Original Article

Machine Learning based Detection of Alzheimer's disease in MRI images

M.Rajendiran[1], Dr.K.P. Sanal Kumar[2], Dr.S.Anu H Nair[3]

[1]Department of Computer and Information Sciences, Annamalai University, Chidambaram, India
[2] PG Department of Computer Science, R. V. Government Arts College, Chengalpattu, India
[3]Department of CSE, Annamalai University, Chidambaram, India (Deputed to WPT, Chennai)
E-Mail: [1]rajendiran_m@yahoo.com, [2]sanalprabha@yahoo.co.in, [3]anu_jul@yahoo.co.in
DOI: 10.47750/pnr.2022.13.S08.196

Abstract

Alzheimer's disease (AD) is a debilitating neurological disorder that most commonly affects the elderly. Alzheimer's disease patients have substantial memory loss. The Memory loss is caused by atrophy in the hippocampus, amygdala, and other areas of the brain in Alzheimer's patients. Identification and categorization of Alzheimer's disease are considered challenging research subjects due to the vast number of Alzheimer's patients and the absence of effective diagnostic procedures. And also traditional identification of Alzheimer's disease is taking more time consuming. In order to tackle this issue, we have to use the Artificial Intelligence technologies, which are driven by machine learning base AD classification and identification.
The combined SIFT and SURF feature is used in this study to describe an AD Classification based on images. These combined feature parameters are then fed into a machine learning classifier for additional classification accuracy. There were three distinct machine learning classifiers compared to the system: SVM, DT and k-NN. For testing the proposed AD system, we have gathered a benchmark dataset that includes four categories: Mild, Moderate, Non Demented and Very Mild. The experimental results showed that SVM achieved higher accuracy than other classifiers.

Keywords: Alzheimer's disease, machine learning, disease diagnosis, Support Vector Machine, k- Nearest Neighbour, Decision Tree.

1. Introduction

Alzheimer's disease (AD) is a type of mental illness that is caused by a neurological abnormality of the brain. Those who suffer from this disorder lose their ability to think rationally, read or write, and in severe situations, they may even lose their ability to remember their own names. Alzheimer's disease (AD) is the most common type of dementia, affecting persons who have beta-amyloid deposits in their brain cells. Alzheimer's disease is the most common type of dementia. As a result, these individuals may require the assistance of a full-time caregiver. Alzheimer's disease is predicted to affect 5% of people over the age of 65 in developed nations, with a much higher incidence (about 30%) among people over the age of 85 in these countries. As life expectancy increases around the world, it is expected that the number of Alzheimer's patients would increase considerably. According to a recent study [1], Alzheimer's disease (AD) is the 8th leading cause of death in India.
Almost 12 million Indians are providing unpaid care worth $234 billion to 6 million Indians suffering from AD disease [2]. The death rate from heart attacks has decreased by 9% in the last two decades, whereas the death rate from AD disease has increased by 145%. Only 16 percent of the older persons in this group receive sufficient care and regular checkups. In 2019, the expense of Alzheimer's and other dementia disorders increased to 290 billion dollars, a significant loss, and someone suffers from AD or dementia every 65 seconds [3]. Normal healthy, mild cognitive impairment (MCI), and Alzheimer's disease are the three stages that lead to AD disease. The patient's initial stage of dementia must be transformed to MCI before an accurate diagnosis of AD can be made [4].

Early detection and appropriate treatment can prevent the patient from developing severe Alzheimer's disease. The shrinking of the brain cortex is one of the most common variables that has a significant impact on the human brain [5,6]. The affected person's cortex shrinks, whereas normal shrinking occurs primarily in the hippocampus. This area is responsible for thinking and remembering daily activities, and a decrease in this area causes the brain cortex to atrophy and the ventricles to grow. The National Institute on Aging developed several clinical evaluation parameters for the diagnosis of Alzheimer's disease, including the NPI-Q, FAQ, CDR, MMSE, GDS, and others. The use of multimodality data to detect and classify Alzheimer's disease has recently been proved in research studies. Patients' clinical records, as well as multimodality imaging data such as Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), X-rays, and CT scans, are all examples of multimodality data [7]. Although MRI has been demonstrated to be more effective in recognising Alzheimer's disease than CT scans when using traditional and manual disease identification methods. There are still a number of difficulties with these techniques when using traditional and manual methods. A few of the difficulties are as follows:

- In order to establish an accurate diagnosis, these approaches take time and require substantial diagnostic knowledge (for data labelling).
- Many imaging modalities may not give perfect results if low-level features are extracted manually, and pre-processing for manual feature extraction can be error-prone.

The following is the structure of the remainder of this article: During the section 2, we conduct a review of the literature on traditional Alzheimer's disease classification methods. Section 3 discusses the proposed steps involved in selecting and pre-processing MRI data and extracts the feature and classifies the disease using machine learning algorithms. The experimental results of various traditional classifiers are compared in Section 4. After that, the conclusion and recommendations for further work are presented in Section 5.

2. Literature Survey

Many researchers have created numerous image processing techniques like artificial intelligence, machine learning for the diagnosis of AD disease throughout the last few decades. In machine learning based approaches, there are some steps to be follow for effective and efficient classification of Alzheimer's disease. The classification is always starts with pre-processing followed by feature extraction and then classification.

For example, Kaur et al. investigated various image enhancing approaches for the detection of AD disease in MRI images [8]. Current AD disease detection approaches [9] are evaluated using colour retinal images that have had their red and green components corrected. The sensitivity and specificity of a method for diagnosing AD disease in the public healthcare context are evaluated in order to establish the most effective strategy. Li et al. developed a method for dealing with complicated image segmentation [10]. This method involves a two-level segmentation strategy, which is divided into two categories: background and target [11]. The newly revealed retinal layer boundaries have been successfully used to diagnose AD disease and glaucoma [12]. Using linear mixed modelling techniques, Rao et al. [13] predicted the impact of axial length, age, TSS, and ocular birefringence on the diagnosis of Alzheimer's disease. For the purpose of evaluating the effectiveness of the proposed approach, one eye image is randomly picked from a pool of 48 images of the eyes.

Using individual OCT images, Uji et al. proposed interpolation and super-resolution (SR) approaches to diagnose AD diseases [14]. When it comes to diagnosing Alzheimer's illness, the experimental findings showed that the proposed interpolation and super-resolution algorithms performed well in the field. Li and colleagues developed a technique for dealing with tough image segmentation problems. This method makes use of a two-level segmentation strategy, which is divided into two categories: background and target [15]. When Cruz-Roa and colleagues proposed a new strategy [16, 17] for automatically visual mining MRI images, they used Bag of Features (BoF) to show that BoF is a good choice for the representation of MRI images, as it typically allows the extraction of implicit patterns for performing automatic annotation with an accuracy of 80%. With the use of a non-negative matrix factorization, the BoF approach is employed to increase the capabilities of this technology. In a similar vein, the author [18] makes use of piecewise feature extraction approaches with artificial neural networks to retrieve information (ANN).

An automatic classification model for AD in MRI imaging was proposed by Rueda et al. [19], and the model achieved an accuracy of 83%. It was found that Bansal et al. [8] used a variety of statistical methods like naive bayes, random forest, MLP and SMO to identify Alzheimer's disease at an early stage. The CFSSubsetEval feature selection methodology was used in conjunction with the OASIS dataset, and the results showed 82.6 % of accuracy. The accuracy obtained in the previous study is great when neuropsychological data from 16 features from the OASIS dataset is taken into account. A substantial number of features for categorization may be extracted from brain MRI scans, which we investigated.

The feature fusion classifier presented by Aruna et al. [20] combined the features of GLCM, Gabor, ICA, and SVM in order to attain higher classification accuracy. With the help of segmentation and normalisation of MRI scans, Manadhar et al. [21] were able to diagnose dementia in MRI scans using the ANN and k-NN models. The

results showed that the ANN model had 68.91 percent accuracy and the k-NN model had 81.1 percent accuracy. Diaz et al. [22] developed a system for semantic separation of fundamental stain components by combining the BoF technique with local characteristics, which is then used to histopathology images to classify them.
The manual and traditional-based procedures stated above are inefficient because they yield less and poor performance with train and test data, as demonstrated above. A classical model for Alzhiemer's disease identification and recognition is shown here, taking into consideration the aforementioned shortcomings. The model includes SVM, DT, and k-NN among other techniques.

3. Proposed Methodology

In this section, we have to propose an earlier detection and classification framework for Alzheimer's diseases. There are four stages for disease identification and classification namely dataset collection, pre-processing, features extraction and classification. The dataset was collected from benchmark dataset. Next, the dataset was pre-processed by using standard pre-processing techniques. Then, the pre-processed images are extracted in the third stage using combined Scale In-variant Feature Transform (SIFT) and Speed up Robust Features (SURF) techniques. The combined integrated feature values are then fed into traditional classifiers like SVM, DT and k-NN. The architecture of proposed AD disease model is shown in Figure 1.

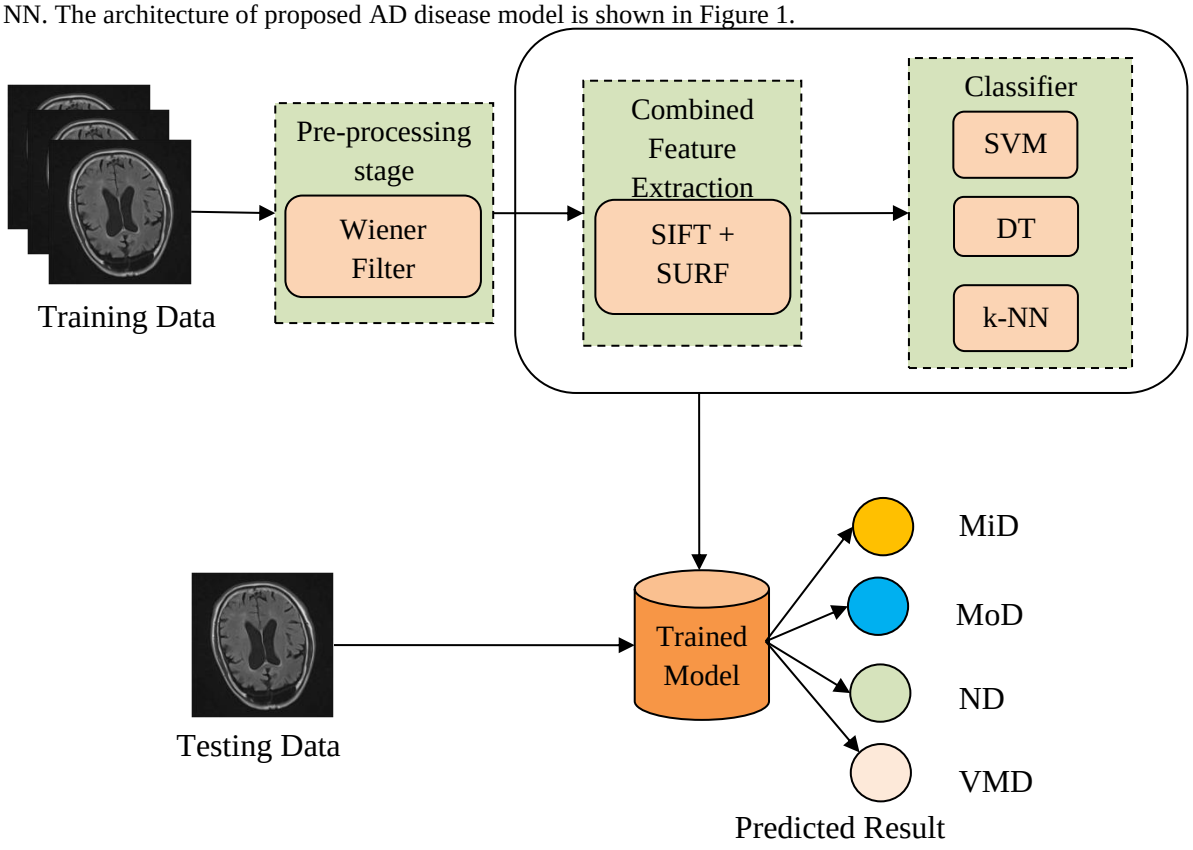

Figure 1 Architecture of Alzheimer's disease system

3.1. Dataset Collection

Open Access Series of Imaging Studies (OASIS) provided the data for this study on Alzheimer's disease [23, 24]. Tests on the model were carried out on the dataset. It has a total of 4 classes with a total of 8,980 Magnetic Resonance Imaging (MRI) images, with each class including 2245 images. Each image has a resolution of 176x208 pixels in the grey colour scheme. In our proposed work, Mild Dementia is labelled as 0, moderate Dementia is labelled as 1, non-demented is labelled as 2, and very mild Dementia is labelled as 3.

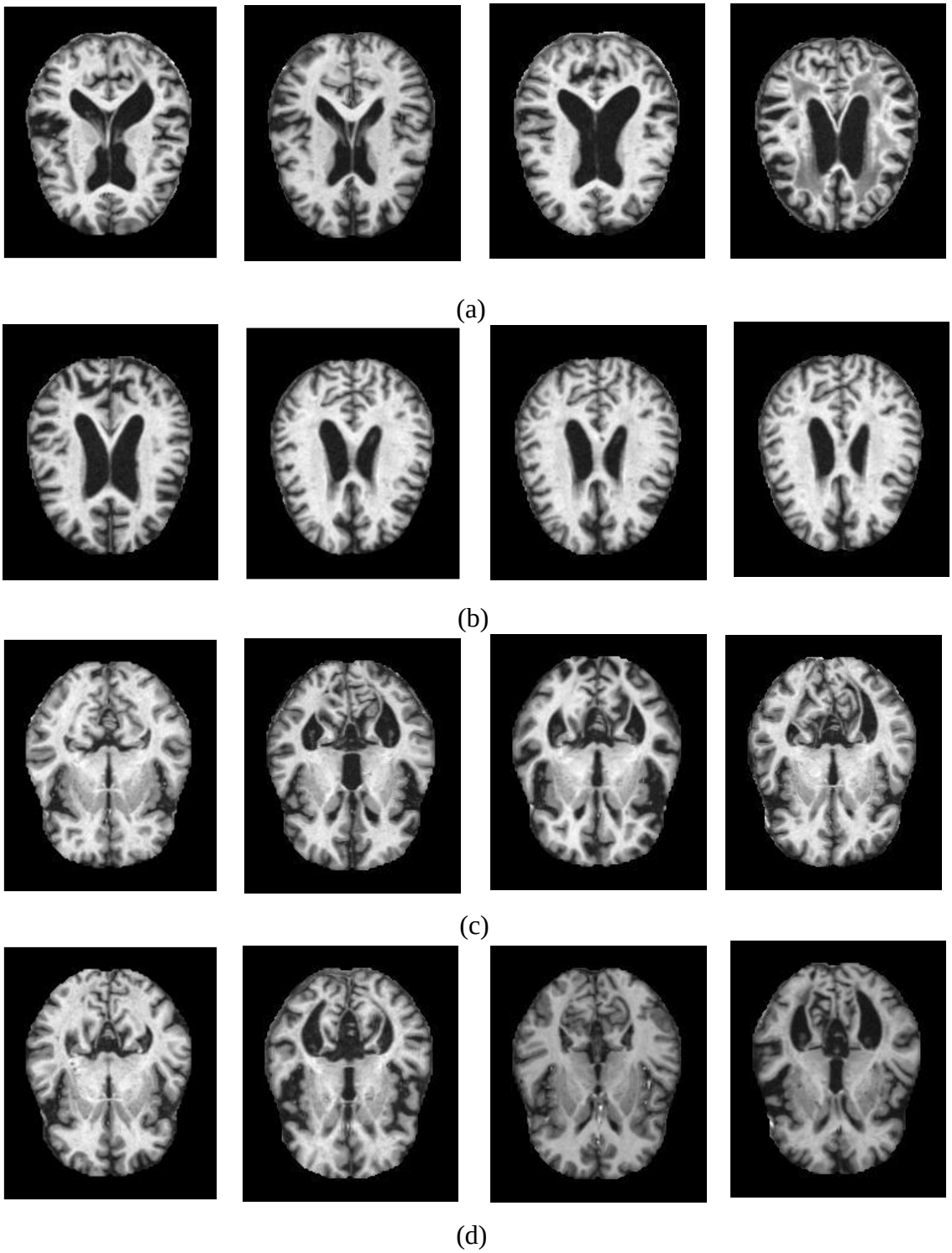

Figure 2 Sample images from OASIS dataset

Figure 2 (a-d) shows several examples of images from the OASIS dataset for Alzheimer's disease identification and recognition in MRI images. Each row displays a selection of images from each class. Separate training and testing sets were created from the dataset. As shown in Table 1, 80% of the dataset is employed to train the model, while 20% is used to test it.

Table 1. Description about the Alzheimer's disease images

S. No.	Disease Type	Total No. of Images	Training Images	Testing Images
1.	Mild Demented	2245	1792	453

2.	Moderate Demented	2245	1792	453
3.	Non Demented	2245	1792	453
4.	Very Mild Demented	2245	1792	453

3.2. Pre-processing

The MRI data acquisition images are contains with some noisy data. The noise information needs to remove from the MRI image. Pre-processing is an important phase in the proposed techniques. There are so many pre-processing techniques available namely, data resize, colour conversion, sharpening the images, smoothing an image, segmentation and so on. For medical images, we have to choose the filtering techniques for removing the noise from the MRI input images.

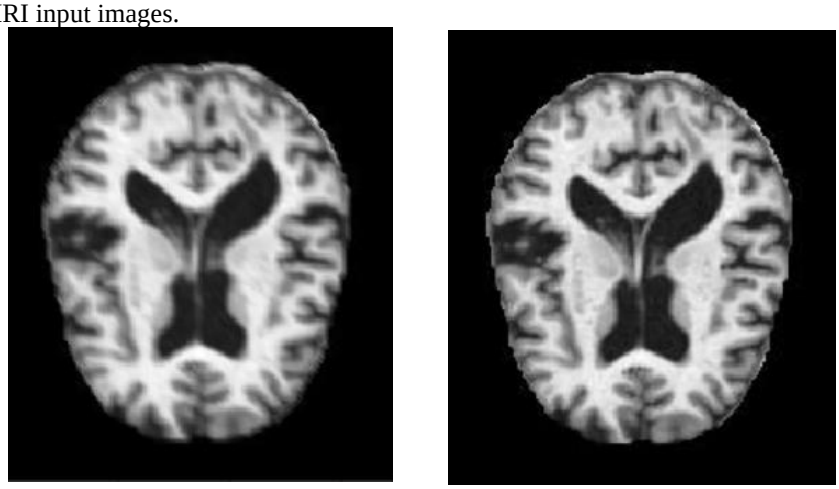

Figure 3 (a) Image original and (b) Processed image

High-frequency smoothing and low-frequency edge detection are the primary goals of filtering, which is an image-enhancing approach in which filters are used primarily to suppress either high-frequency smoothing or low-frequency edge detection. Good noise reduction is achieved by using the wiener filter. The blur is inverted while the additive noise is eliminated. The inverse filtering and noise smoothing techniques have an alternative in the form of Wiener filtering, which has a lower mean square error. Medical images are a better fit for this filtering method. Figure 3 depicts the original and pre-processed versions of the input image.

3.3. Feature Extraction

3.3.1. SIFT Features

The David Lowe introduced [25] the scale invariant feature transform. It finds points of interest in images and provides local descriptions that describe their neighbourhood. This algorithm's first step is to find extrema in the image filtered by the Difference of Gaussian (DoG). It ensures scale invariance by filtering at various scales and gradually downsampling the input image. The pixels are then compared. The level's neighbours (lower and higher) are also assessed. A possible key-point is a pixel that is the maximum or minimum of all adjacent pixels.

Then the key-points are analysed further to select the “best” possibilities. Each key-point has stability. Low contrast and insecure edge positions are deleted. Then each remaining key-point gets an orientation. The algorithm uses gradient orientations near the pixel. The values are weighed by the gradient magnitudes. The generated points are used to build feature vectors (descriptors). The computation uses the pixel's 16×16 neighbourhood. The neighbourhood's gradient magnitudes and orientations are computed. A Gaussian weights their values. In this case, the orientation histograms are constructed for each sub-region. Then a vector of 128 (16×8) values is formed.

3.3.2. SURF Features

In the Speed Up Robust Feature (SURF) feature technique, a local feature detector and a descriptor are used [26]. Scale Invariant Feature Techniques have been improved upon. Image matching is much faster and more reliable using this approach since it relies on invariant aspects of local similarity. SURF begins with the creation of important points. Once these critical locations have been identified, the invariant descriptor can be used to classify, register, calibrate and determine correspondence between two similar images, among other uses. Figure 4 depicts the four steps in the SURF feature extraction process.

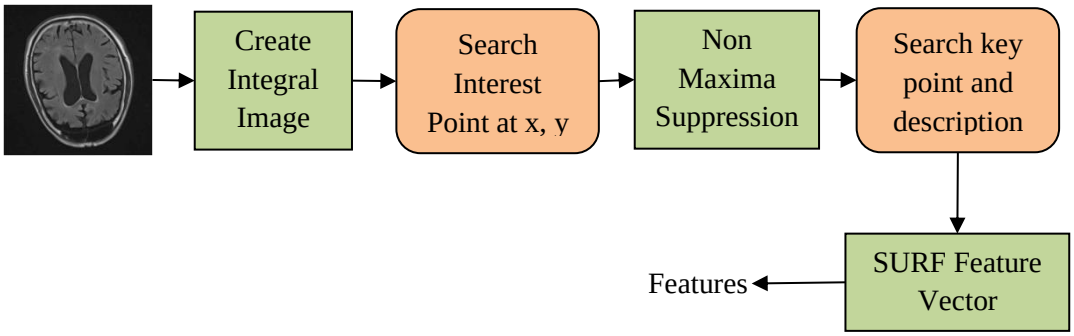

Figure 4 Working principles of SURF Features

This is the initial stage of the SURF process and is a fast and efficient method of computing the sum of values in an input image. It is also known as the integral image. An image's average brightness can also be determined with the use of this technique. After that, seek for the coordinates of the location that you are interested to visit. In general, a point of interest is a position where the direction of an object's boundary or edge varies fast. Because of its widespread use and familiarity, the Harris corner detector is not a scale invariant detection method. The Hessian matrix was used to automatically choose scales for the challenge, which was successfully completed. For point detection in images, SURF takes use of a Hessian matrix approximation that is both scale and rotation invariant, which is a Hessian matrix approximation.

After identifying the image's feature candidate, the non-maxima suppression approach is employed to identify the image's key point candidate, which is then eliminated. The final step in the SURF process is to describe the significant point that has been uncovered. After identifying the pixel distribution of neighbours around a key point in an input image, an SURF feature vector is constructed for that image. A SURF feature vector for an input image is generated at the end of the method. The 64 dimension of feature vector are extracted from the each input image.

3.3.3. Combined SIFT + SURF Features

By combining the SIFT and SURF features, we've come up with this new description. There are 128 dimensions in the SIFT descriptor, while there are 64 dimensions in the SURF descriptor. These two descriptors are normalised and concatenated to produce a vector with a length of 192.

Following are the steps involved in creating a realistic-looking portrait of a person's face:

- Detection of SIFT key points
- Detection of SURF key points
- The SIFT and SURF descriptors are calculated for each of the key-points that have been identified.
- Normalization of the SIFT and SURF descriptors
- Building the combined descriptor by concatenating the two vectors

When the key-point locations determined by both techniques are combined, we predict better resilience will be achieved. The total combined extracted features are fed into the traditional classifiers like SVM, DT and k- NN. There are 1,34,700 feature descriptors were used for Alzheimer's disease dataset. The original input image and corresponding SURF feature extracted images are shown in Figure 5.

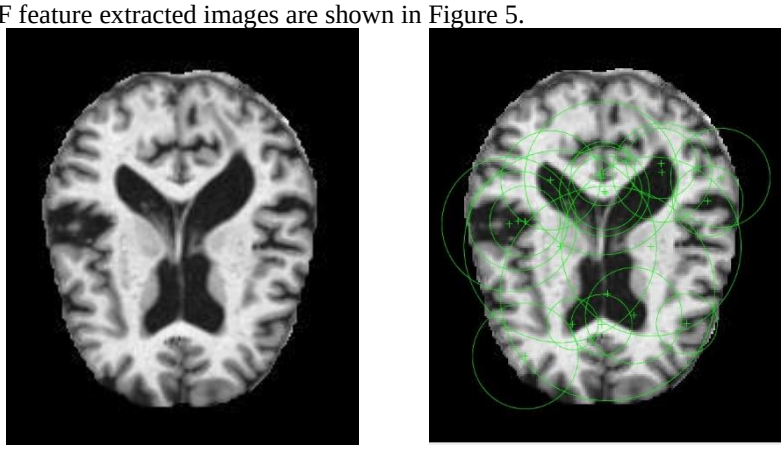

Figure 5 (a) Original Image (b) Combined SIFT +SURF Extracted Image

3.4. Classification

To detect and classify Alzhiemer's Diseases from input images, the combined SIFT+SURF extracted features were given to classifiers. Different classifiers perform differently depending on the dataset and characteristics of

images, as has been demonstrated in the literature [27]. As a result, we've put together a detailed evaluation of the performance of three distinct classifiers: SVM, DT, and k-NN. Because they are well-known classifiers in the literature, a brief explanation of each is provided below:

3.4.1. Support Vector Machine

SVM is a form of supervised algorithm, which is helps to maximize the hyperplane between the datasets of various classes. In general, the SVM used to solve the linear and non linear problems[28,29]. SVM with kernel (SVM-k) solve the issues of non linear separable problem, whereas linear SVM has no kernel function and it solves the linear separable problem. The hyper plane for the SVM model is written as given below:

$$h(x) = \alpha^T * x + \beta \quad (1)$$

Where α^T represent as weight vector and β denotes as bias, the distance between class instances, or margin, is calculated using the training data. The SVM's goal is to discover the hyper plane with the greatest margin, and it uses an algorithm that seeks to have the greatest margin with the fewest points. The Figure 6 represents the linear SVM model for AD disease classification.

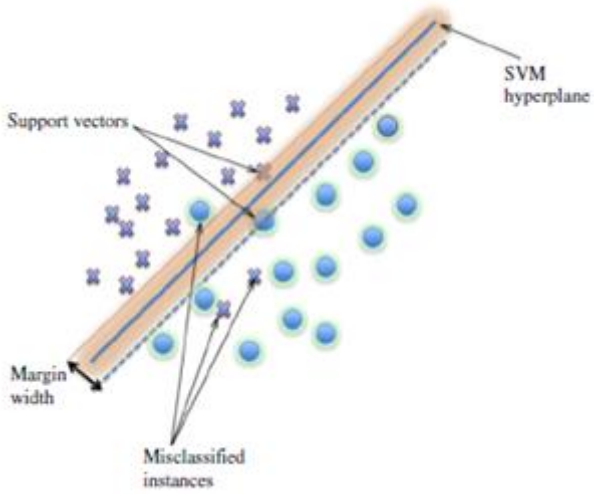

Figure 6 Process of linear support vector machine

3.4.2. Decision Tree (DT)

When it comes to classification and regression, the Decision Tree (DT) is an effective non-parametric supervised learning technique. This node is made up of three nodes: the root node, a group of internal nodes, and a group of leaf nodes (Terminal node). Splitting decisions and relevant splitting attributes are associated with root and internal nodes in categorization. Each leaf can be labelled with a class label. There are two steps in the DT training phase. The splitting measurements and splitting attributes are selected first. The records among the child nodes are separated in the second stage using the decision rule from the first step.

3.4.3. K- Nearest Neighbours

K-Nearest Neighbours is a machine learning approach that uses the training dataset to generate a machine model for all possible scenarios. Based on the similarity measure, the testing data is received and categorised into one of the available cases. It is determined to which class label the feature belongs. In the k-Nearest neighbour algorithm, the selection of the best-k value is the significant challenge. The model's performance is determined by the choice of k value. For each k value, a different level of precision is achieved. The size of the feature data collection has a significant impact on getting a high accuracy rate. Because calculating the distance between each point is difficult, this model only works well with a restricted collection of feature datasets. It does not function well with huge datasets or high-dimensional data.

4. Experimental Discussions and Analysis

Using conventional machine learning methodologies, this section evaluates the proposed earlier identification and recognition of Alzheimer's disease in MRI images and the results of that evaluated. An i5 processor with 8GB of RAM, and a 1TB hard disc drive were used to build the suggested model using Python and the Anacondo IDE.

4.1. Performance Metrics

To assess the proposed model's performance, performance assessment metrics are employed. Traditional machine learning methods can be evaluated using a variety of performance metrics, including Precision (Pr), Recall (Re), F1-measure (F) and Accuracy (A). The confusion matrix, as shown in Figure 7, is used to compute these measures. Actual classes are listed in the row, whereas predicted classes are listed in the column.

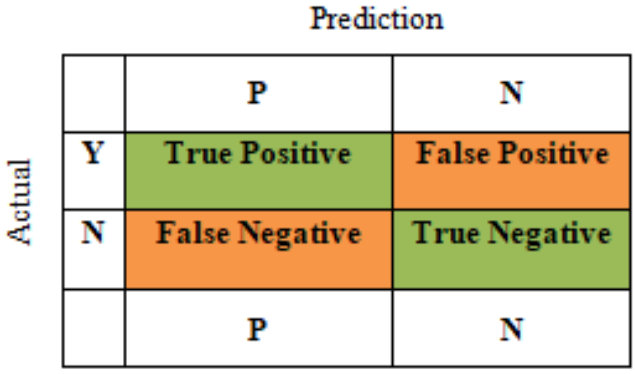

Figure 7 Confusion Matrix

The TP denotes a result in which the models accurately predict the positive class of variables. The TN is the result of successfully calculating the negative class by the models, which is the outcome. When the models incorrectly predict the positive class, this is referred to as the FP. When the models predict the negative class incorrectly, this is referred to as the FN.

Precision (Pr): Precision is one of the most common ways to measure how far a metrics will work. It is used to find out how many correctly predicted events there were out of all predictions. In this way, we can measure the precision:

$$Pr = \frac{tp}{tp+fp} \tag{2}$$

Recall (Re): Recall is the percentage of occurrences that were successfully predicted over the total number of occurrences.

$$Re = \frac{tp}{tp+fn} \tag{3}$$

Accuracy (A): Accuracy is measured by the number of instances that were correctly classified. The accuracy of a classification system is equal to the ratio of the correct classification divided by the total number of classifications.

$$A = \frac{tp+fp}{tp+fp+tn+fn} \tag{4}$$

F1-Score (F): The measures of precision and recall are balanced by using the F1-measure (harmonic mean). The formula for calculating an F1-score is as follows:

$$F = 2 \times \frac{Pr \times Re}{Pr+Re} \tag{5}$$

4.2. Results Analysis

In this section, we have looked at how well traditional classifiers like the SVM, DT and k-NN worked. It is shown in Table 2 how each traditional classifier measures up against each other in terms of Precision, recall, F1 score and accuracy. The evaluated results of AD disease classification was labelled and showed in Figure 8.The Support Vector Machine had the best performance accuracy of 86.05%. The accuracy of decision tree was the second highest level of the traditional classifier with 85.43% of accuracy. The accuracy of k- Nearest Neighbors was the worst of the three traditional classifiers, with 67.88% of accuracy. This was the lowest of the above mentioned three classifiers.

Table 2 Traditional classifiers performance analysis

S. No.	Classifier	A	Pr	Re	F1- S
1.	Support Vector Machine	86.05	86.25	86.75	86.0
2.	Decision Tree	82.40	82.0	82.75	82.0
3.	K-Nearest Neighbors	67.88	67.5	68.5	65.0

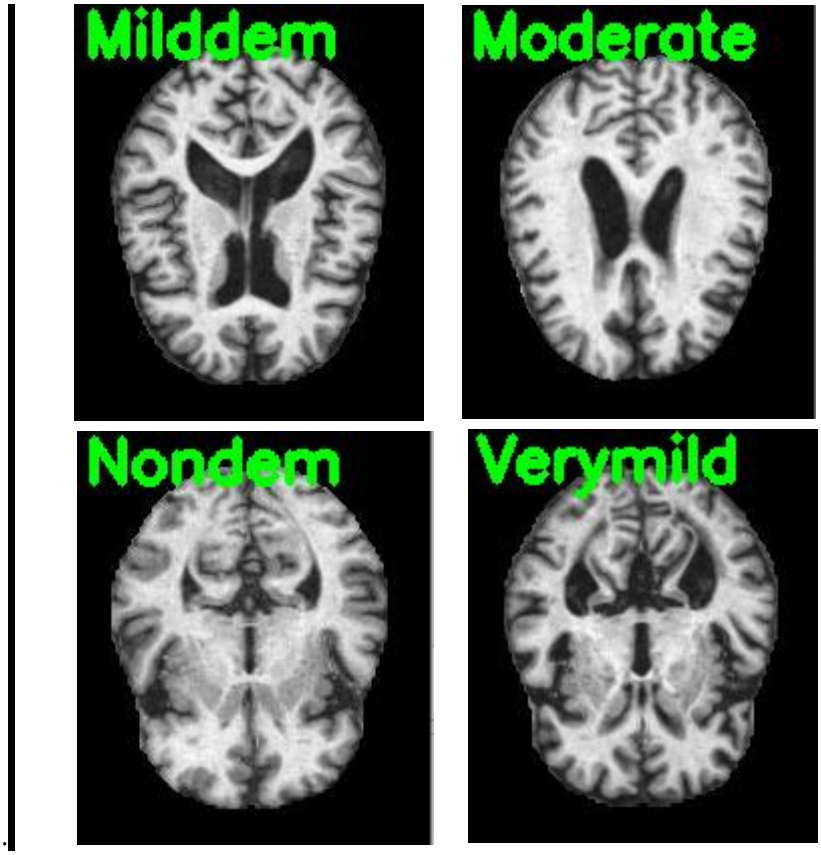

Figure 8 Test result of AD disease classification

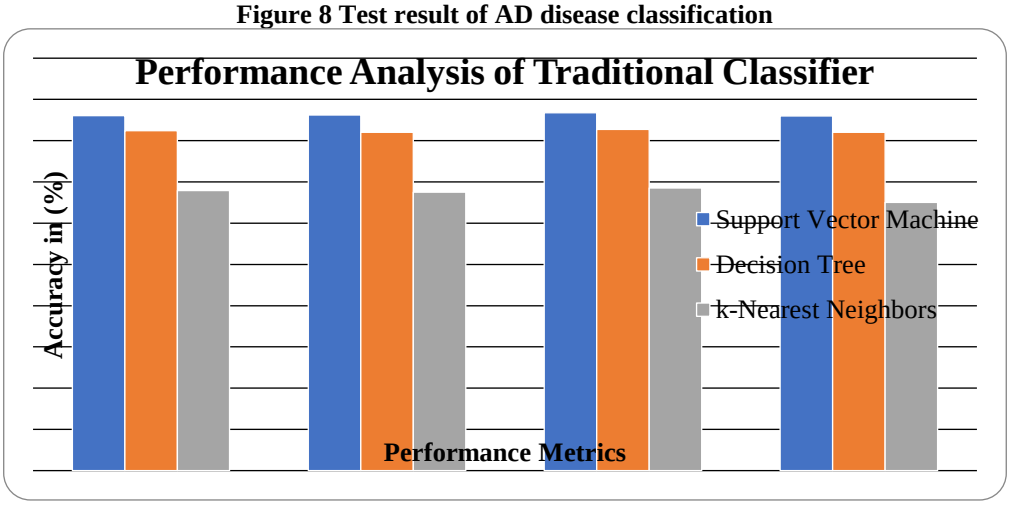

Figure 9 Performance of three traditional classifiers

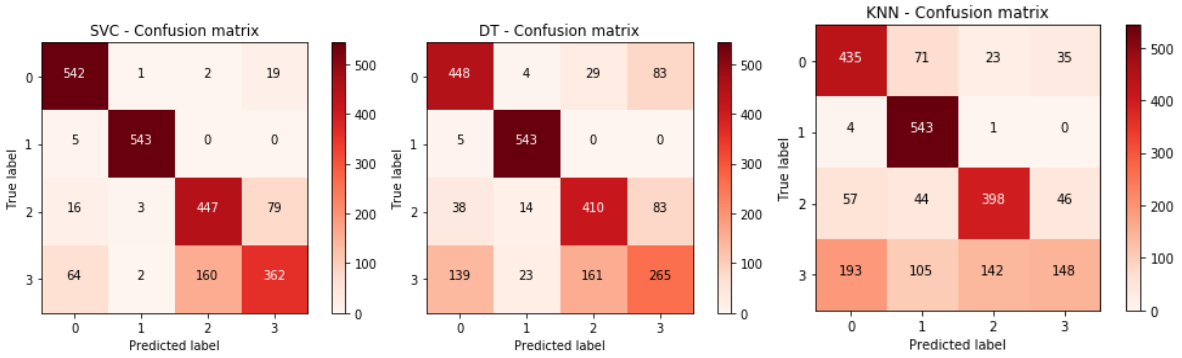

Figure 10 Confusion matrix of three traditional classifiers

The performance of different traditional classification algorithms, such as SVM, DT and k-NN, is shown in Table 2 and Figure 9. The table 2 shows that SVM models outperform other traditional classifiers, despite the fact that their performance is comparatively high. The traditional models' confusion matrix is presented in Figure 10.

Conclusion

Detection and classification of AD disease in MRI images is a difficult task since objects belonging to the same category might have very different appearances. So, in order to achieve decent results, we've proposed a combined SIFT+SURF feature extractor, which entails features rather than a single extraction techniques. SVM, DT, and k-NN are three traditional classifier approaches that are explored in this research. In the suggested models, we found that Support Vector Machine performs best and outperformed than other two traditional classifiers decision tree and k–nearest neighbours. Still, there is opportunity for development of Alzheimer's disease system. Instead of traditional machine learning approaches to handle large image datasets, deep learning techniques can be reduce complexity and improve classification accuracy.

Statements and Declarations

Funding There is no funding for this research work.

Conflict of interest The authors have no conflicts of interest to declare.

Author contributions Corresponding author has implemented the proposed methodology, results and paper writeup. Co-author has done the literature survey, results development and manuscript preparation. Total manuscript is prepared by both the authors together.

Data availability Enquiries about data availability should be directed to the authors.

Ethical approval The manuscript should not be submitted to more than one journal for simultaneous consideration. Results should be presented clearly, honestly, and without fabrication, falsification or inappropriate data manipulation.

Informed consent All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report.

References

1. M.A. Ansari, S. Gul, M. Yaseen, Alzheimer's disease: A bibliometric study", TRIM, Vol. 2, pp. 130-140, 2006.
2. I. O. Korolev, `Alzheimer's disease: A clinical and basic science review", Med. Student Res. J., vol. 4, no. 1, pp. 2433, 2014.
3. NIH. Alzheimer's Disease: A Clinical and Basic Science Review. Accessed: Jul. 13, 2020.
4. C. Humpel, Identifying and validating biomarkers for Alzheimer's disease, Trends Bio technology, Vol. 29(1), pp. 26–32, 2011.
5. C. Ledig, A. Schuh, R. Guerrero, RA. Heckemann and D. Rueckert, Structural brain imaging in Alzheimer's disease and mild cognitive impairment: biomarker analysis and shared morphometry database, Science Representation, Vol. 8(1), pp.11258–11284, 2018.
6. P.M. Thompson, K.M. Hayashi, G. De Zubicaray , A.L. Janke, S.E. Rose, J. Semple, D. Herman, M.S. Hong, and D.M. Doddrell, Dynamics of gray matter loss in Alzheimer's disease, Journal of Neuro. Science and Technology, Vol. 23(3), pp.994–1005, 2003.
7. R. Banzi , P. Camaioni, M. Tettamanti and U. Lucca, Older patients are still under-represented in clinical trials of Alzheimer's disease, Alzheimer's Res Ther, Vol. 8(1), pp. 25-32, 2016.
8. A. Kaur, and P. Kaur, A comparative study of various exudate segmentation techniques for diagnosis of diabetic retinopathy. Int. Journal. Curr. Eng. Technol. Vol. 46(1), pp. 142–146, 2016.
9. R.C. Petersen, P.S. Aisen and L.A. Beckett, "Alzheimer's Disease Neuro imaging Initiative (ADNI) clinical characterization", Journal of Neuro Image, Vol. 74, pp. 201-209, 2010.
10. Li,G., Ma,M., Liu, C., Shu,Y.: Routing in taxi and public transport based heterogeneous vehicular networks. In:Region Conference (TENCON), 2016 IEEE, pp. 1863–1866. IEEE, 22 Nov 2016.
11. A. Farooq, S.M. Anwar, M. Awais and M. Alnowami, Artificial Intelligence based Smart Diagnosis of Alzheimer's Disease and Mild Cognitive Impairment, IEEE Transaction on Image Processing, vol. 17(2), pp. 1-12, 2017.
12. M. Zaabi and N. Smaoui, Comparative Study of Two Classification Methods for the Detection of Alzheimer's Disease, Current Medical Imaging Reviews, Vol. 14(1), pp. 88-94, 2017.
13. Rao, M., Wagner, S.R., Pedersen, C.F., Beevi, F.H., Hansen, F.O.: Ambient assisted living healthcare frameworks, platforms, standards, and quality attributes. Sensors 14(3), 4312–4341 (2014)
14. B. Uji, L. Mesrob and S. Kinkingnéhun, Support vector machine-based classification of Alzheimer's disease from whole-brain anatomical MRI, Journal of Neuro radiology, Vol. 5(1), pp. 51–73, 2009.
15. Y. Li, X. Zheng, J. Shi, and Q. Zhang, Multi-Modality Stacked Deep Polynomial Network based Feature Learning for Alzheimer's Disease Diagnosis, IEEE, vol. 16, pp. 851-854, 2016.
16. Cruz-Roa, A., Caicedo, J.C., González, F.A., Visual pattern mining in histology image collections using bag of features. In: Artificial Intelligence in Medicine Vol. 1(12), pp. 1-12, 2011.
17. Cruz-Roa, A., Díaz, G., Romero, E., González, F.A., Automatic Annotation of Histopathological Images Using a Latent Topic Model Based On Non-negative Matrix Factorization. Journal of Path Inform. Vol. 2(1), pp. 2011.
18. Kavita, K., Navin, R., & Madan, A. S., Piecewise feature extraction and artificial neural networks: an approach towards curve reconstruction, Indian Journal of Science and Technology, Vol. 9(28), pp. 121-134, 2016.
19. Rueda, A., Arevalo, J., Cruz, A., Romero, E., & González, F. A., Bag of features for automatic classification of Alzheimer's disease in magnetic resonance images. In Iberoamerican Congress on Pattern Recognition, Springer, Berlin, Heidelberg, pp. 559-566, 2012.
20. Aruna, S. K., & Chitra, S., Machine Learning Approach for Identifying Dementia from MRI Images. World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, Vol. 9(3), pp. 881-888, 2016.

21. Manandhar, A., Gautam, S., Shrestha, D. K., Sauden, S., and Pant, D. R., Identifying Dementia in MRI Scans Using Artificial Neural Network and K-Nearest Neighbor. Zerone Scholar, Vol. 1(1), pp. 22-25, 2016.
22. Diaz, G., and Romero, E., Micro-structural tissue analysis for automatic histopathological image annotation. Microscopy Research and Technique, Vol. 2(4), pp. 343–358, 2011.
23. OASIS Brains. Open Access Series of Imaging Studies. Accessed: Jul. 13, 2020. [Online]. Available: https://www.oasisbrains.org
24. ADNI. Alzheimer's Disease Neuroimaging Initiative: ADNI. Accessed: Jul. 13, 2020. [Online]. Available: http://adni.loni.usc.edu/data-samples/access-data
25. David G. Lowe. Object recognition from local scale-invariant features. In International Conference on Computer Vision, 1999.
26. Bay H, Tuytelaars T and Van Gool L., Surf: Speeded up robust features, In Computer vision–ECCV, Springer, pp. 404–417, 2006.
27. Zanaty E.A., Support Vector Machines (SVMs) versus Multilayer Perceptron (MLP) in data classification, Egyptian informatics Journal, pp.177-183, 2012.
28. Rohini, M., Surendran, D. Toward Alzheimer's disease classification through machine learning. Soft Comput **25,** 2589–2597 (2021).
29. Arafa, D.A., Moustafa, H.ED., Ali-Eldin, A.M.T. et al. Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey. Multimed Tools Appl (2022).