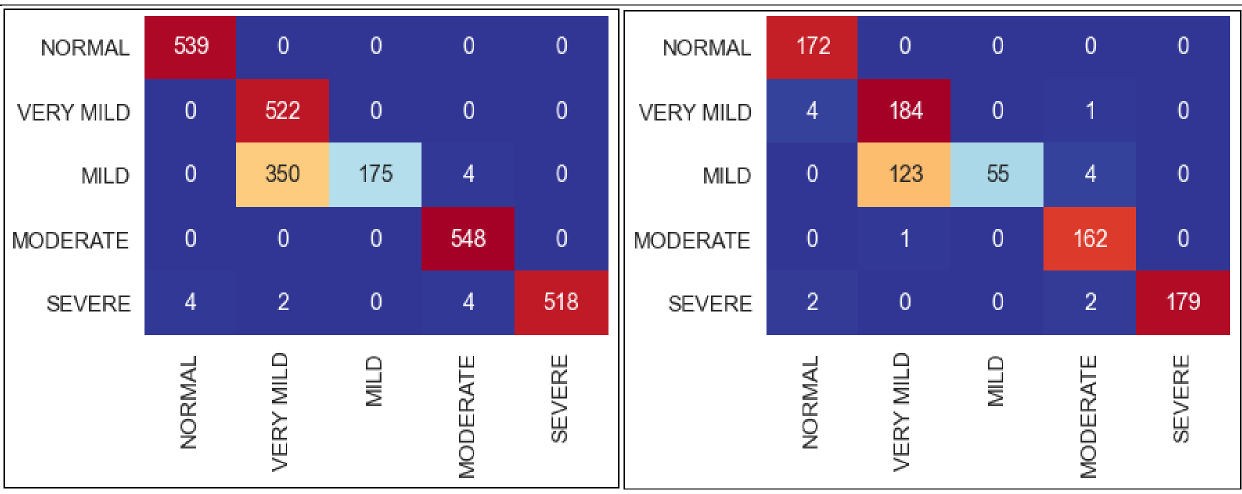
4. RESULTS AND DISCUSSION

4.1. RBF Network Performance

In this work, the data samples from dementia dataset are rebalanced using SMOTE. It provides greater performance for training and testing samples and also reduces overfitting problem. The training data samples are first trained in input, hidden, and output layers of RBF network. After performing training, the RBF network model and trained parameters are applied over the testing data samples to detect the class labels. Table 2 shows the RBF based dementia detection performance and Fig. 3 shows their Confusion matrix. The average performance of RBF method achieves F1-score is 0.83, recall is 0.85, precision is 0.91, and accuracy value is 0.83.

Table 2: Performance of RBF network based dementia identification

		Dementia Data			
S. No	**Method Name**	**Accuracy value**	**Precision value**	**Recall value**	**F1-Score Value**
1	RBF Network (Training)	0.85	0.93	0.89	0.88
2	RBF Network (Testing)	0.80	0.88	0.80	0.78
3	**RBF Network (Average)**	**0.83**	**0.91**	**0.85**	**0.83**



(a) Training **(b) Testing**

Figure 3. Confusion matrix of RBF based dementia detection

4.2. Comparison of RBF performance with Machine Learning Methods

The predicted RBF network based dementia class labels are compared with the calculated performance values of Random Forest, and Naïve Bayes detection methods. Table 3 and Fig. 4 depict the performance comparison of RBF network with machine learning methods.

Table 3: comparison of RBF network with machine learning methods

Dementia Data					
S. No	Method	Accuracy Value	Precision value	Recall value	F1-Score value
1	Random Forest	0.75	0.63	0.75	0.67
2	Naïve Bayes	0.84	0.87	0.85	0.85
3	Proposed RBF Network	0.83	0.91	0.85	0.83

A Naïve Bayes yield F1-score is 0.85, accuracy value is 0.84, recall is 0.85, and precision is 0.87. Random Forest produces F1-score is 0.67, recall is 0.75, precision is 0.63, an accuracy value is 0.75. Naïve Bayes method has less performance than the Random Forest method. Thus, our proposed RBF network achieves 15%, and 29% of higher accuracy respectively than Naïve Bayes and Random Forest methods.

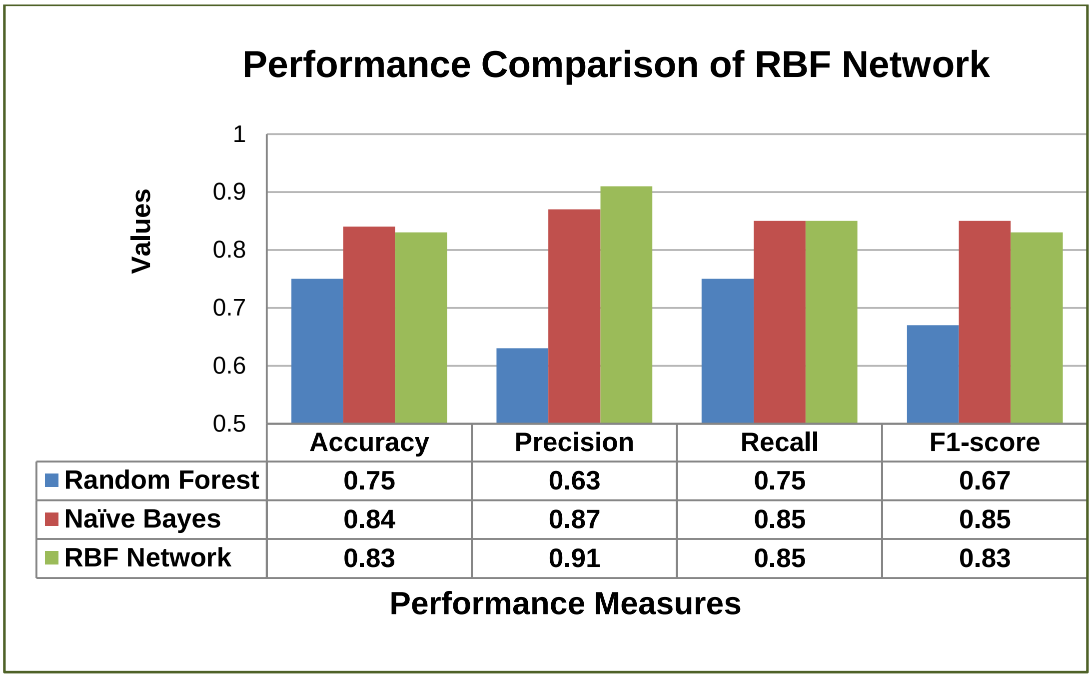


Figure 4. comparison of RBF network with machine learning methods

5. CONCLUSION

The identification of Dementia severity class labels from the symptoms of affected patients' is still challenging for the medical practitioners, which will help us to improve the disease diagnosis as well as treatment process. In this work, the ANN based RBF network is used for dementia identification. The imbalanced class labels are first rebalanced using SMOTE and processed in input, hidden, and output layers of RBF network for dementia prediction. The performance of RBF network based dementia detection achieves F1-score is 0.83, accuracy value is 0.83, recall is 0.85, and precision is 0.91, which is 7% and 29% higher accuracy respectively than the Naïve Bayes and Random Forest algorithm.

REFERENCES

1. Altug, Y & Zerrin, I 2018, ‘Application of Artificial Neural Networks in Dementia and Alzheimer’s Diagnosis’, 978-1-5386-1501-0/18/$31.00 ©2018, IEEE Access, pp. 1-5, doi: 10.1109/SIU.2018.8404447
2. Battineni, G, Chintalapudi, N, & Amenta, F 2020, ‘Comparative Machine Learning Approach in Dementia Patient Classification using Principal Component Analysis’, Proceedings of the 12th International Conference on Agents and Artificial Intelligence (ICAART 2020) – vol. 2, pp. 780-784, doi: 10.5220/0009096907800784.
3. Bhagya Shree, SR, Sheshadri, HS 2014, ‘An initialinvestigation in the diagnosis of Alzheimer’sdisease using various classification techniques’,InternationalConferenceonComputational IntelligenceandComputingResearch,IEEE,2014.
4. Bin-Hezam, R & Ward, TE 2019, ‘A Machine Learning Approach Towards Detecting Dementia Based on Its Modifiable Risk Factors’, International Journal of Advanced Computer Science and Applications, vol. 10, no. 8, pp. 1-9.
5. Doan, DNT, Ku, B, Choi, J, Oh, M, Kim, K, Cha, W & Kim, JU 2021, ‘Predicting Dementia With Prefrontal Electroencephalography and Event-Related Potential’, Frontiers in Aging Neuroscience, vol. 13, no. 659817, doi: 10.3389/fnagi.2021.659817
6. Gill, S, Mouches, P, Hu, S, Rajashekar, D, MacMaster, FP, Smith, EE, Forkert, ND, & smail, Z 2020, ‘Using Machine Learning to Predict Dementia from Neuropsychiatric Symptom and Neuroimaging Data’, Journal of Alzheimer’s Disease, vol. 75, pp. 277–88, doi: 0.3233/JAD-191169
7. Grueso, S &Viejo-Sobera, R 2021, ‘Machine learning methods for predicting progression from mild cognitive impairment to Alzheimer’s disease dementia: a systematic review’, Alzheimer's Research & Therapy, vol. 13, no. 162, pp. 1-29, doi: https://doi.org/10.1186/s13195-021-00900-w
8. Mathkunti, NM, & Rangaswamy, S 2020, ‘Machine Learning Techniques to Identify Dementia’, SN Computer Science, vol. 1, no. 118, pp. 1-7, https://doi.org/10.1007/s42979-020-0099-4.
9. Mukherjee, M & Khushi, M 2021, ‘SMOTE-ENC: A Novel SMOTE-Based Method to Generate Synthetic Data for Nominal and Continuous Features’, Applied system innovation, vol. 4, no.18, https://doi.org/10.3390/asi4010018.
10. Nori, VS, Hane, CA, Martin, DC, Kravetz, AD, Sanghavi, DM 2019, ‘Identifying Incident Dementia by Applying Machine Learning to a Very Large Administrative Claims Dataset’. PLOS ONE, vol. 14, issue. 7, no. e0203246, doi: https://doi.org/10.1371/journal.pone.0203246.
11. Shanmuga Skandh Vinayak, E, Shahina, A & Nayeemulla Khan, A 2020, ‘Dementia Prediction on OASIS Dataset using Supervised and Ensemble Learning Techniques’, International Journal of Engineering and Advanced Technology (IJEAT), ISSN: 2249-8958, vol. 10, issue 1, pp. 244-254.
12. Latchoumi, T. P., & Parthiban, L. (2022). Quasi oppositional dragonfly algorithm for load balancing in cloud computing environment. Wireless Personal Communications, 122(3), 2639-2656.
13. Ranjeeth, S., Latchoumi, T. P., & Paul, P. V. (2021). Optimal stochastic gradient descent with multilayer perceptron based student's academic performance prediction model. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science), 14(6), 1728-1741.
14. Garikapati, P., Balamurugan, K., Latchoumi, T. P., & Malkapuram, R. (2021). A Cluster-Profile Comparative Study on Machining AlSi7/63% of SiC Hybrid Composite Using Agglomerative Hierarchical Clustering and K-Means. Silicon, 13(4), 961-972.
15. Karnan, B., Kuppusamy, A., Latchoumi, T. P., Banerjee, A., Sinha, A., Biswas, A., & Subramanian, A. K. (2022). Multi-response Optimization of Turning Parameters for Cryogenically Treated and Tempered WC–Co Inserts. Journal of The Institution of Engineers (India): Series D, 1-12.