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Patch base segmentation for classification of dementia disorder with optimize feature weight and random forest based approach

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ABSTRACT

Alzheimer's disease (AD) is one of the most common forms of dementia, and so far there is no cure to avoid or reverse its progression. Since AD is one of the most leading cause of death these days and the cost of caring for this condition is expected to raise significantly, early diagnosis is very important. This paper represents a Computer Assisted Diagnostic method (CADs) for diagnosing Alzheimer's disease method for conducting early diagnosis of AD is proposed that combines a set of SVMs trained on different texture descriptors (which minimize dimensionality) extracted from slices of Magnetic Resonance Image (MRI) with a set of SVMs trained on markers built from the texture of MRIs. The dimension of the texture-based features is reduced by using optimization and patch base optimization of features and use these features by Random forest and SVM learner. In experiment Random forest with optimize features improve significantly compare to other approaches.

1. Introduction

Now a day, Dementia has become one of the major health problems worldwide among people having age ranging from 50 to 70 and onwards. It has been serious threat as approx. 2.5 million people are added to pool of dementia related issues in Europe.

In fact Dementia is a neurological disorder in which gradual and continuous loss of memory occurs. It is not only seen in elderly people but more cases among young population has put the researchers on high alert and motivated them to examine the neuro-disorder resulting in loss of memory, delay in recalling from memory. Dementia, if detected at early stage can help the patient to slow down it to certain extent. Most scientists seem to agree that there are two proteins in the brain that are heavily involved. One is beta-amyloid which reaches abnormal level and forms plaques that collect between neurons and disrupt cell function. The other is called tau which also reaches abnormal levels, and forms neurofibrillary tangles inside neurons which block the neuron's transport system [1].

Deep look into statistics of dementia has indicated that>75 million people will be suffering from dementia by 2030 and most worst scenario may be in 2050 where number be >120 million in this category [17].

a) Clinical diagnostic

As per the medical science to diagnose any disease, after examining the patient the clinician next step is always a scanning of problem area. So in the similar manner in case of cognitive impairment after interviewing the patient the next step of clinician is brain Scan to study it thoroughly to reach the root cause of the problem. Image modalities available for clinicians are:

i. MRI (Magnetic Resonance Imaging)-It is defined as image which is developed by the usage of magnetic waves generated by magnets. On the basis of this MRI clinicians are able to study the various problems of brain which includes dementia as well. This MRI gives the clear picture of connectivity of different regions of brain which seems different in patients with Alzheimer's disease.
ii. PET (Positron Emission Tomography)-In this again an image is developed but by injecting radio-tracers in bloodstream of a patient, which further helps in visualizing blood flow, oxygen and glucose in the brain through PET. This is also a way of diagnosing dementia in a person because it gives the view of the functioning of the brain.
iii. SPECT (Single Photon Emission Computed Tomography)-This is nuclear imaging technique which captures brain image. It helps to evaluate the functioning of the brain and connectivity between various regions of brain through blood flow.

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As we know that dementia is a neurodegenerative disease which not only affects a person's cognitive impairment but also its functional abilities. As it affects functional abilities of a person which further leads to change in the pattern of daily activities. The future analysis of dementia all depends on usage of machine learning to help clinicians diagnose early symptoms of dementia and its treatment. So the development of new technologies to solve problem related to diagnosis of dementia is interesting motivation in research. As dementia is syndrome which has not yet any effective treatment and prevention therapy is a motivation in itself to help the human community in finding the way to diagnose it. It is a serious issue as it is a concern only for patients but also has impact on caregivers, family and society. As per 'G8 Dementia Summit' an action plan for research:

- To find better methods to diagnose.
- To help the patient and society.
- To find cure of dementia.

2. Related work

An automatic Acoustic bathroom Monitoring system [2]: Chen, j., zhang, j., harvey, a. and Shue, L. probed bathroom activity report of elderly people is sent to doctor to analyze. A regular report is taken in this paper to check whether there is any change in the daily routine of the patient due to decline in cognitive skills. Development of laughter motion on the cognitive robot "Bono-02"Assisting group Conversation [3]:- Nergui, M., Komekine, k., Nagai, H. and Otake, M. proposed a robot with laughter motion is developed which will help aged people in conversation and will make them laugh with its laughter sounds. Laughter sounds were also divided into three types and degree of smile is calculated. As dementia is occurring in aged people because of their less interaction with other people and less conversation and laughter is further increasing the rate of dementia among people. So this robot has various motions which are a cause of laughter.

Detection of Abnormal Behaviour for Dementia Sufferers using Convolutional Neural Networks [4]:- Arifoglu, D. and Bouchachia, A. explored the various behavioural difficulties of people with dementia also used Convolutional neural network by combining it with LSTM to detect their behavioural patterns which is differentiated on the basis of normal behaviour pattern of humans and then CNN was compared with other state of art models. Results from data sets shown a better behaviour pattern recognition using CNN than other models. Comparison of Feature Selection Techniques in Machine Learning for Anatomical Brain MRI in Dementia [5]:- Tohka, J., Moradi, E. and Huttunen, H. compared various techniques in anatomical neuroimaging as machine learning detection is increasingly used. In this paper it is concluded that embedded feature gives greater performance than filter based methods. Eyetracking metrics in young onset Alzheimer's disease: window into cognitive visual functions [6]:- Pavisic, I.et al probed three eyetracking techniques such as fixation stability, Pro-saccade and Smooth pursuit were applied on 36 participants with young onset Alzheimer disease(YOAD). Data retrieved from these techniques were statistically analyzed as well. After that machine learning classification model was also presented for pilot automatic classification on the basis of smooth pursuit. Paper was concluded that patients with YOAD has abnormal eye movement ie visual cognition than their age-matched healthy people. The feasibility of a vision-based sensor for longitudinal monitoring of mobility in older adults with dementia [7]:- Dolatabadi, E.et.al monitored older adults with dementia using vision based sensor. Monitoring was based on two problems i.e gait and balance function which shows deterioration of cognitive skills in older adults. All the measurement were done on the basis of walking patterns of individual so that individual falls due to balance and gait can be monitored using vision based sensors and informed in advance about decline in health. Machine-learning based identification of undiagnosed dementia in primary care: a feasibility study [8]:- Jammeh, E. et al. designed a machine learning based model which will help general practitioner to diagnose those having risk of having dementia. A collected data based on daily routine is fed into the system which will help GP to diagnose the patient which this model is giving results with 84.47% and 86.67% accuracy is obtained. The model was able to diagnose patients who were undiagnosed. Magnetic resonance imaging in Dementia [9]:- Rodríguez, L. et al. had provided the finding on types of dementias of degenerative origin such as Alzheimer's disease, vascular cognitive impairment, dementia with lewy bodies and various other types of dementia with the help of MRI images.

Machine learning of neuroimaging for assisted diagnosis of cognitive impairment and dementia: A systematic review. Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring [10]:- Pellegrini, E. et al. presented a review of the research done on identifying occurrence of dementia through neuroimaging using advance machine learning algorithms. Data was collected from various well known databases, which was further extracted and compared using combination like healthy vs Alzheimer's patient, healthy controls vs mild cognitive impairment, Non –converting vs converting mild cognitive impairment patients etc. This paper proposed that more machine learning algorithm needs to be designed to compared various clinical data set. Robust automated detection of Microstructural white matter degeneration in Alzheimer's disease using machine learning classification of multicenter DTI data [11]:- Dyrba, M. et al. proposed a machine learning analysis of degeneration of white matter in brain using DTI (Diffusion tensor imaging) and MRI and if not done on time will further leads to cognitive impairment. Analysis is done by taking a data set from various places of European centres which is divided randomly into ten folds. Data was graded using Support vector Machine (SVM) and Naive Bayes by keeping in mind the diagnostic classification as Fractional anistrophy (FA), Mean diffusivity (MD), Grey matter density (GMD), White matter density (WMD). All these calculation has shown an accurate result in predicting the dementia patients. Application of machine learning methods for diagnosis of dementia based on the 10/66 battery of cognitive function tests in south India [12]:- Bhagya Shree, S. et al. proposed that machine learning algorithms are used to help doctors to easily diagnose the patient using the techniques explored in the paper. The accuracy rate using these techniques is quite high. The techniques used is a set of cognitive test which includes global cognitive test, speech clarity and memory measurement test. Results of the above mentioned tests was taken from a psychologist on which various machine learning algorithms are applied to reach the correct diagnosis. Automated detection of brain atrophy patterns based on MRI for the prediction of Alzheimer's disease [13]:- Plant, C. et al. proposed a system in which comparison of Alzheimer's patient and healthy control brain were done. Out of Alzheimer's patient those patients were detected who were likely to get converted from mild cognitive impairment to Alzheimer's disease. In predicting this data three classifiers are used such as support vector machine, Bayes and voting feature interval which had given accurate prediction of the taken data set. What should we know about dementia in the 21st Century? A Delphi consensus study [14]:- Annear, M. et al. revealed knowledge about dementia disease which will help caregiver, Doctor, Nurse and patient to know about this disease. In this paper data set of people are taken who were related to dementia patient in any way. Questionnaire is prepared on the basis of various facts of dementia and people in data set were told to fill the questionnaire. Next the received statements were rated by experts and after that another set of experts were told to again rate the statements received from previous experts. These results will be of great help to Doctors, caregiver and patients as well. MRI visual rating scales in the diagnosis of dementia: evaluation in 184 post-mortem confirmed cases [15]:- Harper, L. et al. Probed the data set of 184 were taken which includes101 Alzheimer's disease, 28 with dementia with lewy bodies, 55 with Fronto temporal lobar degeneration and 73 of healthy control scans were taken. In this paper visual rating was done by experts by using MRI's. After that six experts also gave their assessment without knowing the previous history of the patient. This paper shows that if we combine the visual rating scale results with other diagnostic techniques or even if we diagnose the disease by only using visual rating, it gives accurate results about dementia in an individual. Location prediction using GPS trackers: Can machine learning help locate the missing people with dementia? [16]:- Wojtusiak, J. and Nia, R. proposed a model to track the movement of aged people having dementia using GPS trackers. With dementia people forget where they are going and they keep moving in certain patterns or loops. GPS tracker will help caregiver and family member to trace the lost person. This paper also proposed to help doctors to detect on the basis of movement in pattern about the deterioration in the health of patient. This paper has a limitation as well as there is no surety that a wearable will wear it or charge the battery on time.

2.1. Proposed methodology

This involve different steps as mentioned below:

Step1: Enter the MRI image and improve the Gaussian distribution of images. This Gaussian distribution normalizes the value of each pixel of the images and enhances images through noise reduction Fig 3.1.

Step2: After improving the next task of the images is to enhance the selection of features by identifying the particular area on the image, where the maximum disease possibilities are present. Both areas differentiated by segmentation utilizing clustering methodology and enhance the clustering through GWO i.e. grey wolves' optimization Fig 3.2

The traditional GWO algorithm needs to update its hunters to the prey based on the leader wolves i.e. alpha, beta, and delta. Nevertheless, with regard to the wolves' inadequate diversity in some cases, the GWO population still is liable to stagnate at the local extreme, and the issues of immature convergence persist. DE can assist GWO in obtaining the globally optimal way to prevent above--mentioned concerns. To use this definition one can, ensure that GWO can more efficiently perform global searches. To get the full benefit of clustering fitness setting function is used. Fitness function being a standard provided by the analytical method, is used to measure individual wolves' fitness. The smaller it is, the stronger the individual seems to be, and the larger the individual would be, the worst it is. The combination of clustering and GWO algorithm defines GWO's fitness function as in:

$$= \begin{cases} \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(m-1)}}, d_{jk} \\ 1, d_{jk} = 0, j = k \\ 0, d_{jk} = 0, j \neq k, \end{cases} \tag{1}$$

$$v_i = \frac{\sum_{k=1}^{n}(\mu_{ik})^2 x_k}{\sum_{k=1}^{n}(\mu_{ik})^m}, \tag{2}$$

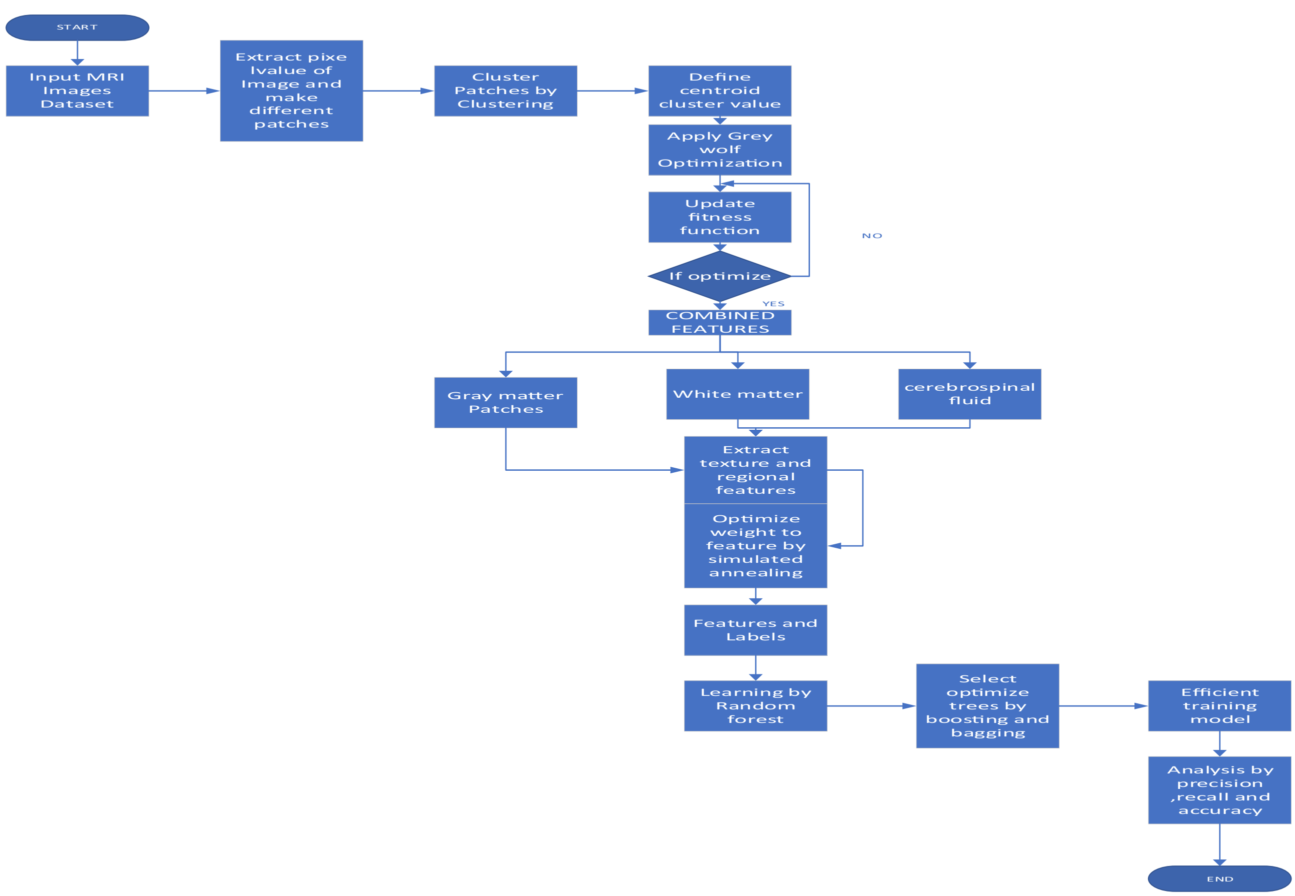

Fig 3.1. Proposed approach flow chart.

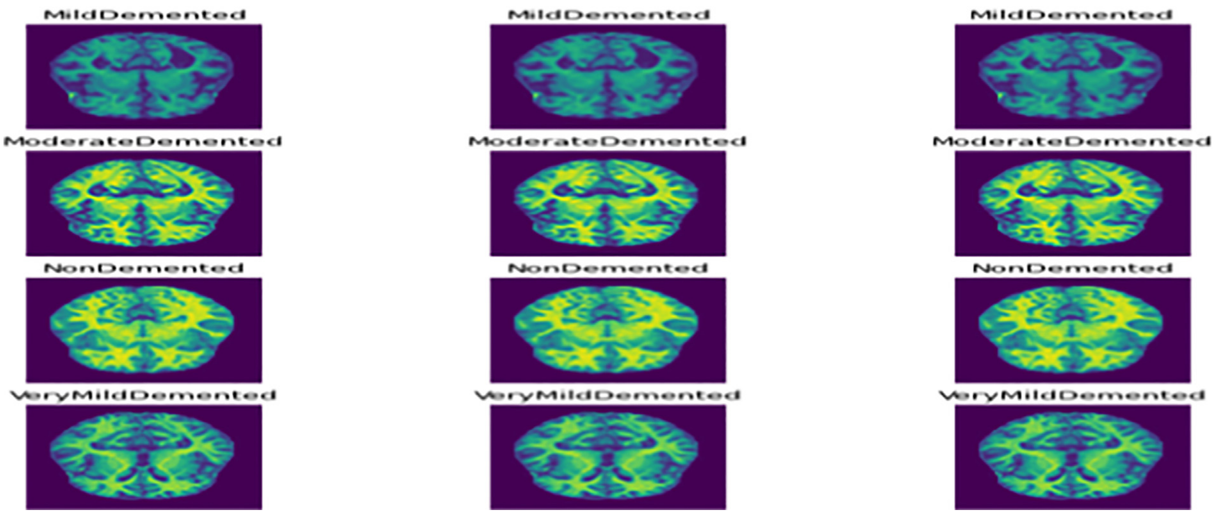

Fig 3.2. Different classes in segmentation phases.

The stronger the clustering effect, the lower the C-GWO value. By iterating the positions of the algorithm, the fitness function can be expressed and defined as the initial clustering centre.

$$\left\{X_i(0)\middle|x^L_{i,j} \le x_{i,j}(0) \le \middle|x^U_{i,j}; i = 1, 2, \cdots\cdots, N.P; j = 1, 2, \cdots.., D\right\} \quad (3)$$

$$x_{i,j}(0) = x^L_{i,j} + rand(0, 1)\left(x^U_{i,j} - x^L_{i,j}\right) \quad (4)$$

Initialization of the population. As per common ways of initialization based on swarm intelligence algorithm, such that the populace in the algorithm has randomness and diversity, the usual masks are used to detect the edges. A spatial filtering mask can be classified as an m × n size w matrix. i Assuming that n = 2β + 1 and m = 2ɪɪɪ+1, where α, β represent non-zero-positive integers. For such a reason, the smallest size of the mask is 3 × 3. These mask coefficients display a coordinate configuration. The image region below the mask above is seen Fig. 3.2 for edge detection.

Step 3: After clustering the basic segmentation extracts various features, the extraction of features via segmented patches extract gray matter, white matter and cerebrospinal fluid texture features optimize by algorithm 3 using simulated annealing. This optimizer given feature weights for improving domain of classifier.

Step 4: After this, the selection of features is done using four classes. In various classes, learning is accomplished using SVM and RF the analysis is done via accuracy, recall, and precision.

Algorithm 1: Segmentation (Image)
Input: Input Images
Output: Segmented Images
Begin
N ← no. of Images
P ← i × j Pixels
Define centroid $\{X_1, X_2, \cdots\cdots\cdots\cdots, X_n\}$
While (Centroid > 0)
Start
Define the population of grey wolves
GW ← Centroid
$G_\propto$←G(P)
G_β ← N
G_δ ← P
Update weights

$$w^{n+1} = \frac{w_0 G_\propto + \sum GW}{G_\propto + G_\beta + G_\delta} \quad (5)$$

End

Algorithm 2: Features Extraction
Input: Segmented Images
Output: Texture features
Begin
While (pixel > 0)
Start
Image divided into (128x128)
generate Gray matrix, white matter matrix and cs fluid flattened matrix
End
Apply Simulated annealing (flattened matrix)
Weighted features
Finish

Algorithm 3: simulated annealing (flattened matrix)
Input: feature matrix
Output: weighted feature matrix
Iter <- max _iter
x_{curr} ← weighted matrix
xbest ← xcurr
for i = 1 **to** $iter_x$ **do**
x_{prop} ← Neighbour Config(x_{curr})
$temp_{curr}$ ← CalcTemp(i, T)
if Weight(x_{prop}) ≤ Weight($x_{current}$) **then**
xcurr ← xprop
if Weight(x_{prop}) ≤ Weight(x_{best}) **then**
xbest ←^{x}prop
end if
else if exp {weight (X_{curr}) - weight(x_{prop})/$temp_{curr}$} > *Random*(0, 1) **then**
xcurr ← *prop*
endif
end for
return x_{best}, $Weight(x_{best})$

Algorithm 4: classification(image)
Input: Images
Output: Classified cancer or not cancer
N ← number of images
While (N > 0)
Start
Pre-process (N_i)
Start
Pre-process (N_i)
Segmentation (N_i)
Features (N_s)

N_s←(features, label)
LBP (N_s)
Texture (N_s)
Finish
Feature←$\{x_1, x_2, \cdots\cdots\cdots, x_n\}$
Label←$\{l_1, l_2, \cdots\cdots\cdots, l_n\}$
T_s←(features, label)
Train ← Random forest (T_s)
Test ← Train (T_s)
Analyze Precision, Recall and Accuracy
End

3. Experiments and result analysis

3.1. Experiment setup

Parameters	Values
Dataset	ADNI
Classes	4
Optimizer	GWO and simulated annealing
Features	Texture
Classifier	Random forest and SVM
Metrics	Precision, recall, accuracy and F-score

Dataset: Using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset that is freely accessible on the web (http:/adni.loni.usc.edu/). The ADNI aims to identify more sensitive and reliable approaches for diagnosing Alzheimer's disease at earlier times, as well as to demonstrate the development of AD by biomarkers. In this work, a total of 694 structural MRI scans were used which were initially labelled as AD (n = 198), NC (n = 230), pMCI (n = 166) and sMCI (n = 101) at baseline. Te 166 pMCI subjects were initially diagnosed with MCI at baseline, but conversion to AD was recorded within a 36-month follow-up period. Te subjects were between 55 and 90 years of age and the range of MMSE scores for each category was 20–26 (AD), 24–30 (MCI) and 24–30 (NC).

3.2. Metrics

1 Accuracy (AC) is the extent of the absolute number of right expectations. Accuracy is one of the most intuitive performance measures. It is resolved to utilize the condition:

$ACCURACY = \frac{p+s}{p+q+r+s} \cdots\cdots\cdots\cdots..(1)$

2 The review or genuine positive rate (TP) is the extent of positive cases that were effectively distinguished, as determined to utilize the condition:

$RECALL = \frac{s}{r+s} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (2)$

3 Precision (P) is the extent of the anticipated positive cases that were right, as determined to utilize the condition.

$PRECISION = \frac{s}{q+s} \cdots\cdots\cdots\cdots..(3)$

Experiment

3.3. Results analysis

- In experiment use Alzheimer's disease neuroimaging initiative (ADNI) dataset with four classes. These classes are Mild, moderate, very mild Demented and Non-Demented. Analysis proposed model on machine learning classifier with feature extraction and feature weighting by optimizer.
- In analysis use four approaches two existing approaches using support vector machine (SVM) and Random Forest (RF). In proposed approach add up feature extraction and optimization using swarm intelligence.
- Analysis Divided into two parts approach wise model performance which show in Fig. 4.1 and class wise proposed model performance depict in Fig. 4.2, Fig 4.3 and Fig 4.4.
- Analysis all experiment one by one:
- In Fig. 4.1 show the experiment performance on 10-fold validation approach. 10-fold validation analysis the model 10 times and give cumulative performance metrics.
- If analysis the Fig. 4.1 clearly show the performance of features optimization perform well compare to without feature optimization.
- Reason of performance improvement, In features collect texture of grey matter, white matter and cerebrospinal fluid which show changes get in features or not but its increase the dimension these dimension optimize by simulated annealing.

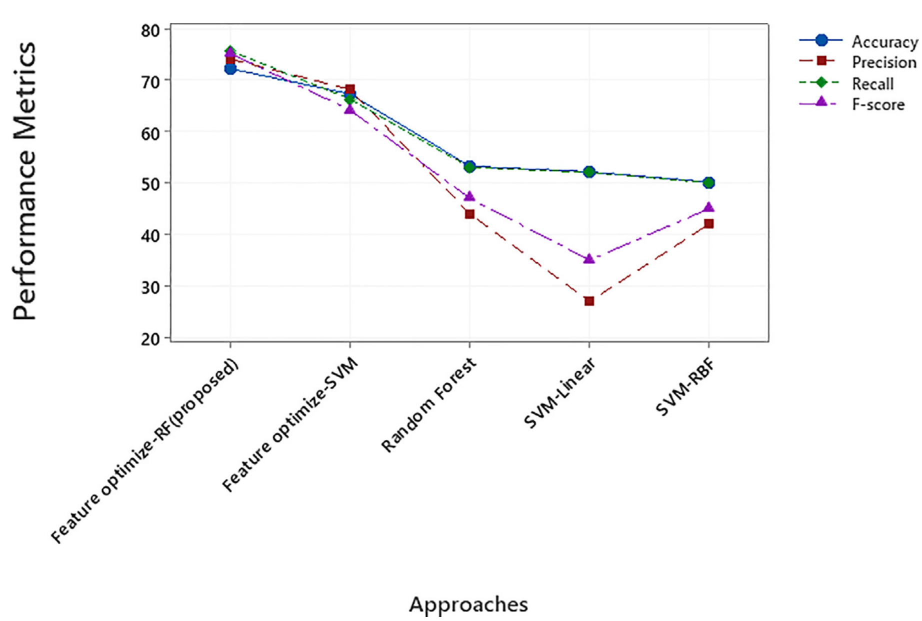

Fig 4.1. Comparison of different classifier on performances metrics.

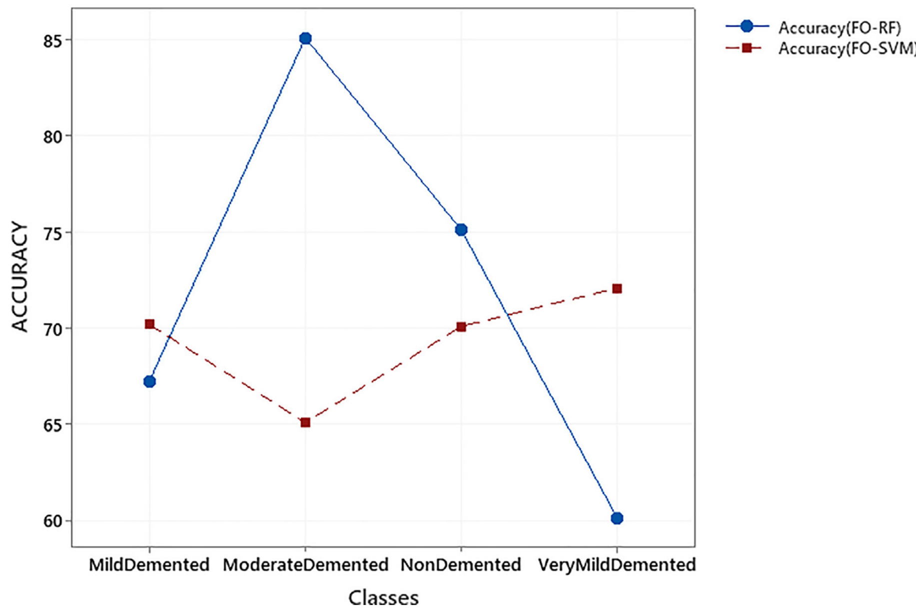

Fig 4.2. Accuracy of different classes in feature optimization with RF and SVM.

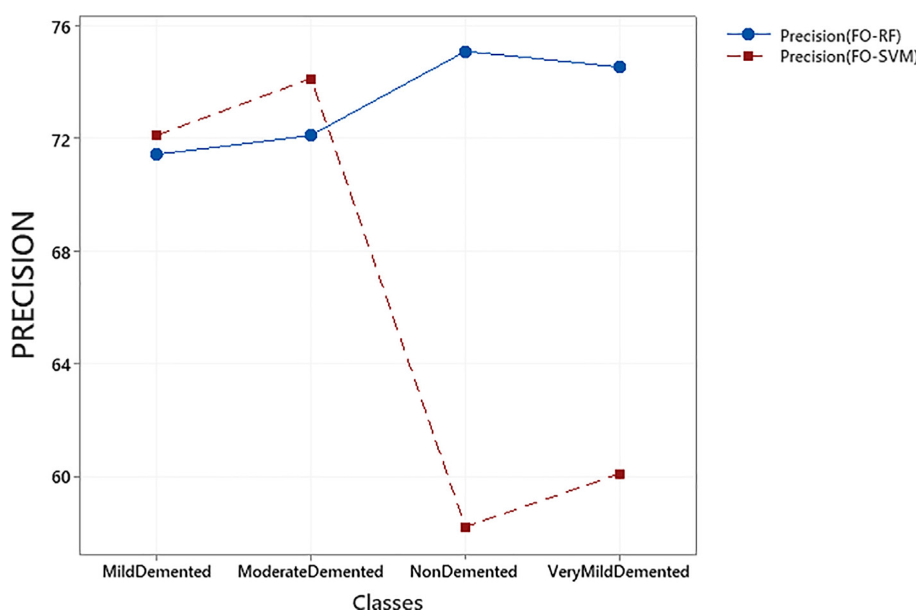

Fig 4.3. Precision of different classes in feature optimization with RF and SVM.

- Above reason improve the domain knowledge class wise and given efficient pattern and these patterns improve the performance metrics.
- In Fig. 4.2 analysis the accuracy, because Fig. 4.1 not able distinguish feature using classifier efficiently, so this analysis need for distinguish which classifier efficient improve class wise. In Fig. 4.2 show random forest (RF) perform well in two classes compare to SVM but SVM also improve in two classes compared to RF.
- In Fig. 4.3 show the precision but its show the same performance pattern like Fig. 4.2 but inf Fig. 4.2 RF perform well in moderate demented and non-demented but in Fig. 4.3 RF perform well in non-demented and very mild demented. These show that random forest able to efficient prediction of non-demented compare to other classes.
- In Figs. 4.4 and 4.5 show recall and f-score in both cases RF perform well. If take average of performance metrics RF perform well because of following reasons. First reason its ensemble learner and optimize decision tree. Second decision tree reduce the overlapping of features.

4. Conclusion

The experimental results of the ADNI data showed that our model achieved favourable performance and efficiency compared to the existing state-of-the-art models. However there are many drawbacks to this study: firstly, since the number of subjects used in the training and test phases was still small to facilitate end-to-end learning, any progress in performance relative to previous traditional models is minimal. Present analysis of the classification of

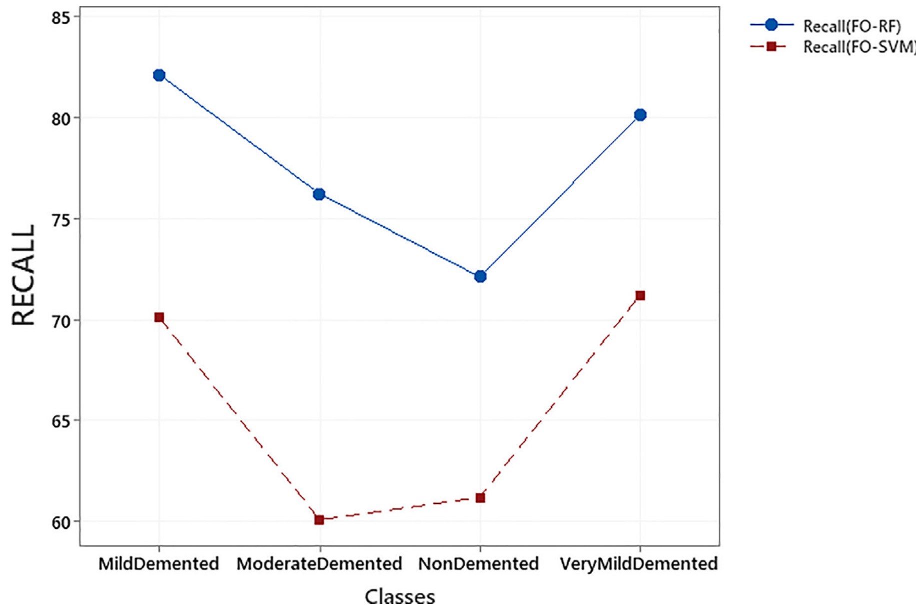

Fig 4.4. Recall of different classes in feature optimization with RF and SVM.

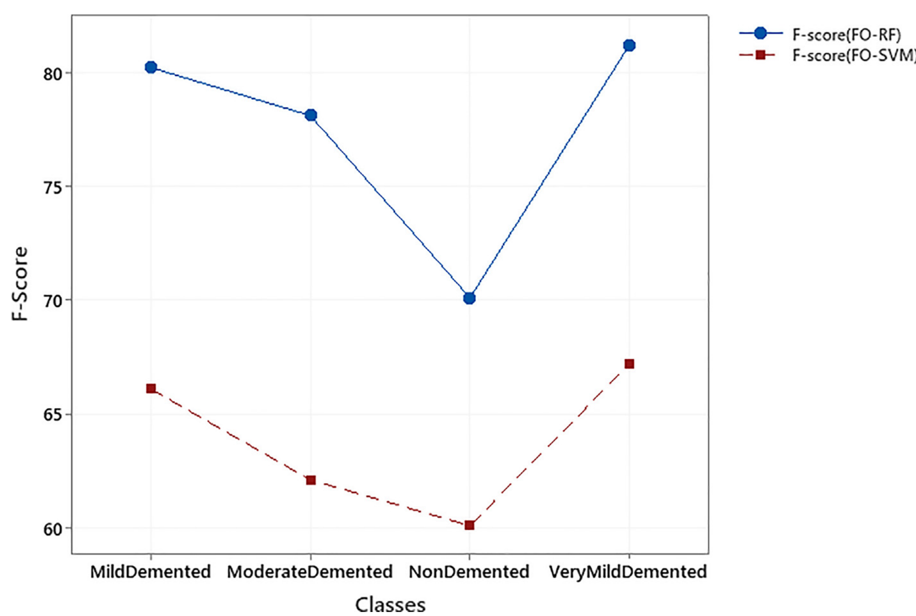

Fig 4.5. F-score of different classes in feature optimization with RF and SVM.

four classes by patch base texture features and optimization of the features with the Random forest ensemble learner and the SVM classifier. Random forest in proposed approach improve 15–20% without optimize features but with optimize features classifier does not improve as much as it improved in random forest 2–3%. In proposed approach accuracy improve 2–3%, recall 1–2% ,precision 1–2% and f-score 2.2–3.3%.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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