Local post-hoc interpretable machine learning model for prediction of dementia in young adults

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ABSTRACT

Dementia is still the prevailing brain disease with late diagnosis. There is a large increase in dementia disease among young adults. The major reason is over indulgence of young adults on social media resulting in denial of disease and delayed clinical diagnosis. Dementia is preventable and curable if diagnosed at an early stage, however, no attempts are being made to mitigate dementia in young adults. Today artificial intelligence (AI) based advanced technology with real-life consultations in clinical or remote setups are proved beneficial and is used to detect dementia. Most AI-based test is dependent on computer-aided diagnosis (CAD) tools and uses non-invasive imaging technology such as magnetic resonance imaging (MRI) data for disease diagnosis. In this paper, a local post-hoc interpretable machine learning (LPIML) model for prediction of dementia in young adults is proposed. The performance parameters are computed and compared based on accuracy, specificity, precision, F1 score and recall. The proposed work yields 98.87% training accuracy on original images and 99.31% training accuracy on morphologically enhanced images. The performance results are intrinsic and intuitive in learning the prediction results of individual case. The adoption of the proposed work will accelerate the diagnosis process in the era of digital healthcare.

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1. INTRODUCTION

Strategic Market Research LLP [1] ongoing brain research it is projected to have a market share of 8 billion by 2028 with an approximate growth rate of 7.20%. The amount of money invested in brain research is growing exponentially which is nearly 8 billion US dollars in 2028. There are various factors affecting the human brain and its related diseases. At present several use cases related to memory loss can be seen. According to the world health organisation more than 55 million people are diagnosed with dementia, with a projection of a 10 million increase every year. Dementia, one of the most prevalent disease, is such that it has the potential to drain out the psychological space, social well-being, emotional outbursts and economical strain on the immediate family of the diseased. Dementia is a disease leading to the slow death of brain cells, eventually leading to memory loss. In the absence of awareness for the diseased, its early measurement tools, regulated policies, and lack of knowledge, sensitivity and awareness of caretaker, the number of people affected from dementia is expected to rise exponentially. The quantum of patients to be affected by 2050 with dementia is nearly 131 million. The measurement tools to diagnose population subjected to dementia is yet to be regulated and validated [2]. Motor impairment is one of the early symptoms for the diagnoses of dementia. Mikuła [3]

the association between the cognitive function of a subject including grip strength is identified as a common and one of the early symptoms for dementia. Currently most of the AI based techniques to predict dementia is based on biomarkers. Bansal *et al*. [4] recent studies it has been observed that dementia is prevailing in young adults. The average onset period of the disease is 20 years resulting in the diminishing cognitive ability of the subject to perform their daily task and routines. Venugopalan *et al*. [5] there are broad 3 categories of patients leading to dementia mentioned. The first one is hereditary. The second is of type mild cognitive impairment (MCI). This stage is an early onset of Alzheimer's disease. The third is type dysfunction of the brain due to accident, trauma or frequent consumption of alcohol leading to dementia. Other nominal and prevailing symptoms adding to the onset of the disease are uneven gait movement, speech impairment and gradual deformation of handwriting. Currently, young adults commonly experience symptoms associated with constant engagement in the virtual world, including a decrease in attention span, difficulty retaining information, and suffering from depression due to self-isolation and resentment caused by social media engagements. These factors are often overlooked despite their significant impact on this demographic.

The global dementia observatory is platform for creating global action plans on dementia, it accumulates data from 35 key dementia indicators such as action plan at regional, national and global level. The global societal cost of dementia is 1.3 trillion US dollars. At present people living with dementia related disease such as mild, moderate or severe are 55.2 million and this figure is expected to increase three folds by 2030. Dementia is the ranked 7th as most leading cause of death and the major observation states that 65% of patients dying of dementia related diseases are women.

In a recent report a blood test is developed to measure the tau protein associated with brain changes due to Alzheimer. These tests are costlier and requires specialised labs. The sample of more than 400 patient were collected. The study found the Alzheimer with healthy pateints suffering from other type of neudegenerative disease. Futher, on going research are made to detect Alzheimer with cost effective blood test. At present some of the methods in [6]–[9] detect dementia based on the clinical history of patients, psychological and neurological examinations and neuroimaging. The methods and systems at present are based on magnetic resonance imaging (MRI) clinical studies and are subject to the presence of the patient in the hospital. In the past, it is observed that early onset of symptoms similar to Alzheimer's disease (AD), vascular dementia (VaD), lewy body, frontotemporal dementia (FTD), Parkinson's disease and alcohol-related dementia eventually led to dementia are detected at a later stage that cannot be reversed.

The primary objective of the proposed work is to augment LPIML model using MRI for result interpretation of the medical images to accurately diagnose progression and classification of dementia. The organization of paper is as: section 2 is dedicated towards the related work in the field of brian disease. Section 3 elaborates the material and methods used for the study. Section 4 describes the proposed model and working algorithm. Section 5 contains the details of evaluating parameters and datasets along with the experimental observations and result analysis. Section 6 concludes the work.

2.   LITERATURE REVIEW

The objective of study is to represent the AI based solution present in early diagnosis of the brain disease. Carós *et al*. [9] and Raj *et al*. [10] the reminiscence theracy is automated for the classification of dementia patient, a chatbot namely Elisabot interacts with patient and enquire about their past experiences. The chatbot uses visual question generator (VQG) which tries to make the dialogue more engaging allowing for targets to improve communication skills and stimulate memory. It uses convolutional neural network (CNN) and long short-term memory (LSTM) based question generators shown to the patient. The system is tested on limited dataset. Battineni *et al*. [11] describes the machine learning based model using regression-based prediction on automated facial expression for disease prediction, but it is still prone to human error. In a survey [12] a systematic review and meta-analysis on the onset of dementia is discussed, pointing that the most common type of dementia among world population are Alzheimer and vascular dementia, while AI-based detection techniques are having accuracy ranging from 73% to 89%, and further the techniques are facing limitation of limited search term base with static databases.

Aggarwal and Sharma [13] namely, mini-mental state examination (MMSE) is described. In this, three different congnitive tests such as addenbrooke's cognitive examination-revised (ACE-R), montreal cognitive assessment (MoCA), and clock drawing test using pen and paper method is conducted, followed by clinical diagnosis. The sensitivity rate of these tests ranges from 79% to 87% where specificity ranges between 82% to 90%. The process of diagnosis using MMSE is time consuming and requires expert's supervison and conduct. Termine *et al*. [14], a CAD based MONAI and clinica frameworks to detect frontotemporal dementia (FTD) is proposed to classify and benchmark prediction methods. The framework for FTD classification demonstrates 0.80 accuracy, 95% confidence with intervals of 0.64, 0.91, 1 sensitivity, 0.6 specificities, 0.83 F1-score, and 0.86 area under the curve (AUC). The framework lacks a standardized pipeline for detection and adoption

classification method for demented pateints. The classification method in [15] uses weight maps with 10-fold CV SVM for prediction of dementia. The studies shows major diffrenciation between FTD and classification on late onset AD with an accuracy of 72%. Although the studies need improvement in radiology method and clinical routine. Sun *et al*. [16] states the use of oculometric biomarkers for the detection of demented people. The method uses tracking of eye movement to detect dementia. The model uses to improve the efficiency of eye-tracking methods to detect dementia. The simulation results show 88% accuracy in detection of mild cognitive impairment. The quality of the dataset collected determines the result accuracy and affects the efficiency of implementation.

Zheng *et al*. [17] discusses a language-based classifier for detecting dementia. The application uses three different models for detection of patient's affected from dementia using classification approach of stop words, context words and part-of-speech (PoS) sequences. The model shows an accuracy of 76.16%, 70.00% and 81.54% respectively. Small language parsers may be induced on the larger dataset. Khan *et al*. [18] shows implementation of video-based computer vision algorithm detecting violent behaviour in dementia-diagnosed people, having an accuracy of 75.4%. The detection of violence is detectd using single camera view that classify violence. The comparison result shows improved performance efficiency when compared with non-dementia-diagnosed patient. Kim *et al*. [19] deploys passive infrared (PIR) based sensor enabled monitoring system for predicting dementia. An accuracy of 63.38% was achieved using deep neural network (DNN) with principal component analysis (PCA) method with standard scaler intervention. Here a step count method is used to monitor and predict dementia and observation is based on a very small dataset of 18 patients only.

Khan *et al*. [20] uses stacked deep dense neural network (SDDNN) model for text classification and prediction of demented and non demented patient. The accuracy achieved by this model is improved to 93.31%. The SDDNN model is tested for accuracy using 10-fold cross-validation approach. This method faces limitation of not including multiclass classification of large dataset to claim the improved efficiency. Minamisawa *et al*. [21] classifies dementia scale score. The maximum accuracy achieved in this method is 87.1% with a linear support vector machine (SVM) model. The result lacks inclusion of larger location and sleep datasets to identify the dementia scale score. Hadiyoso *et al*. [22] Alzheimer's disease detection network (ADD-Net) defines various stages of AD. The ADD-Net achieved the following values for evaluation metrics: 98.63%, 99.76%, 98.61%, 98.63%, 98.58%, and 0.0549% accuracy, AUC, F1-score, precision, recall, and loss, respectively. The results achived are based on network devices and parameters achieved. Finetuning and deployment of federated learning models is needed to improvise the results achieved in real time environment.

The results claimed in the previous studies are based on preassumptions on a smaller dataset. The results so achieved are biased and can be validated if a supporting post analysis of result is obtained. Further, the results so obtained must corelate with the clinical diagnosis.

3.   MATERIALS AND METHODS

In this paper, LPIML model is proposed for prediction of dementia in young adults. The dataset derived from github for the experimentation purpose. Goolge Colab is used to evaluate the performance of the dataset.

3.1. Tools and libraries

In the proposed work, Keras and Tensorflow libraries are used. Both the libraries are extensively used for open platform devices to build CNN models. The performance evaluation of the collective dataset is executed using Tensorboard tool. In this, segmentation is applied to fraction different portions of the image in various categories related to object classification. Each pixel in an image is classified. Segmentation of the image based on pixel classifies the image and draws useful insights from the image. Further, it helps in the understanding of region of interest from the boundary of the image.

In most cases, image segmentation is based on areas of study for the medical fraternity. In general, image segmentation is classified into major categories like manual segmentation, semi-automatic segmentation and full segmentation. Manual segmentation is considered the gold standard for minutely detecting the disease and analysing the deterioration or improvement of the patient. The semi-automatic segmentation uses three points of user interaction defining the region of interest, its evaluation and feedback. It is classified as segmentation based on a threshold value, edge detection, cluster-based and region based. The result of the semi-automatic segmentation is user-dependent. Similar work on identification of images is referred in [23], [24]. Another method of segmentation is based on clustering, in this clustering is done based on pixels. This is also considered unsupervised learning from the finite set of image pixels. Segmentation based on thresholding is different as compared to the other segmentation process discussed before. Here the image is set against a global threshold value in which it is a constant for the entire image whereas in the local thresholding the image is subdivided into sub-images in which the local threshold value is set for each sub-part of the image. In segmentation based on region, the segmentation is done based on sub-regions while splitting the region of interest and then merging the image into unconnected regions with similar characteristics of interest. In

segmentation based on edge detection, the image classification having sharp intensity adjustment. The only limitation of this technique is that it loses its accuracy over discontinued image boundaries. Edge detection is used where a sharp adjustment in intensity at boundaries is required. Regions that have an extreme transition in intensity can be extracted through this method. This method is generally used in images where the boundaries and edges define the region of interest like in satellite images, and traffic images, with the only limitation being that segmentation can reduce it's accuracy at the discontinuities of a boundary. Canny edge detector and Laplacian edge detector algorithms are used for edge detection [25]. Fully automatic segmentation method does not require user interaction for every step, rather it works on the concept of training and testing with the help of some prior knowledge and artificial intelligence. The objective is to classify the image with dementia and to segment the image to detect the area of dementia [26]. The basic challenge in fully-automatic segmentation [27], [28] is to identify dementia with accurate edge detection and position, but still at the time of testing and validation the greatest challenge is to classify the disease correctly [29]. Fully automatic segmentation models [30] are divided as discriminative [31] and generative models. Discriminative methods which focies on learning based on the relationship between an input image and ground truth, while generative methods focues on probabilistic models having some prior knowledge like spatial context and location.

Although many architectures like Resnet, Alexnet, and Vgnet are implemented for image segmentation, U-net gives the highest accuracy in the case of medical image segmentation. For the implementation U-net is taken for experimentation here. This is known as the supervised method since it requires manually segmented training data at an initial step to automatically segment the new data. It works on the concept of identifying the nearest neighbour with the closest intensity. K-nearest neighbour classifier is a common classifier used for nonparametric segmentation. Another frequently used nonparametric segmentation classifier is the Parzen window, where classification depends on a predefined window of the features space cantered at the unlabelled pixel intensity [32]. Alexnet is a deep convolutional network consisting of five convolutional layers, first is max-pooling, second is rectified linear units (ReLUs), three fully connected layers and dropout [33]. Visual geometry group (VGG)-16 is a CNN model having 16 weight layers. High accuracy up to 92.7% can be achieved by using this model. The number of repetitive layers leads to more non-linearity and less parameter-dependent, which in turn makes the decision function more discriminative and easier to train. In Googlenet, a CNN network contains 22 layers and an inception module, which can be arranged in any customizable structure. The basic architecture contains a network of a network, a large-sized convolution layer and a small-sized convolution layer with a pooling operation. All the layers are computed and executed in parallel with 1×1 convolution operation to reduce the dimensionality and requirement of a large number of parameters. In U-net, CNN model is prominently used in bio-medical image semantic segmentation. CNN model performs localization to find out the pixel location of a single class and classify the localized pixels. The shape of architecture is U, consisting of a downslope (contracting path), an upslope (expansive path) and a skip connection. During the contracting path, the network learns to classify the objects and processes the input MRI image, while during the expansive path, the network learns to localize the pixels and produces the labelled output. In U-net total of sixteen convolutional layers are present and spread over four convolution blocks and four de-convolution blocks. Each block contains 2 convolutional layers, one dropout layer and one max pooling layer. The input image size taken for U-net is 256×256, it is fragmented up to 32×32 during the downslope and again restructured to the size 256×256 during the up-sample path. Total 662,385 parameters are used.

4. SYSTEM MODEL AND PROPOSED METHOD

In this section, the system model and proposed methodology are introduced for LPIML. The basic methodology starts with the acquisition of online dataset on github taken for training, testing and evaluation. Figure 1 illustrates the three observation cycles in which DACP is used for evaluation and validation purposes. The training is done in two stages, one for original images and the other for morphologically enhanced images. The testing is conducted to observe the changes in parameters. It is trained on original and morphologically enhanced images and trained on original images to compare the performance and accuracy.

Considering a patient individual data where each MRI is collected as a repository of patient on each visit as RP. Each MRI scan is a set of multipls N images denoted as SC, where each pateint scan is belonging to a P as a collection $sc_1, \ldots, sc_k, \ldots, sc_n$. RP is structured and stored for connecting the MRI for P pateints within one diaganostic centre as DC, where each P belonging to a DC. There are maximum of N DC, each denoted by $dc_1, \ldots, dc_i, \ldots dc_n$. A post hoc model is selected to analyse the SC of P. MS is a set constructed of masking of images. All the acronym and its abbreviation defined for LPIML is listed in Table 1.

The working of the Algorithm 1 is divided into two stages namely LPIML initialization and modelling phase. In the initialization phase, for all the scanned images, resize the images to obtain morphologically enhanced images and them=n LPIML model is applied. In this, for each scanned image SC Xi point is taken on MRI for plotting labels to predict the instances around point Xi by adding gaussian noise to DACP. INS is

generated and weighed to obtain distance of each point to assign simple linear model. This phase helps in identifying progression of dementia. Algorithm 2 defines the steps to train and test the DACP using LPIML model on morphologically altered images and evaluating the results by applying LPIML model to create confusion matrix.
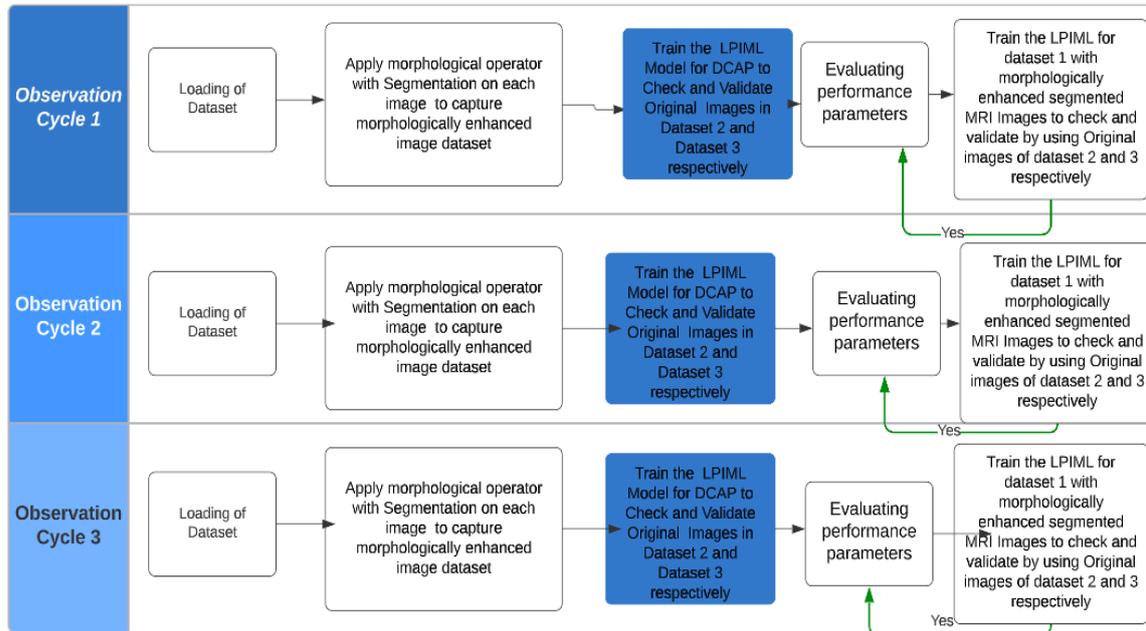

Figure 1. Three-step observation cycle of LPIML

Algorithm 1. LPIML initialization

```
Input: RP, SC, DC
Phase 1: Initialization
    1.  Set SC(1) as the initial data, P(1) = 0,
    2.  Resize of [P(MSi)], ∀ i =1 to n
    3.  Obtain morphologically enhanced dataset M[DACP]
    4.  Applying LPIML Model
    5.  Repeat step 2 to 4, to import the DACP
Phase II: LPIML Model
    1.  For each i ∑SC take a point Xi on MRI
    2.  Plot labels using LPIML
    3.  Predict instances around point Xi by adding random gaussian noise to DACP
    4.  Generate INS
    5.  Weigh INS to dist(Xi)
    6.  Assign simple linear model on weighted INS
Output: Detect dementia progression on linear model
```

Algorithm 2. Training and testing the DACP for LPIML model

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Input: DACP Original and Morphilogically Altered Dataset
Phase I: Observation Cycle 1:
    1.  Train the model for DACP
    2.  Test the model ∀ M[DACP]
    3.  Evaluate the results by applying LPIML
    4.  Creating confusion matrix
    5.  tn=res[1][1]; tp=res[0][0] ; fn=res[1][0]; fp=res[0][1]
    6.  Sensitivity=(tp)/(tp + fn) ; Specificity = (tn)/(tn + fp)
    7.  Precision= (tp)/(tp+fp) ; Recall= (tp)/(tp+fn)
    8.  Dice=(2*tp)/((2*tp)+fp+fn)
    9.  Evaluate training model by using model.evaluate(X_train,Y_train)
    10. Evaluate testing model by using model.evaluate(X_test,Y_test)
    11. Saving the model
    12. Repeat the step 1 to 10 for execution of observation cycle 2 and 3
```

Table 1. List of notation and its abbreviation defined for LPIML

Notation	Abreviation
DACP dataset	Dementia Alzheimer classification prediction dataset
P	Patient
RP	Patient repository
SC	Scanned MRI images
DC	Diagnostic centre
INS	Instance
Dist	Distance
tn	True negative
Tp	True positive
Fn	False negative
Fp	False positive
M[DACP]	Morphologically enhanced DACP

5. RESULTS AND DISCUSSION

The online available dementia dataset is taken for experimentation and analysis of image classification. The basic details of datasets are discussed in Table 2. DACP is consisting of 1,279 images comprising of 179 subjects diagnosed with miled dementia, 12 with moderate dementia, 448 with very mild dementia and 640 subjects with non demented stage. The unique values of subjects aged from 18 to 96 years. Each subject has been scanned more than twice in a gap of one year resulting in a total of 1,279 images. The dataset includes both men and women all are right-handed. Out of 150 subjects, 72 were identified as non-demented, 64 were suffering from dementia at the time of their initial visits and remained for subsequent scans including 51 individuals with mild to moderate Alzheimer's disease. Some 14 subjects were diagnosed with dementia later in the visits.

Table 2. Dataset used for analysis and experimentation for image classification

Dataset	Subject with mild dementia	Subject with moderate dementia	Subject with very mild dementia	Subject non dementia
DACP dataset [34]	179	12	448	640

All the images in the dataset are comprised of dementia patients. The main target of the system is to segment dementia-affected subjects from the scanned images. DACP is split into 80:20 ratio for training and validation. The effectiveness of the proposed LPIML is validated by evaluating the performance parameters at each observation cycle. The performance parameters used for the quantitative analysis of the proposed technique are dice, recall, precision, sensitivity, specificity and F1 measure. The mathematical extension of these parameters is as:

$$Sensitivity = (TP)/(TP + FN) \tag{1}$$

$$Specificity = (TN)/(TN + FP) \tag{2}$$

$$Precision = (TP)/(TP + FP) \tag{3}$$

$$Recall = (TP)/(TP + FN) \tag{4}$$

$$F1 = 2*(Precision*Recall)/(Precision + Recall) \tag{5}$$

$$Dice = (2*TP)/((2*TP) + FP + FN) \tag{6}$$

The training of the model is conducted in two phases to judge the difference in the observation of performance parameters. When a system is trained on normal images, it performs the testing of normal images of the other two datasets. Figures 2 to 5 showing sample brain MRI images of patient not suffering from dementia, suffering from very mild dementia, mild dementia and moderate dementia. The qualitative and quantitative analysis is discussed.
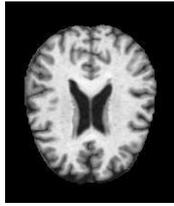
Figure 2. MRI of subject not suffering from dementia
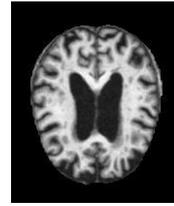

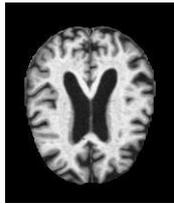Figure 3. MRI of subject suffering from very mild dementia

Figure 4. MRI of subject suffering from mild dementia

Figure 5. MRI of subject suffering from moderate dementia

The testing images taken for validation of the model trained on original and morphologically enhanced images od DACP. Each testing image contains a demented area of different dimensions and shapes. The LPIML is capable of classifying the dementia area from any test image. Table 3 shows the observed values for all performance parameters for 3 cycles of training and testing. The observation is taken in 3 cycles having 2 phases each. For cycle 1, the first phase consists of training of model with original images of dataset 1 and testing for dataset 2 and 3 respectively. For cycle 2, the first phase consists of training of model with original images of dataset 2 and testing for dataset 1 and 3 respectively. For cycle 3, the first phase consists of training of model with original images of dataset 3 and testing for dataset 2 and 1 respectively. The performance analysis is evaluated based on the values for sensitivity, specificity, precision, recall, F1-measure and dice similarity observed during the simulation.

Table 3. Observations of model trained and tested on different datasets

			Sensitivity	Specificity	Precision	Recall	F1 Measure	Dice
Observation cycle 1	Model trained on dataset 1(original images)	Dementia dataset 1	0.935	0.671	0.82	0.935	0.677	0.67
		Dementia dataset 3	0.9223	0.2392	0.6723	0.9223	0.7775	0.745
	Model trained on dataset 1 (morphological enhanced images)	Dementia dataset 2	0.9972	1	1	0.9972	0.9935	0.9935
		Dementia dataset 3	0.95587	0.2404	0.746	0.9658	0.7827	0.7827
Observation cycle 2	Model trained on dataset 2 (original images)	Dementia dataset 1	0.871	0.851325	0.8213	0.84	0.801	0.8101
		Dementia dataset 3	0.811	0.1747	0.5822	0.8911	0.7043	0.7043
	Model trained on dataset 2 (morphological enhanced images)	Dementia dataset 1	0.8906	0.8347	0.8633	0.9406	0.8369	0.8369
		Dementia dataset 3	0.8909	0.1842	0.7404	0.8909	0.7451	0.7451
Observation cycle 3	Model trained on dataset 3 (original images)	Dementia dataset 1	0.7694	0.623	0.4806	0.7694	0.5917	0.5917
		Dementia dataset 2	0.8522	0.5051	0.4838	0.8522	0.6172	0.6172
	Model trained on dataset 3 (morphological enhanced images)	Dementia dataset 1	0.8912	0.6772	0.5253	0.912	0.7969	0.7969
		Dementia dataset 2	0.871	0.583	0.5161	0.861	0.6825	0.6425

In Table 3, the observed values of performance parameters for all three observation cycles are discussed. Figure 6 showing the comparative analysis of observed values for LPIML Model trained on original images and morphologically enhanced images. Figures 6(a) to 6(e) provides a visual result of all the performance parameters namely sensitivity, specificity, recall, precision, F1 measure and dice coefficient respectively. It is observed that improved results are seen in every observation cycle. The performance parameter and it's accuracy is calculated for a model trained on morphologically enhanced images and it is compared with the accuracy of original images. The comparison of training and the testing accuracy is shown in Table 4.

(a)   (b)

(c)   (d)

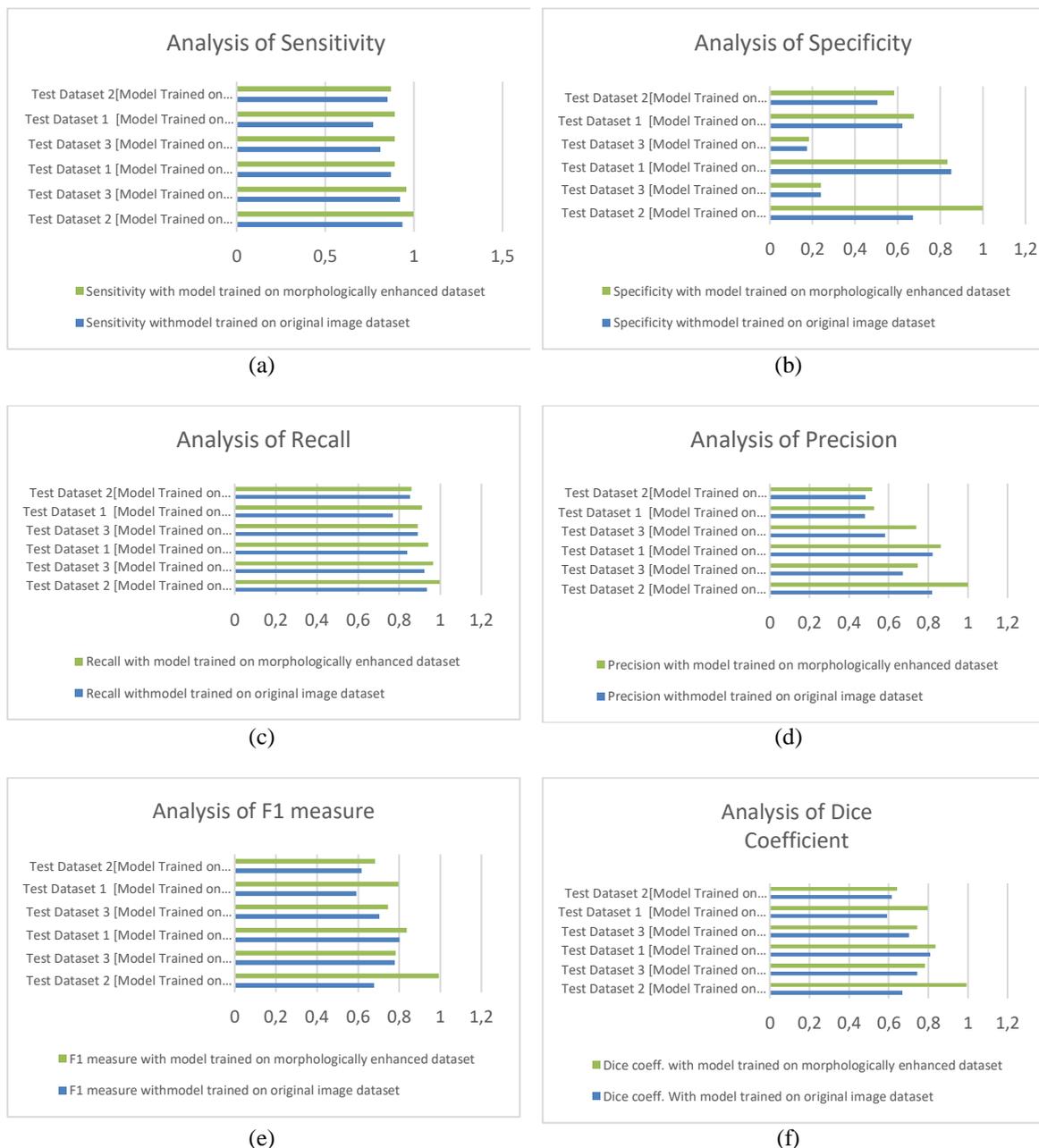(e)   (f)

Figure 6. Comparative analysis of observed values for LPIML model trained on original images and morphologically enhanced images; (a) analysis of sensitivity, (b) analysis of specificity, (c) analysis of recall, (d) analysis of precision, (e) analysis of f1 measure, and (f) analysis of dice coefficient

The accuracy of the proposed model obtained in Table 4 shows that the images enhanced using morphological operators give improved results than without applying morphological operators. To further compare the results obtained from the hybrid hidden Markov model it is compared with the existing work. Table 5 represents a comparison of the proposed model with other existing models based on different performance parameters.

Table 4. Model accuracy

Model	Training accuracy	Validation accuracy
LPIML model trained on original images	98.87%	97.66%
LPIML model trained on morphologically enhanced images	99.31%	98.41%

Table 5. Comparison of the hybrid hidden Markov model with other existing models

Paper	Year	Framework used	Dice coefficient	Precision	Specificity	Sensitivity	Recall	F1 Score
Tejas and Padma [35]	2016	Region growing and threshold segmentation	0.9707	0.9860	-	-	0.9987	0.9797
Salehi et al. [36]	2017	3D fully CNN	56.42	-	-	65.57	-	57.32
Hashemi et al. [37]	2018	3D fully convolutional deep neural networks	65.74	-	-	66.77	_	_
Sajid et al. [38]	2019	2 path CNN model	0.86		0.91	0.86		
Ravikumar and Shivaprasad [39]	2021	bidirectional convolutional LSTM XNet	_	0.91	0.98	0.91	_	0.88
Srinivas and Rao [40]	2020	U-Net and VGG-Net	0.96702	_	_	_	_	_
Proposed work	2023	LPIML	0.9935	1	1	0.9972	0.9972	0.9935

Note: *Missing values are denoted as "-"

In Table 5, the LPIML Model is compared with the existing systems like region growing and threshold segmentation, 3D fully convolutional network, 3D fully convolutional deep neural networks, U-net with VGG net, 2 path CNN model and bidirectional Xnet for six parameters like dice coefficient, precision, specificity, sensitivity, recall and F1 score. The comparative analysis shows that the LPIML Model performs better than the existing system in terms of observed values of performance parameters. The observations state that LPIML model provides enhanced accuracy and results thereof as compared to the other existing models.

6.   CONCLUSION

The result analysis of the LPIML Model is presented for detecting dementia by using a morphological operator. DACP datasets are used for the evaluation and testing of the designed model for brain MRI image classification and segmentation. The proposed model is trained for a total number of 1,279 images in two stages and testing is conducted. The methodology is constructed of three observation cycles. Observation cycle I consist of the implementation of the original image of dataset 1 to train the model and testing with original images of the other two datasets in its first stage. In the second stage, the model is trained with morphologically enhanced images of dataset 1 which were further used to train the model and it is tested for the other two datasets with their original images. Similarly, observation cycle 2 for dataset 2 and observation cycle 3 for dataset 3 is conducted and analysed in the same manner. The average dice similarity of 0.707 for dataset 1, 0.7575 for dataset 2 and 0.6063 for dataset 3 is being observed respectively for the first stage of three cycles. The average dice similarity observed in the second stage is 0.888 for morphological enhanced dataset 1, 0.791 for morphological enhanced dataset 2 and 0.7197 for morphological enhanced dataset 3. The proposed work yields 98.87% training accuracy on original images and 99.31% training accuracy on morphologically enhanced images. The proposed model is compared with the other existing systems and found to be more efficient for MRI image classification and segmentation for accurate detection of prevailing dementia. The future scope of the study will involve complex AI-based environment for dementia affected people. The implemention of an automated environment specially for a dementia-affected person needs accuracy, privacy and cost-effectiveness. In future, smart environments having combinations of indoor positioning systems and smart wearable will be exciting research areas in dementia.

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