A Deep Learning Approach for Automated Detection and Classification of Alzheimer's Disease

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Abstract. Alzheimer's Disease is progressive dementia that begins with minor memory loss and develops into the complete loss of mental and physical abilities. Memory-related regions of the brain, such as the entorhinal cortex and hippocampus, are the first to be damaged. A person's mental stability is harmed as a result of the severity. Later on, it affects cortical regions that engage with language, logic, and social interaction. Subsequently, it spreads to other parts of the brain, resulting in a substantial reduction in brain volume. Although computer-aided algorithms have achieved significant advances in research, there is still room for improvement in the feasible diagnostic procedure accessible in clinical practice. Deep learning models have gone mainstream in the latest decades due to their superior performance. Compared to typical machine learning approaches, deep models are more accurate in detecting Alzheimer's Disease. To identify the labels as demented or non-demented, the researchers used the Open Access Series of Imaging Studies (OASIS) dataset. The novelty comes in doing extensive research to uncover crucial predictor factors and then selecting a Deep Neural Network (DNN) with five hidden layers and carefully tuned hyper-parameters to achieve exemplary performance. The assertions were supported by evidence of 90.10% correlation accuracy at various iterations and layers.

Keywords: Alzheimer's Disease · Dementia · Deep learning model · Hyper-parameters

1 Introduction

Alzheimer's disease (AD) is defined by disordered brain function caused by the deterioration of neurons. The condition originates in the temporal lobe of the brain hemisphere and extends to other areas of the brain. AD is one of the most critical public health conditions globally and a widespread neurodegenerative phenotype. Multiple cognitive impairments, such as memory, executive control, linguistics, and visuospatial skills, form Alzheimer's disease [1]. According to Alzheimer's Association research, 10% to 20% of adults aged 45 or older have Mild Cognitive Impairment (MCI), an introductory stage of AD. The Mental Health Gap Action Program designated dementia as a high-priority health problem that requires immediate attention [2].

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Dementia is not the same as the usual mental decline with age [3]. Dementia patients frequently lose track of time and place, and they may forget to eat regularly or maintain proper hygiene. It's an expected fact that the aetiology of AD and other brain disorders involves the destruction of brain cells, which can be seen through imaging The cerebral cortex, shrinkage is a factor for Alzheimer's disease. The formation of amyloid plaques and neurofibrillary tangles culminates in irreversible atrophy. Amyloid protein plaques adhere to and damage neuron synapses (the connections between neurons), causing memory lapses, which is an onset of Alzheimer's disease. When a protein strand is twisted, neurofibrillary tangles develop, causing damage to neurons and nerve synapses [4].

Furthermore, the WHO's prevalence rate projections indicate that the proportion of individuals living with dementia would continue to climb, primarily among the elderly. According to the Alzheimer's Association's 2019 global statistics, 47 million individuals worldwide have Alzheimer's Disease; As a result, it has become a substantial public health issue in contemporary society. Furthermore, the total number of cases is predicted to reach 76 million by 2030 [5]. The increasing number of AD cases is attributed to various factors, including population expansion, ageing, and changing social and economic development behaviours. At present, there is no treatment available that can halt or reverse this disease's progression. However, if detected early enough, the condition can be controlled. Diagnosis of AD patients usually with brain imaging techniques such as MRI scans combined with clinical exams that search for indications of memory impairment [6]. Many explorations in the writing have investigated the potential outcomes of Deep Learning (DL) approaches in the domain of neurodegenerative illnesses like Alzheimer's Disease. The use of information created from attractive reverberation imaging (MRI) or positron emanation tomography (PET) has been widely read up for this reason [7]. Brain shrinkage, particularly in the hippocampal regions, shows the loss of cognitive abilities associated with AD. The main goal of this research is to detect Alzheimer's Disease with a deep neural network model using brain image analysis and clinical examination.

The mini-mental state examination (MMSE), clinical dementia rating (CDR), and Alzheimer's disease assessment scale (ADAS) are all longitudinal clinical tests that have shown a significant association with Alzheimer's disease progression [8]. The mapping of this link is advantageous since it enables practitioners to act during the undiagnosed stage. While Alzheimer's disease has no therapy, it can be delayed if symptoms are handled early enough. Memory medications, behaviour mediation, sleep and occupation therapies, and supported living are common treatments [9, 10].

The current work incorporates the prediction of dementia, the OASIS dataset is utilized to perform a hierarchical analysis of all accessible data points. Experimentation with various deep neural network parameters is carried out for achieving the best parameter for the DNN model, and compare the results of the proposed model to those of previously implemented deep learning and machine learning classifiers to demonstrate its efficacy.

The following describes the structure of this paper: Sect. 2 discusses the related works, Sect. 3 depicts a summing-up of the proposed methodology and the explanation of the Deep neural network, Sect. 4 discloses the experiment results, which describes

the dataset and predictor variables and experiment work performed with the deep neural network on the given dataset and results explains performance measure of the classifier and accuracy results with confusion matrix and ROC curve inculcated to depicts the effectiveness of proposed work. Finally, Sect. 5 inscribes the conclusion with future work.

2 Research Background

This division aims to evaluate the recent approaches in predicting and classifying Alzheimer's disease using predictor variables with the help of different types of computational models. To trace the progression of Alzheimer's Disease throughout all six phases, complex nonlinear multifactorial multimodal modelling is necessary. The reduction of preclinical MMSE scores in adults over 75 years old (n = 528) was simulated using growth mixture modelling (GMM) [11]. The study used a subset of the OASIS data to develop approaches for identifying binary-coded AD using Eigenbrain imaging It excluded persons under the age of sixty and data that was incomplete, defined Alzheimer's Disease, confined their analysis with a few numbers of a sliced image of the cortex, and performed a cross fold validations from 10–50 [12]. For 1,000 patients, the MMSE scores and the ADAS scale were used to predict AD symptom development classes over six years. To predict AD progression, the researchers employed MR Imaging, genetic proteins and clinical-based data, and a Siamese neural network with two identical equally weighted subnetworks [8].

In paper [13, 14] the electronic health record scores were utilized to detect dementia. A cross-sectional initial data collection, ADNI registry data sets, MRI measures, and artificial neural network for dementia prediction were also utilized by the researchers. Another analysis created discriminating maps using MRI brain images to implement perfusion technique in the brain tissues and its scores are utilized to properly identify AD and its stages.

The paper [15] developed a deep learning strategy based on sparse autoencoders and 3D convolutional neural networks. An MRI scan should predict if an individual has Alzheimer's disease or has a healthy brain. A workflow for extracting multivariate neuroimaging features for multiclass AD diagnosis was provided in the article. It developed a deep-learning model that maintains all relevant information stored in imaging data using a zero-masking methodology. It had an accuracy rate of 87% [16]. The research discussed in the paper, [17, 18] utilized profound learning-based pipelines and neuroimages to recognize Alzheimer's infection from sound controls records for a specific age range. It was almost difficult to recognize Alzheimer's patients from solid minds.According to the study in paper [19, 20], biomarkers for predicting progression of AD from Mild Cognitive Impairment (MCI) include volumetric MRI-based assessments of regional brain atrophy, notably medial temporal volume loss. For decades, the most extensively used screening test for identifying AD is MMSE. It is not capable of detecting MCI, but it can detect AD at a much higher rate. The hippocampus volume, entorhinal cortex thickness, middle temporal gyrus, and retrosplenial cortex weightings for each ROI obtained using a linear discrimination analysis are used to generate the atrophy score. the greatest way to tell the difference between Alzheimer's sufferers and healthy controls.

Deep learning (DL) has shown promise in clinical information systems for diseases such as diabetes, cancer, and Alzheimer's disease through statistics and imaging analysis. DL's key advantage over other shallow learning approaches is it's capable of learning the best forecasting characteristics directly from the raw information given a set of labelled cases.. In the case of incomplete data, deep learning approaches can help with training and prediction [21].

This work proposes a deep neural network-based automated AD recognition method. The goal is to develop deep neural network models that can accurately identify the existence of Alzheimer's Disease utilizing deep learning techniques combined with clinical evaluations and brain atrophy volume.

3 Proposed Methodology

Our work employed a Deep Neural Network (DNN) model for training and testing, Alzheimer disease prediction criteria called predictor variables to categorise demented and non-demented persons. The neural network model's hidden layers learn the categories incrementally. Figure 1 depicts the proposed deep neural network model for predicting Alzheimer's Disease by taking into account risk variables. The AD Predictor variables dataset contains a set of seven parameters. It can be considered as two sets; the first set typically analyses a subject's cognitive ability. The second is to provide brain volume statistics, as it plays a more significant role in identifying AD patients because the particular disease can shrink the brain. The dataset contains information about both genders. Inconsistent and improper data have been deleted with the benefits of data preprocessing. Feature Elimination was used to delete features that were no longer relevant.

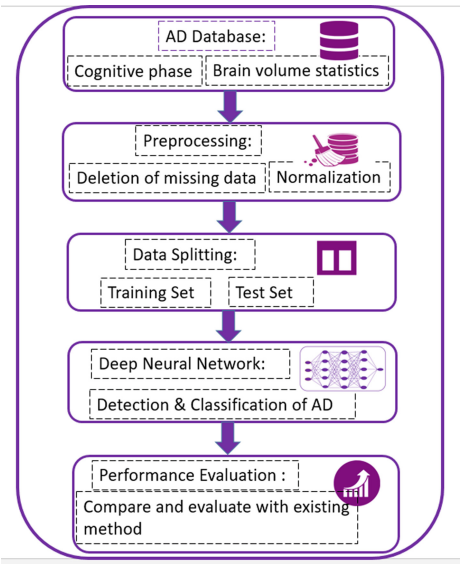

Fig. 1. The proposed model architecture.

A DNN-based prediction model was constructed to detect demented and non-demented people to locate the AD afflicted patients. The model's performance was assessed by comparing it to other best deep and machine learning models found in prior studies. The model has used a layout of 400 data, given a training-test ratio of 70:30 and used five hidden layers to acquire its best performance in accurately classifying the data.

3.1 Deep Neural Network

The current study suggested a DNN model predict AD using a dataset of predictor factors. A DNN is a type of artificial neural network (ANN) that contains numerous hidden layers between the input and output layers and has lately become popular for classification. Each unit in a DNN receives connections from all units in the preceding layer since it is ultimately linked. As a result, each unit has its own bias and weight in two consecutive layers for every pair of units. The net input was computed by multiplying each input by its weight and adding the results. Each unit applied the activation function to the net input in the hidden layer. As a result, the computation of a network with hidden layers and its output layer may be described as in Eqs. 1 & 2.

$$h_i = \phi\left(\sum_j W_{ij}x_j + b_i\right) \tag{1}$$

$$y_i = \phi\left(\sum_j W_{ij}h_j + b_i\right) \tag{2}$$

The x is the input units, b is the bias, w is the weight allotted to the network, h represents the hidden layer of DNN, y is the output units, and ϕ is the activation function. Figure 2 depicts a sample diagram of a DNN.

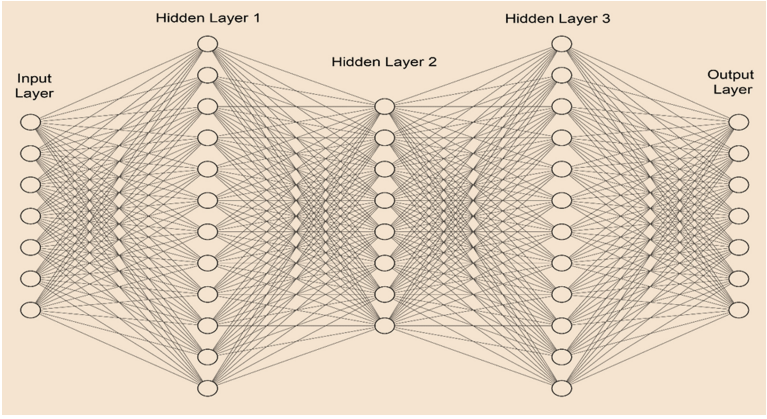

Fig. 2. A sample deep neural network architecture with three hidden layers

4 Experimental Setup

The section describes the set of parameters explored for the proposed work. The experiments are conducted under Windows 10 with an Intel i7 processor of 2.10 GHz with 8 GB of RAM. The software requirements used for the model is set with Python (3.7.6) through the Keras (2.4.3) framework and as Tensorflow (2.3.1) the backend with the libraries of the deep learning model. Many investigations have investigated the capability of Deep Learning (DL) procedures in the field of neurodegenerative problems, for example, Alzheimer's DiseasOne of the most difficult parts of building profound brain networks models is picking the mixes of hyper-boundaries utilizing a circling methodology to expand the exactness and productivity of the model. Profound Learning with matrix search helps in choosing the reasonable boundaries to acquire the best expectation model that keeps away from overfittinge.. Our Neural Network has explored various ranges of hidden layers with a different set of nodes, learning rates, optimizers, activation functions, batch size, epochs, dropouts and output functions to build the network to obtain a network with fine-tuned parameters. The model with different boundary ranges is recorded in Table 1.

Table 1. Hyperparameter setting for the proposed network.

Hyper-parameters	Values explored
Hidden layers	3, 5, 7, 10, 15
Optimizers	SGD, Adam, Adamax, Adagrad
Activation functions	Sigmoid, Relu, Leaky Relu, Tanh
Number of nodes	12, 16, 20
Number of epochs	100, 150, 200, 250, 300, 350, 400
Learning rate	.0001–.01
Batch size	16, 32, 64, 128
Output function	Softmax

4.1 Dataset

The proposed model is tested using data from the Open Access Series of Imaging Studies (OASIS) [22]. The data set consists of 400 observations from 142 participants ranging in age from 58 to 96. There are both men and women in the dataset, and all are right-handed. Medical statistics, such as intracranial volumes (eTIV) and brain volumes (nWBV) of the participants, are included in addition to the Electronic Health Records(HER) such as Clinical Dementia Rate (CDR) and Mini-Mental State Examination (MMSE). The CDR scale has four levels: 0, 0.5, 1, and 2 respectively. A CDR of 0 indicates that the patient is not mentally ill. Very mild dementia, mild dementia, and severe dementia are all represented by CDR values of 0.5, 1 and 2. This medical test is significant

in determining whether or not a person is an Alzheimer's patient. The MMSE is a 30-question questionnaire designed to assess people's cognitive abilities in arithmetic, memory, and orientation. Demented and non-demented controls are the two categories considered in the current work for predicting Alzheimer's Disease [23].

4.2 Predictor Variables

- MMSE (Mini-mental-state-examination): The MMSE is a 30-point valid and reliable questionnaire for detecting dementia.It asses the mental stability based on language skills, visual-spatial skills, orientation skills, memory and attention
- The Clinical Dementia Rating (CDR): It is an ordinarily involved clinical method for rating dementia seriousness, with values going from 0 (no impedance) to 3 (extreme weakness). It checks a singular's judgment ability, critical thinking abilities, local area undertakings, individual consideration and leisure activities to figure out mental dependability.
- Estimated Total Intracranial Volume (eTIV) aka Intracranial volume (ICV): It is frequently employed in volumetric brain research as a measure of pre-morbid brain size as well as to account for inter-subject variability in head size.
- Normalized whole brain volume (nWBV): This element represents the total mass of the brain. Individual subject data benefit from brain normalization since it enables reporting observed active areas in a standard spatial coordinate system.
- The Atlas scaling factor (ASF): It's a parameter scaling factor that enables eTIV comparisons based on human anatomical differences. Table 2 summarizes the dataset's characteristics.

Table 2. Features and the associated range of values in the OASIS database for AD.

Factors	Description	Value ranges
Subject ID	Each subject is assigned a unique identifier	1–142 (Number of subjects)
Age	Represents human growth factor	60–96
Group	For labelling the class	Non-demented controls or demented controls
Gender	Represents the main category of the human being	Male or Female
MRI ID	Each test is identified by a unique identity. For a single person, there might be many MRI IDs	1–354
CDR	Clinical dementia rating	0–2
MMSE	Mini-mental state examination	0–30
eTIV	Estimated total intracranial volume	1488 ± 176.13

(*continued*)

Table 2. (*continued*)

Factors	Description	Value ranges
nWBV	Whole-brain volume normalised as a percentage of all voxels ("constant" for an estimate of total intracranial volume)	0.730 ± 0.037
ASF	For the size of the brain, there is a volume scaling factor:- Atlas Scale Factor	1.195 ± 0.138

4.3 Performance Measures

The proposed method's performance was assessed using four metrics for quantitative evaluation and comparison as Accuracy, Sensitivity, Recall or Specificity, Precision and F1-Score. The following Table 3 describes the definitions for each of these parameters.

Table 3. Performance measures.

Parameter	Equation
Accuracy	$A = \left[\frac{tp+tn}{tp+fp+tn+fn}\right]$
Precision	$P = \left[\frac{TP}{TP+FP}\right]$
Recall	$R = \left[\frac{TP}{TP+FN}\right]$
F1 Score	$F1 - score = 2\left[\frac{P \times R}{P+R}\right]$

The TP, TN, FP, FN in the table indicates True Positive shows the number of subjects categorized correctly. True Negatives represents the number of subjects who were incorrectly classified. False Positives denotes the number of subjects classified as non-demented controls and False Negatives means the number of subjects who were non-demented is classified as demented controls.

5 Results and Discussion

Our approach used the predictor variables from the OASIS dataset and train the features in a deep neural network model with five hidden layers, with distinct neurons in each. The network optimizes its weight with a learning pace of .001 and a batch size of 32 to lower the loss function. The predictor variables are iterated for 400 epochs using the categorical cross-entropy and Adam optimizer for compiling the Keras framework. The network used Rectified Linear Unit (ReLu) as the activations for all the units in the hidden layer and considered the softmax for the output function to optimize the network performance. Table 4 Illustrates the specifics of the proposed DNN for AD's

improved hyper-parameters. The performance of our model is assessed by training the deep network with 15 layers and 10 layers but has shown a significant decline of accuracy rate. As a result, we have chosen our architecture with few layers and it reciprocated with an accuracy of 90.10%. The acquired features of the OASIS dataset focused on two main criteria the Electronic Health Records (EHR) of the cognitive abilities and the brain volumes of each person for predicting AD. The proposed model has exhibited a remarkable inference in classifying the demented and non-demented controls. F1-Score.

Table 4. Optimized hyper-parameter applied in the DNN Model

Hyperparameter	Optimized value
Hidden layers	5
Activation function	ReLu
Learning rate	.001
Maximum iteration	400
Optimization algorithm	Adam
Batch size	32
Output function	Softmax

The performance metrics for the binary classification of AD detection with the deep neural network model is depicted in Table 5. The study has concentrated a dataset of size 400 from OASIS with seven parameters to obtain the demented and non-demented subjects, with a training and test ratio of 70 and 30. The chosen parameters were optimum enough to do binary classification with the proposed network model. As shown in Table 5, the model acquired an accuracy of 90.10%, precision with 89.5%, Recall of 91.5% and F1score of 90.5%.

Table 5. Model performance acquired for the AD detection

Class	Accuracy	Precision	Recall	F1 score
Non-demented	.92	.89	.92	.91
Demented	.88	.90	.91	.90

In addition to the model performance, the complete Confusion Matrix (CM) for the OASIS dataset is shown in Fig. 3. It can derive a conclusion about the performance of the classification algorithm. The model displays better accomplishment in analyzing the non-demented compared to the demented group. As present in CM, the model predicted true negative values and true positive values as .92 and .88. It describes that the non-demented class is predicted well, whereas 12% of the demented class is misplaced as non-demented, which needs more focus in further work. Figure 4 Depicts the ROC

curve for the binary classification AD detection. The Receiver Operating Characteristics (ROC) defines a trade-off between the two-parameter metrics sensitivity (True Positive Rate) and specificity (1-False Positive Rate). Its purpose is to identify the accuracy rate of given classifiers. In this method, the ROC curve depicted an analysis based on a TPR and FPR by considering AD parameters for determining demented and non-demented controls. The correlation of area under the curve (AUC = 1) classifies the ROC curve in visualizing a high assurance in accurately organizing healthy controls and affected subjects.

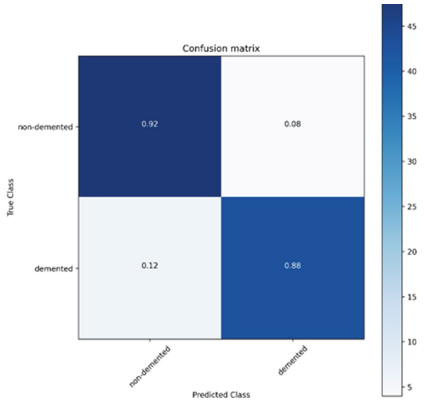

Fig. 3. Confusion matrix: the classification of demented Vs non-demented controls

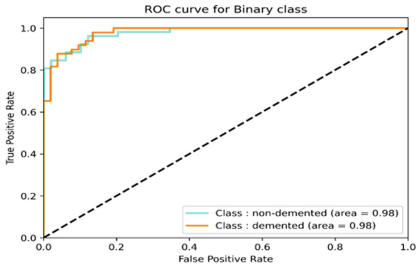

Fig. 4. ROC curve for AD classification

6 State of the Art Comparison

The outcomes acquired by the DNN with indicator factors for AD discovery are quantitatively contrasted and cutting edge outcomes with the latest discoveries and examinations. The near outcomes are introduced in Table 6. The examination grasps that the proposed strategy shows the best outcome.

Table 6. State of the art recognition accuracy for OASIS dataset.

Method	Accuracy	Methodology	Dataset
Proposed	90.10%	DNN	OASIS
Battineni et al. [15]	68.75%	SVM	OASIS
Priyanka et al. [16]	87%	SVM	OASIS
Hamzah et al. [17]	78%	ANN & ML	OASIS

7 Conclusion

The proposed work has exhibited a productive way to deal with Alzheimer's Disease finding utilizing a bunch of indicator factors that are clinically supported. The work examined the viability of the profound DNN model in grouping AD and sound control subjects.The current DNN model of five hidden layers and the fine-tuned hyperparameters could achieve 90.10% accuracy in the binary classification for diagnosing AD. The model has undergone various iterations with distinct parameters to finalize the best-tuned parameters. The predictor variables stated in the current paper focused only on cognitive stability and brain volume size. They are adequate for categorizing demented and non-demented subjects, and the proposed model could pinpoint it firmly. Future research can work on the same area for classifying the stages of mild cognitive impairment (MCI) and stages of AD. Electronic health records, gene and blood proteins, and MR images can combine to obtain a more accurate outcome in predicting and classifying disease stages and also to build a more comprehensive e-health system.

References

1. Lee, S.-W., Bülthoff, H.H., Müller, K.R. (eds.): Recent Progress in Brain and Cognitive Engineering. Springer, Netherlands (2015)
2. World Health Organization: mhGAP intervention guide mental health gap action programme version 2.0 for mental, neurological and substance use disorders in non-specialized health settings. World Heal Organ **2016**, 1–173 (2016)
3. Alzheimer's Facts and Figures Report | Alzheimer's Association https://www.alz.org/alzheimers-dementia/facts-figures. Accessed 21 Oct 2021
4. What Happens to the Brain in Alzheimer's Disease? | National Institute on Aging. https://www.nia.nih.gov/health/what-happens-brain-alzheimers-disease. Accessed 21 Oct 2021
5. Almustafa, K.M.: Classification of epileptic seizure dataset using different machine learning algorithms. Inform. Med. Unlocked **21**, 100444 (2020)
6. Cabral, C., Margarida, S.: Classification of Alzheimer's disease from FDG-PET images using favourite class ensembles. In: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2477–2480. IEEE (2013)
7. Oommen, D.K., Arunnehru, J.: A comprehensive study on early detection of Alzheimer disease using convolutional neural network. In: Proceedings of AIP Conference, vol. 2385, no. 1. AIP Publishing LLC (2022)
8. Bhagwat, N., Viviano, J.D., Voineskos, A.N., Chakravarty, M.M., Initiative, A.D.N.: Modeling and prediction of clinical symptom trajectories in Alzheimer's disease using longitudinal data. PLoS Comput. Biol. **14**(9), e1006376 (2018)
9. Huang, L., Gao, Y., Jin, Y., Thung, K.-H., Shen, D.: Soft-split sparse regression based random forest for predicting future clinical scores of alzheimer's disease. In: Zhou, L., Wang, Li., Wang, Q., Shi, Y. (eds.) MLMI 2015. LNCS, vol. 9352, pp. 246–254. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-24888-2_30
10. Arunnehru, J., Geetha, M.K.: Motion intensity code for action recognition in video using PCA and SVM. In: Prasath, R., Kathirvalavakumar, T. (eds.) MIKE 2013. LNCS (LNAI), vol. 8284, pp. 70–81. Springer, Cham (2013). https://doi.org/10.1007/978-3-319-03844-5_8
11. Bansal, D., Chhikara, R., Khanna, K., Gupta, P.: Comparative analysis of various machine learning algorithms for detecting dementia. Procedia Comput. Sci. **132**, 1497–1502 (2018)

12. Collij, L.E., et al.: Application of machine learning to arterial spin labelling in mild cognitive impairment and Alzheimer disease. Radiology **281**(3), 865–875 (2016)
13. Bhagwat, N., et al.: An artificial neural network model for clinical score predictionin Alzheimer disease using structural neuroimaging measures. J. Psychiatry Neurosci. JPN **44**(4), 246 (2019)
14. Arunnehru, J., Chamundeeswari, G., Prasanna Bharathi, S.: Human action recognition using 3D convolutional neural networks with 3D motion cuboids in surveillance videos. Procedia Comput. Sci. **133**, 471–477 (2018)
15. Battineni, G., Chintalapudi, N., Amenta, F.: Machine learning in medicine: Performance calculation of dementia prediction by support vector machines (SVM). Inform. Med. Unlocked **16**, 100200 (2019)
16. Priyanka, G., Priya, R.T., Vasunthra, S.: An effective dementia diagnosis system using machine learning techniques. J. Phys. Conf. Ser. **1916**(1). IOP Publishing (2021)
17. Hamzah, H.A., Diazura, A.M., Alfatah, A.E.: Design of Artificial Neural Networks for Early Detection of Dementia Risk Using Mini-Mental State of Examination (MMSE) (2020)
18. Vaijayanthi, S., Arunnehru, J.: Synthesis Approach for Emotion Recognition from Cepstral and Pitch Coefficients Using Machine Learning, pp. 515–528. Springer, Singapore (2021)
19. Sarraf, S., Tofighi, G.: Alzheimer's disease neuroimaging initiative. DeepAD: alzheimer's disease classification via deep convolutional neural networks using MRI and fMRI. BioRxiv, 070441 (2016)
20. Arunnehru, J., Kalaiselvi Geetha, M.: Automatic human emotion recognition in surveillance video. In: Dey, N., Santhi, V. (eds.) Intelligent Techniques in Signal Processing for Multimedia Security. SCI, vol. 660, pp. 321–342. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-44790-2_15
21. Duc, Nguyen T., et al.: 3D-deep learning based automatic diagnosis of Alzheimer's disease with joint MMSE prediction using resting-state fMRI. Neuroinformatics **18**(1), 71–86 (2020)
22. Venugopalan, J., et al.: Multimodal deep learning models for early detection of Alzheimer's disease stage. Sci. Rep. **11**(1), 1–13 (2021)
23. LaMontagne, P.J., et al.: OASIS-3: longitudinal neuroimaging clinical, and cognitive dataset for normal aging and alzheimer disease. medRxiv 2013 (2019)