Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 9, August 2021: 6561-6573

An Automated Multi-phase Dilated CNN for Pattern Classification in Detection of Dementia

G. Sophana[a] , Dr. V. Joseph Peter[b]
[a]Research Scholar, Research Department of Computer Science, Kamaraj College, Affiliated to Manonmaniam Sundaranar University.
[b]Associate Professor, Research Department of Computer Science, Kamaraj College, Affiliated to Manonmaniam Sundaranar University.

Abstract

This research work proposed an automated Multi-phase Dilated Convolutional Neural Network (MDCNN) based pattern classification approach for early detection of dementia. In this, there are thirteen early symptoms related features are extracted from dementia dataset and their patterns are classified to detect five dementia severity classes like normal, very mild, mild, moderate and severe. First, the imbalanced numbers of samples in each dementia classes' from a dataset are pre-processed or rebalanced using Synthetic Minority Oversampling Technique (SMOTE) for getting more reliable and accurate performance. This rebalanced outcome is further processed using proposed MDCNN architecture to extract features automatically from input data. These outcome features are further flattened and fed into sigmoid activation to predict targeted class labels. From experimental evaluation, this proposed dementia detection method achieves 15% higher accuracy than machine learning methods and 7% higher accuracy than deep learning methods.

Keywords: Artificial Intelligence, Dementia Detection, Deep Learning, Machine Learning, Multi-phase Dilated Convolutional Neural Network (MDCNN), Synthetic Minority Oversampling Technique (SMOTE).

1. Introduction

Dementia is a group of various symptoms that accompanies the impairment of cognitive function of brain by changes in emotional control, motivation, behavior and mood [12]. Dementia affected people can have problems with communication, attention, memory, problem solving, judgement and reasoning etc. The major cause of dementia is biological aging or it occur when parts of brain used for memory, learning, language and decision making are damaged or diseased [3]. Currently, more than 10 million new cases are affected every year and there are 65 million people are live with dementia [20]. Based on symptoms and signs, the dementia disease lies in three stages: early stage; middle stage and late stage. An early stage symptom of dementia includes memory lose like time or familiar places forgetfulness [19]. The middle stage symptoms of dementia include forgetfully of people's names or recent events, communication difficulty, repeated questioning and behavioral changes [22].

The symptoms and signs of last dementia stage are having difficulty in recognizing friends and relatives, becoming unaware of the place and time, having walking difficulty, increasing the need for assisted self-care and aggressive behavioral changes, etc. The timely and automated identification of proper responses and early warning to dementia occurrence can enhance medical treatment [4]. There are many machine and deep neural network learning approaches are producing promising results in dementia disease identification [7]. This work proposes a pristine MDCNN algorithm to predict dementia using the collected data from 600 affected patients from Rengasamy nursing home in Thoothukudi district, Tamilnadu, India.

The dementia data is collected based on the five disease severity values [16] like normal (severity value is 0 to 0.4), very mild (severity value is 0.4 to 0.75), mild (severity value is 0.75 to 1.5), moderate (severity value is 1.5 to 2.5) and severe (severity value is 2.5 to 3) for thirteen symptoms namely repetitive talking, context understanding, cleaning up, forgetting one of two items, self-meditation, time consuming, planning, complex topics, loss of interest, irritable and suspicious, indifference about clothing, delusion and illusion. These collected data are preprocessed using SMOTE and classified using proposed MDCNN algorithm to predict dementia. The rest of paper organized into following: section 2 discusses the relative dementia detection methods; section 3 focuses the description of proposed dementia detection methodology; section 4 details their experiments and section 5 concludes this paper.

2.Review Of Related Studies

An accurate identification of dementia severity from the dataset is essential for medical assessments and also for treatment planning. Mostly, the authors are used computer-aided machine learning algorithms for dementia detection. Machine learning methods identify complex patterns in a high-dimensional input data, which are then used for clinical predictions in real-time datasets [14]. Naïve Bayes and Random Forest algorithms are performing better in dementia identification [10]. Fubao et al [11] implemented Random Forest based algorithm for diagnosis of dementia severity classes like, mild dementia, mild cognitive impairment, and normal dementia unaffected patients. These methods need handcrafted features for dementia identification.

Gloria et al [13] have been trained and tested dementia dataset with three different machine learning algorithms namely, Artificial Neural Network (ANN), Support Vector Machine (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS). **Xiaojing et al** [17] developed deformation based machine learning method to predict mild cognitive impairment of dementia. **Priyanka et al** [18] diagnosed dementia using different machine learning algorithms like, XgBoost, Linear Discriminant Analysis, Random Forest, K-Nearesr Neighbor (KNN), AdaBoost and Support Vector Machine (SVM). These existing machine methods need programmer interaction, which produces volatile performance on real-world dementia dataset.

To overwhelm existing limitations, deep neural networks are assisted in dementia dataset to learn features in an automated manner [6]. **Jungyoon et al** implemented a deep neural network to predict dementia using big data collected from korea national health survey [1]. **Danial et al** [2] applied deep learning models like Bidirectional Long-Short Term Memory (BLSTM) Network, and Multi-Layer Perceptron for predicting Mild Cognitive Impairment

(MCI) of dementia. These methods perform well in structured data. But, the CNN (Convolutional Neural Network) based methods are having the ability to learn features automatically from large unstructured clinical data [21]. To overcome the existing drawback, an automated MDCNN based classification approach is proposed for early detection of dementia.

3. Proposed Methodology

The proposed MDCNN predicts dementia severity classes among affected patients. There are four major steps for accomplishing this proposed method. Step 1 - Experimental Data, explains about the data collection and class labels present in the dataset. Step 2 - preprocessing, details the data preparation method before classification. Step 3 – feature extraction and classification using MDCN, elaborates the automated feature extraction and classification of dementia class labels using proposed method. Step 4 – performance calculation, the classification performance over dementia severity classes are calculated. The overall proposed MDCN workflow is shown in Figure 1 and elaborated in below subsections.

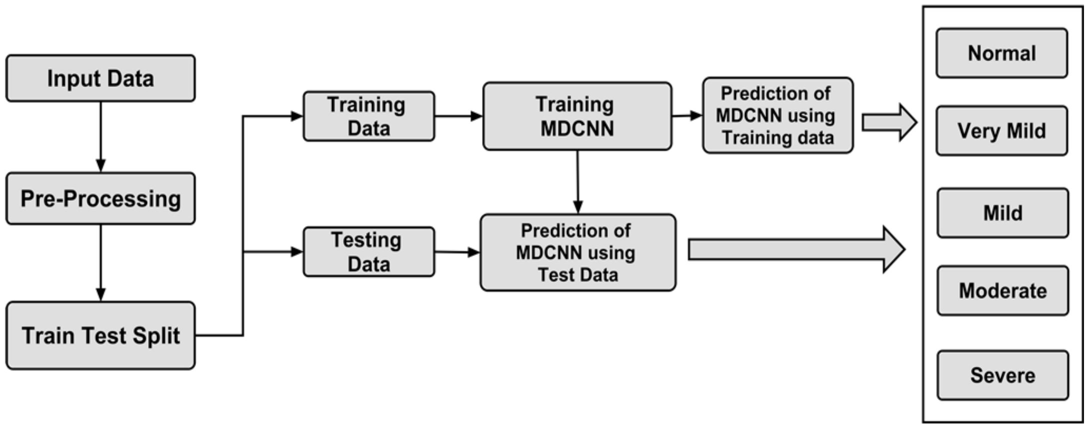

Fig.1. The overall proposed workflow

3.1. Experimental Data

The dementia dataset is manually collected from 600 affected patients from Rengasamy nursing home in Thoothukudi district, Tamilnadu, India. The dementia severity values of thirteen early symptoms related questioners are prepared and collected from affected patients. Then, the Clinical Dementia Ratings (CDR) values [15] are calculated by the average of dementia severity values. This dataset contains five dementia severity classes based on CDR values: normal (CDR value is 0 to 0.4); very mild (CDR value is 0.4 to 0.75); mild (CDR value is 0.75 to 1.5); moderate (CDR value is 1.5 to 2.5) and severe (CDR value is 2.5 to 3).

3.2. Pre-processing of dementia dataset

The dementia dataset composed of imbalanced severity classes. These class labels are rebalanced using SMOTE for getting more reliable and accurate performance. This technique is used for synthesizing the new examples in the minority classes in the dataset to balance the class distribution. It selects the random example from minority class and their nearest neighbors are calculated. The synthetic examples are further created based on the feature space between random examples and their neighbors. The number of samples in dementia dataset contains 75 data in class 0, 164 data in class 1, 186 data in class 2, 152 data in class 3 and 23 data in class 4. The SMOTE technique is applied over these imbalanced numbers of data samples in dementia classes to resample as same number of data samples. Table 1 details the numbers of data in each class before and after pre-processing. Here, class 2 (Mild) contains the maximum number of data that is 186. So, the number of data samples in each class is converted into maximum sample size that is 186 using SMOTE.

Table 1. The dementia data pre-processing using SMOTE.

Dementia Dataset						
Class Labels	**Class 0 (Normal)**	**Class 1 (Very Mild)**	**Class 2 (Mild)**	**Class 3 (Moderate)**	**Class 4 (Severe)**	**Total**
Number of Samples in dataset	75	164	186	152	23	600
Number of Samples after Pre-processing	186	186	186	186	186	930

3.3. Training and Prediction using MDCNN

The pre-processed data in dementia dataset are divided into training and testing data. Totally 600 data present in dementia dataset in which 75% is divided for training and remaining percentage is divided for testing. The training data are first trained using MDCNN network to extract the dementia severity features automatically. This network contains hierarchy of two Dilated Convolutional (DC) blocks, two max pooling [5] layers and sigmoid activation function. The workflow architecture of MDCNN is depicted in Figure 2. First, the preprocessed input data is processed in two different dilated 1D (1- Dimensional) convolutional phases in first DC block. In first phase, input x_i is convolved using Dilation rate 2, kernel size 3 with weight w_i and bias b_i to form 1st phase feature map p_1 is given in Eq. (1).

$$p_1 = f\left(\sum_{\boldsymbol{i=1}}^{n} [w_i * x_i] + b_i\right) \qquad \ldots (1)$$

This first phase feature map is again processed separately using dilated 1D convolution with dilation rate 2 and dilated 1D convolution with dilation rate 4 to yield two different p_{11} and p_{12} feature maps is defined in Eq. (2) and Eq. (3).

$$p_{11} = f\left(\sum_{\boldsymbol{j=1}}^{n} [w_j * x_j] + b_j\right) \qquad \ldots (2)$$

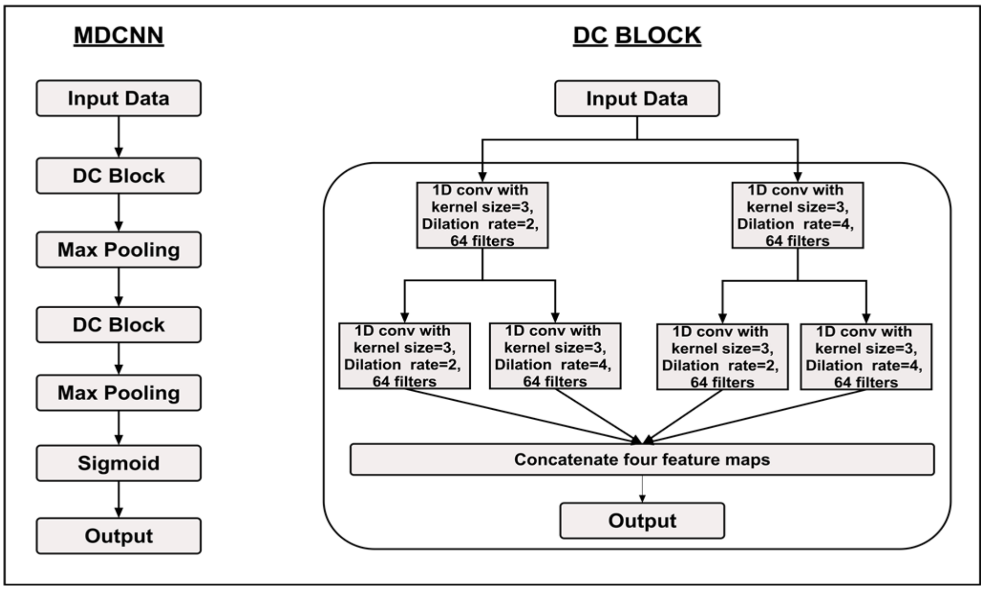

Fig.2. The workflow architecture of MDCNN

$$p_{12} = f\,(\textstyle\sum_{\boldsymbol{k=1}}^{n} \,[w_k \,*\, x_k] + b_k\,) \qquad \ldots (3)$$

In second phase, the preprocessed input x_i is convolved using dilation rate 4, kernel size 3 with weight w_i and bias b_i to form 2nd phase feature map p_2 is given in Eq. (4).

$$p_2 = f\,(\textstyle\sum_{\boldsymbol{i=1}}^{n} \,[w_i \,*\, x_i] + b_i\ ) \qquad \ldots (4)$$

This second phase feature map is again processed separately using dilated 1D convolution with dilation rate 2 and dilated 1D convolution with dilation rate 4 to yield two different p_{21} and p_{22} feature maps is defined in Eq. (5) and Eq. (6).

$$p_{21} = f\left(\textstyle\sum_{\boldsymbol{j=1}}^{n} \left[w_j \,*\, x_j\right] + b_j\right) \qquad \ldots (5)$$
$$p_{22} = f\,(\textstyle\sum_{\boldsymbol{k=1}}^{n} \,[w_k \,*\, x_k] + b_k\,) \qquad \ldots (6)$$

The outcome of two different phases' p_{11}, p_{12}, p_{21}, and p_{22} are concatenated to produce first DC block outcome dc_1 is defined in Eq. (7).

$$dc_1 = p_{11} + p_{12} + p_{11} + p_{12} \qquad \ldots (7)$$

The concatenated outcome dc_1 is then processed in 1st max pooling layer with pool size 2 for reducing dimensionality and computational load. The downsampled outcome further processed in the upcoming second DC block and second max pooling layer to extract dementia severity features from the dataset.

Table 2: The detailed description of parameters used in proposed MDCNN architecture.

MDCNN					
Layer Name	**Phase Name/ Phase Layer Name**	**Input Size**	**Input Variable Name**	**Parameters**	**Output Size**
Dense	**Phase 1 / Conv 1**	14x1	Pre-processed Input	1D Conv, Dilation rate = 2, Stride =1,	14x64

Block 1				ReLU [9], kernel size=3, 64 filters.	
	Phase 2 / Conv 2	14x1	Pre-processed Input	1D Conv, Dilation rate = 4, Stride =1, ReLU, kernel size=3, 64 filters.	14x64
	Phase 1 / Conv 11	14x64	Conv 1	1D Conv, Dilation rate = 2, Stride =1, ReLU, kernel size=3, 64 filters.	14x64
	Phase 1 / Conv 12	14x64	Conv 1	1D Conv, Dilation rate = 4, Stride =1, ReLU, kernel size=3, 64 filters.	14x64
	Phase 2 / Conv 21	14x64	Conv 2	1D Conv, Dilation rate = 2, Stride =1, ReLU, kernel size=3, 64 filters.	14x64
	Phase 2 / Conv 22	14x64	Conv 2	1D Conv, Dilation rate = 4, Stride =1, ReLU, kernel size=3, 64 filters.	14x64
	Concatenate Layer 1	4 Features of 14x64	Conv 11, Conv 12, Conv 21, and Conv 22	Concatenate four feature maps (Conv 11, Conv 12, Conv 21, and Conv 22)	14x256
Max Pooling Layer 1	-	14x256	Concatenate Layer 1	Pool size=2	7x256
Dense Block 2	**Phase 1 / Conv 1**	7x256	Max Pooling Layer 1	1D Conv, Dilation rate = 2, Stride =1, ReLU, kernel size=3, 64 filters.	7x64
	Phase 2 / Conv 2	7x256	Max Pooling Layer 1	1D Conv, Dilation rate = 4, Stride =1, ReLU, kernel size=3, 64 filters.	7x64
	Phase 1 / Conv 11	7x64	Conv 1	1D Conv, Dilation rate = 2, Stride =1,	7x64

				ReLU, kernel size=3, 64 filters.	
	Phase 1 / Conv 12	7x64	Conv 1	1D Conv, Dilation rate = 4, Stride =1, ReLU, kernel size=3, 64 filters.	7x64
	Phase 2 / Conv 21	7x64	Conv 2	1D Conv, Dilation rate = 2, Stride =1, ReLU, kernel size=3, 64 filters.	7x64
	Phase 2 / Conv 22	7x64	Conv 2	1D Conv, Dilation rate = 4, Stride =1, ReLU, kernel size=3, 64 filters.	7x64
	Concatenate Layer 2	4 Features of 7x64	Conv 11, Conv 12, Conv 21, and Conv 22	Concatenate four feature maps (Conv 11, Conv 12, Conv 21, and Conv 22)	7x256
Max Pooling Layer 2	-	7x256	Concatenate Layer 2	Pool size=2	3x256
Flatten Layer	-	3x256	Max Pooling Layer 2	Dropout=0.1	768x1
Dense Layer	-	768x1	Flatten Layer	Number of Classes = 5	5x1

These extracted features are flattened in Fully Connected (FC) Layer [8] and processed in dense layer with parameter names as number of class is equal to 5. Here, the sigmoid activation function is applied on the extracted dementia features for predicting five severity class labels like normal, very mild, mild, moderate and severe. The detailed description of parameters used in proposed MDCNN architecture is detailed in Table 2. The complete network is processed with all 75% of training data to learn the dataset features. These learned features or network weights are used for predicting class labels from both training and testing data.

3.4. Performance Calculation

The dementia detection performance of five diagnosis class labels using proposed algorithm has been calculated using Accuracy, Precision, Recall and F1-Score is given in Eq. (8) to (11).

$$Accuracy = (t_p+t_n)/(t_p+f_p+f_n+t_n) \quad \dots (8)$$

$$Precision = (t_p)/(t_p+f_p) \quad \dots (9)$$

$$Recall = (t_p)/(t_p+f_n) \quad \dots (10)$$

$$F1\text{-}Score = (2t_p)/(2t_p+f_p+f_n) \quad \dots (11)$$

Here, the correctly identified number of positive dementia classes and negative class labels are called t_p and t_n respectively. The wrongly predicted positive dementia classes and negative class labels are defined as f_p and f_n respectively.

4. Results And Discussion

4.1. Performance of MDCNN

The imbalanced severity class labels of dementia dataset are pre-processed using SMOTE to rebalance their classes, which reduces overfitting and provides greater training & testing performance. These pre-processed data are divided into training and testing data. Here, training data are fed into MDCN architecture for extracting dementia severity features automatically. The extracted severity features are flattened and fed into sigmoid activation to predict targeted class labels. The complete MDCN network is trained with training data and their learning outcome stored as weights. Finally, the training and testing data processed with these learned weights to perform prediction of dementia severity class labels.

Table 3: Performance of MDCNN based detection of dementia

Dementia Dataset				
Method Name	**Accuracy**	**Precision**	**Recall**	**F1-Score**
MDCNN Training	0.97	0.99	0.99	0.99
MDCNN Testing	0.96	0.97	0.97	0.97
Average (Training, Testing)	**0.97**	**0.98**	**0.98**	**0.98**

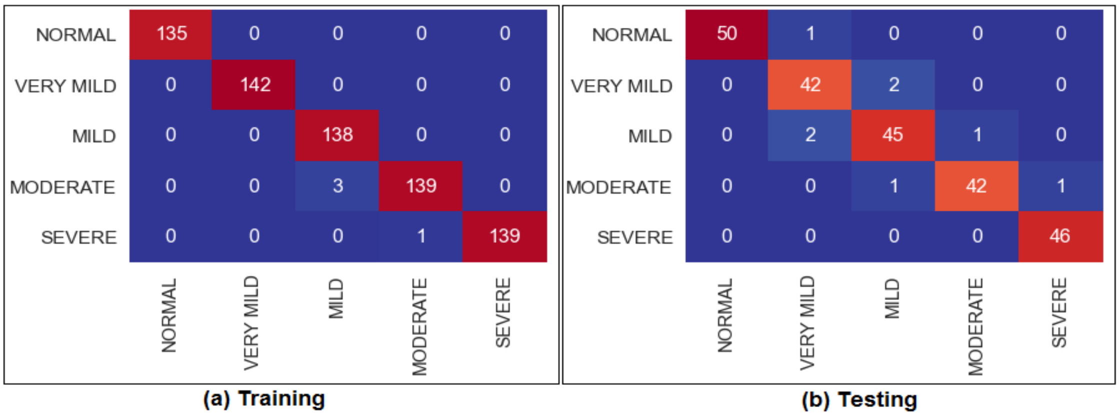

Fig.3. Confusion matrix of MDCNN based detection of dementia

The predicted training and testing class labels are compared with original labels from dementia dataset to find an evaluation. Table 3 shows the Performance of MDCNN based dementia detection and Figure 3 shows the Confusion matrix of the MDCNN based dementia detection. The average performance of proposed dementia detection achieves an accuracy value is 0.97, precision is 0.98, recall is 0.98 and F1-score is 0.98.

4.3. Comparison of MDCNN algorithm with Machine Learning Methods

The predicted dementia class labels of proposed pattern classification approach are compared with the calculated performance values of existing Naïve Bayes and Random Forest detection methods. Table 4 and Figure 4 depict the proposed method performance comparison with machine learning methods.

Table 4: Proposed method performance comparison with machine learning methods

		Dementia Data			
S. No	**Method Name**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
1	Naïve Bayes Training	0.83	0.86	0.84	0.84
2	Naïve Bayes Testing	0.84	0.87	0.85	0.85
3	**Average (Naïve Bayes)**	**0.84**	**0.87**	**0.85**	**0.85**
4	Random Forest Training	0.75	0.64	0.75	0.68
5	Random Forest Testing	0.74	0.61	0.74	0.66
6	**Average (Random Forest)**	**0.75**	**0.63**	**0.75**	**0.67**
7	Proposed Method Training	0.97	0.99	0.99	0.99
8	Proposed Method Testing	0.96	0.97	0.97	0.97
9	**Average (Proposed Method)**	**0.97**	**0.98**	**0.98**	**0.98**

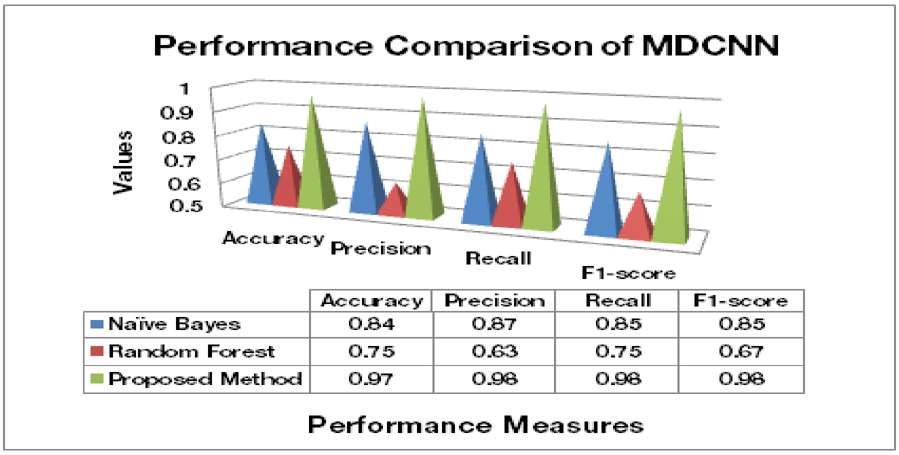

Fig.4. Proposed method performance comparison with machine learning methods

Naïve Bayes yields an accuracy value is 0.84, precision is 0.87, recall is 0.85 & F1-score is 0.85 and Random Forest produces an accuracy value is 0.75, precision is 0.63, recall is 0.75 and F1-score is 0.67. Random Forest method produces higher performance than Naïve Bayes classifier. These methods depend on hand crafted features to get higher performance. Thus, our proposed dementia detection method achieves 15% higher accuracy than Naïve Bayes and 29% higher accuracy than Random Forest methods.

4.4. Comparison of MDCNN algorithm with Deep Learning Methods

The predicted proposed detection results are compared with the calculated performance values of existing Radial Basis Function (RBF) network and CNN networks. Table 5 and Figure 5 depict the proposed method performance comparison with these deep learning methods.

Table 5: Proposed method performance comparison with deep learning methods

		Dementia Data			
S. No	**Method Name**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
1	RBF Network Training	0.85	0.93	0.89	0.88
2	RBF Network Training	0.80	0.88	0.80	0.78
3	**Average (RBF Network)**	**0.83**	**0.91**	**0.85**	**0.83**
4	CNN Training	0.89	0.93	0.93	0.93
5	CNN Testing	0.93	0.94	0.94	0.94
6	**Average (CNN)**	**0.91**	**0.94**	**0.94**	**0.94**
7	Proposed Method Training	0.97	0.99	0.99	0.99
8	Proposed Method Testing	0.96	0.97	0.97	0.97
9	**Average (Proposed Method)**	**0.97**	**0.98**	**0.98**	**0.98**

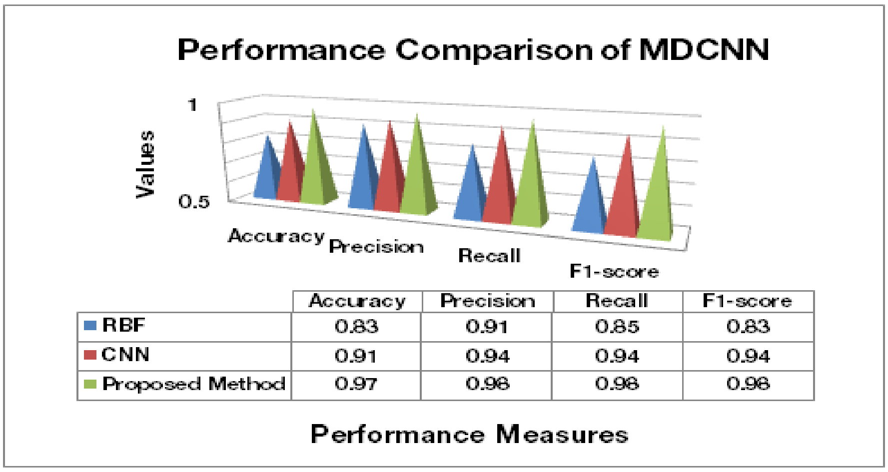

Fig.5. Proposed method performance comparison with deep learning methods

The average performance of RBF network yields an accuracy value is 0.83, precision is 0.91, recall is 0.85 & F1-score is 0.83 and the average performance of CNN network produces an accuracy value is 0.91, precision is 0.94, recall is 0.94 and F1-score is 0.94. Thus, the CNN method produces higher performance than RBF network classifier. Contrasting these methods, our proposed dementia detection method achieves 17% higher accuracy than RBF and 7% higher accuracy than CNN methods.

5. Conclusion

The diagnosis of dementia and their severity type at an early stage is difficult and challenging task. In this research, an automated MDCNN based classification approach is proposed for early detection of dementia severity classes from a collected dataset. The imbalanced class labels from dataset are rebalanced using SMOTE for getting more reliable and accurate performance. These rebalanced data are trained and tested using proposed MDCNN algorithm to extract the dementia severity features automatically. The performance of proposed dementia detection achieves an accuracy value is 0.97, precision is 0.98, recall is 0.98 and F1-score is 0.98, which is comparatively 7% higher accuracy than the recent deep neural network methods.

References

1. K. Jungyoon and L. Jihye, “A Deep Neural Network-Based Method for Prediction of Dementia using Deep Learning”, International Journal of Environmental Research and Public Health, vol. 18, no. 5386, pp. 1-13, year. 2021.
2. S. Danial et al, “Applying Deep Learning to Predicting Dementia and Mild Cognitive Impairment”, IFIP International Federation for Information Processing 2020, pp. 308-319, year. 2020.
3. W. Tim et al, “Identifying dementia cases with routinely collected health data: A systematic review”, Alzeimer’s and Dementia, Elsevier, no.14, pp. 1038-1051, year. 2018.
4. G. Sophana, and V. Joseph Peter, “A study of data mining techniques for diagnosis of dementia”, TEST Engineering and Management, vol. 83, pp: 13304-13311, ISSN. 0193-4120, year. 2020.

5. Z. Qiuyu, and H. Zikuang, “Improving Classification Performance of Softmax Loss Function based on Scalable Batch Normalization”, Applied Sciences, vol. 10, no. 2950, pp. 1-8, year. 2020.
6. F. Y. Osisanwo, J. E. T. Akinsola, “Supervised Machine Learning Algorithms: Classification and Comparison”, International Journal of Computer Trends and Technology (IJCTT), vol. 48, no. 3, year. 2017.
7. H. Xing et al, “Technical Survey Deep Learning”, International Journal of Semantic Computing, vol. 10, no. 3, pp. 417–439, year. 2016.
8. Alzubaidi *et al.*, “Review of deep learning: concepts, CNN architectures, challenges, applications, future directions”, Journal of Big Data, vol. 8, no. 53, pp. 1-74, year. 2021.
9. S. Siddharth, and S. Simone, “Activation Functions in Neural Networks”, International Journal of Engineering Applied Sciences and Technology, vol. 4, issue 12, ISSN no. 2455-2143, pp. 310-316, year. 2020.
10. G. Sophana, and V. Joseph Peter, “Comparative Analysis of Random Forest and Naïve Bayes Algorithm for Diagnosing Dementia”, Studies in Indian Place Names. vol. 40, Issue. 40, ISSN: 2394-3114, year. 2020.
11. Z. Fubao et al, “Machine Learning for the Preliminary Diagnosis of Dementia”, Scientific Programming, Hindawi, vol. 2020, no. 5629090, pp. 1-10, DOI: https://doi.org/10.1155/2020/5629090.
12. D. Dieu Ni Thi et al, “Predicting Dementia with Prefrontal Electroencephalography and Event-Related Potential”, Frontiers in Aging Neuroscience, vol. 13, no. 659817, year. 2021, DOI: 10.3389/fnagi.2021.659817.
13. G. Castellazzi at al, “A Machine Learning Approach for the Differential Diagnosis of Alzheimer and Vascular Dementia Fed by MRI Selected Features”, Frontiers in Neuroinformatics, vol. 14, article. 25, year. 2020.
14. G. Sascha et al, “Using Machine Learning to Predict Dementia from Neuropsychiatric Symptom and Neuroimaging Data”, Journal of Alzheimer’s Disease, no. 75, pp. 277-288, year. 2020. DOI: 10.3233/JAD-191169.
15. Sid. E. O’Bryant et al, “Staging Dementia Using Clinical Dementia Rating Scale Sum of Boxes Scores: A Texas Alzheimer's Research Consortium Study”, Arch Neurol, vol.68, no.8, pp. 1091-1095, year. 2008.
16. A. L. Deborah et al, “Greater Precision When Measuring Dementia Severity: Establishing Item Parameters for the Clinical Dementia Rating Scale”, Dement Geriatr Cogn Disord, vol.34, no.12, pp. 128-134, year. 2012.
17. Long X, Chen L, Jiang C, Zhang L, “Prediction and classification of Alzheimer disease based on quantification of MRI deformation “, Alzheimer's Disease Neuroimaging Initiative, PLoS ONE, vol. 12, issue. 3: no. 173372. OI:10.1371/journal.
18. G. Priyanka et al, “An Effective Dementia Diagnosis System using Machine Learning Techniques”, Journal of Physics: Conference Series, vol. 1916, no. 012173, year. 2021.
19. K. Walters et al, “Predicting dementia risk in primary care: development and validation of the Dementia Risk Score using routinely collected data”, BMC Medicine, vol.14, no. 6, year. 2016.
20. P. Thanaphong et al, “Multivariate prediction of dementia in Parkinson’s disease”, npj nature partner journal, vol. 6, issue. 20, year. 2020.

21. J. B. Bae, "Identification of Alzheimer's disease using a convolutional neural network model based on T1-weighted magnetic resonance imaging", Scientific Reports, vol. 10, no. 22252, year. 2020.
22. W. Tim et al, "Identifying dementia outcomes in UK Biobank: a validation study of primary care, hospital admissions and mortality data", European Journal of Epidemiology, no. 34, pp. 557-565, year. 2019.