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Comparative Analysis of Alzheimer's & Parkinson Disease Identification using Deep Learning Approach for Precise Diagnosis

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Abstract: Alzheimer's disease (AD) and Parkinson Disease is a terrible, severe, and irreversible affliction, yet it also has a positive worldwide impact on human life. It was the sixth most common cause of mortality in the United States and could not be prevented by immunization. The most difficult aspect of discovering new species. The identification of the proteins and genes causing AD/PD will help in understanding the illness's and developing preventative or therapeutic measures. They look into any potential interactions between genes or proteins and Alzheimer's disease and Parkinson Disease using useful techniques and knowledge. A Deep Learning technique for predicting protein connections in Alzheimer's disease and Parkinson Disease was developed using up-to-date data from all known AD /PD proteins and genes. We proposed the comparative analysis approach since MR brain scans are frequently utilized for Alzheimer's diagnosis and Parkinson Disease. The MRI data set's background noise was removed using multi-layer perceptual (MLP) filtering. In the suggested study, we employ CNN VGG 16,VGG19 and InceptionV3 for training, the CNN Algorithm for classifying, the Edge-based for segmenting, and histogram equalization for image improvement. The proposed approach in this work offers a classification accuracy of up to based on experimental data. ADNI-82.20% , OASIS-95.35%.

Keywords*: Alzheimer, Parkinson , CNN, VGG16,VGG19,InceptionV3*

1. Introduction

The similar term for a condition that affects a person's ability for their brain to work normally is dementia. This comprises conditions that significantly impair a person's ability to think clearly, behave, remember things, or solve problems [1]. Although dementia primarily affects individuals over 60, it cannot be considered a disease that develops as a result of ageing. According to a WHO research, 50 million individuals worldwide suffered from dementia in 2019; an additional 10 million new cases are reported year [2]. Dementia is a terrible illness for which there is no known treatment; nevertheless, early diagnosis can lead to monitoring strategies that assist the patient in carrying out everyday tasks.

1.1 Different forms of dementia

There are different kinds of dementia, each with its own unique set of symptoms and distribution throughout the brain [3]. There are two deadly forms of dementia: AD and PD.

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1.2 Alzheimer's Disease

Among all the kinds of dementia, AD is the illness that is most frequently reported. The majority of those who experience it are over 60 years old. The major brain regions like the cerebral cortex, ventricles, and hippocampal regions are primarily affected by this deadly brain illness. [4] Early signs of this chronic neurodegenerative disease include linguistic difficulties and difficulty recalling recent events. Later signs of this illness included mood swings, disorientation, poor judgement, and trouble speaking, swallowing, and walking.

1.3 Parkinson's Disease

Parkinson's disease (PD) is a neurological illness that causes gradual mobility restriction. A few number of brain neurons gradually degenerate into PD. Dopamine, a chemical messenger, is produced as a result in the brain. The substantia nigra, which is located in the central region of the brain, is impacted by the aberrant brain activity caused by a rise in dopamine levels. Constipation, sadness, loss of smell, low blood pressure, and trouble sleeping are among the initial signs of Parkinson's disease. The symptoms have recently progressed to include stiffness, slowness of movement, shaking, and trouble walking.

2. Literature Survey

The primary goal of this research is to examine several machine learning methodologies for use in the diagnosis of Parkinson's disease and Alzheimer's disease using a healthy brain as a reference. In the field of dementia detection, some studies have made astounding contributions [5]. The majority of them focus on employing computer-aided diagnosis to identify a particular form of dementia. Historical data, physical examination results, cognitive tests, lab research, and imaging are some of the several data types they used. Different medical tests can only classify problems as normal or abnormal, rather than visualizing the full body. Thus, employing either a single or a combination of algorithms, medical imaging is the most effective sort of test for classifying different forms of dementia.

The suggested study aims to diagnose various dementia forms using an algorithm. Differentiating between dementia types can be difficult because the diseases' symptoms often resemble one another. Therefore, the most effective method of identifying diseases is to examine how the human brain changes in various dementia conditions.

2.1 Related Alzheimer’s and Parkinson’s diagnosis works:

Using SVM, author focused on the early diagnosis of Alzheimer's disease [5]. They employed a 500*500 MRI-based grayscale picture. They extracted cortical, hippocampal, and corpus callosum regions using segmentation in order to extract characteristics. The photos were then classified as normal or AD using SVM. They used every suggested option and achieved an average accuracy of 71.33%. A study on Alzheimer's disease and its ageing effects on hemodynamic response function using fMRI was developed by atuthor [6]. They made use of 1.5 T Vision System MRI scans, which yielded 128 scanned images. To extract motor and visual cortices from the pictures, they employed the Region of Interest technique. Based on their research, they discovered that older persons will have more noise in the data.

For the classification of Alzheimer's disease researcher created unique hierarchical networks incorporating 3-D texture features. [7]. They employed 710 T1-weighted MRI brain scans as the dataset for their groundbreaking study. They aligned the features using the FLIRT approach and extracted the features using the FAST method. They classified photos using the MKBoost algorithm, and the results showed an 86.56% accuracy rate.

In order to diagnose Alzheimer's disease, had worked on landmark-based characteristics from MRI images. [8]. From the ADNI dataset, they gathered PET and MRI scans. All of the photos in the dataset were aligned linearly, with landmark detection being used for testing and landmark discovery for training. They had an accuracy rate of 88.30%. Authors devised a method for categorizing Alzheimer's disease through the use of magnetic resonance imaging. [9]. They use row concatenation to transform the MRI pictures from the ADNI database into a one-dimensional signal in their work. The brain MRI was characterized using MSA (multiscale analysis) to determine HE (Hurst's exponent) at different scales, and an SVM classifier was employed for classification. Their accuracy rate was 97.1%. A survey on Parkinson disease prediction using machine learning-based techniques was conducted by authors. [10]. They documented the output from Naïve Bayes, K Nearest Neighbour, Random Forest, Artificial Neural Network, and Support Vector Machine. Machine learning methods were used in research to predict Parkinson illness. [11].They gathered voice datasets for Parkinson's disease from the UCI repository. They employed various machine learning algorithms to identify Parkinson illness, and they found that the Random Forest approach works well, with an accuracy of 90.26%. A paper on machine learning techniques for multimodal feature-based Parkinson's disease diagnosis was presented by [12].They made use of other important indicators, olfactory loss, and non-motor characteristics of sleep behaviour disorder (RBD). They used Naive Bayes, Boosted Trees, Support Vector Machine, and Random Forest classifiers to categories the data set photos from the PPMI database. They found that, with an accuracy rate of 96.40%, the SVM classifier performed the best. Presented a study using machine learning approaches to investigate gait and tremor in order to diagnose Parkinson disease. [13]. The Vertical Ground Reaction Force (VGRF) characteristic of the Physionet dataset was utilized by them. For the entries, they also analyze other characteristics including stance, swing, and stride time. For the suggested job, they obtained a 92.7% accuracy rate. Using certain improved machine learning techniques,. predicted Parkinson's illness. [14]. Throughout their analysis, they made use of the PPMI database and 10 prediction algorithms that were equipped with all 93 features. In comparison to previous studies, they reduced the mistake rate in their work by experimenting with various techniques. Based on a review of the literature, it appears that AD and PD were not previously identified from the same kind of brain image data collection. One of the work's main features is the use of a single algorithm for both AD and PD categorization detection.[15]

B. Deep Learning Approaches

[16] authors was to use DL approaches to automatically predict the presence of AD in sagittal magnetic resonance images (MRIs). The DL technique ANN

ResNet feature extractor and the SVM classifier were used. This study's two main conclusions were that sagittal MRI can distinguish between AD-related damage and its stages and that DL models used in both sagittal and horizontal plane MRI gave results that were comparable to the state-of-the-art. The writers [17] A divisional version of the Contractive Slab and Spike Convolutional Deep Boltzmann Machine (CssCDBM) was produced using directly performed Electroencephalogram EEG spectral image categorization utilising a label layer. Better results are obtained than with other generative models because the proposed model connects the dots between feature extraction and classification. The observed decrease in intra-subject variances and rise in inter-subject variations are both critical to the early identification of AD. [18] utilised a hybrid model that integrates traditional machine learning for classification with a stacked auto-encoder (SAE) for feature selection. As a result, the classification of AD and the forecasting of the development of a prodromal stage of AD-moderate cognitive impairment (MCI) both saw increases in accuracy rates. The most effective categorization outcomes were obtained by combining fluid biomarkers with multimodal neuroimaging. When working with multimodal neuroimages, especially in AD research, the evolution of 2D CNN into 3D CNN is essential. [19] addressed many aspects of AD diagnosis, including depth models, the feature extraction strategy, the preprocessing method, and AD-related biomarkers. CNN is the most widely used deep model in the classification space, outperforming other models in terms of performance. Despite the fact that self-management and unsupervised care have improved the field of medical research imaging due to a shortage of medical data, the overfitting problem with the data set needs to be fixed. Typical MRI pictures have been used as inputs in the development of an AD detection model that uses convolutional neural networks (CNN). Transfer Learning (TL) is a technique that uses data from many datasets to fine-tune hyperparameters and increase detection accuracy. The automatic identification of AD by a machine learning model is expected to alleviate the burden on medical personnel and enhance the accuracy of medical judgements. Benefits of the Generative Adversarial Network- Convolutional Neural Network-Transfer Learning (GAN-CNN-TL) approach include enhanced hyperparameter tuning, automated feature extraction, a less biased detection model, and increased data creation, according to author [20]. Deep learning models may perform worse if there are no picture patterns in the data, which might cause overfitting. Deep learning is one versatile learning technology that was created to solve this problem. Deep trine network (DTN) was used as a learning metric by the study's author, [21], to identify AD from brain MRI data. Owing to the scarcity of adequate models, the suggested deep ternary mesh incorporates a fuzzy function to enhance the model's precision. The conditional triplet (CT) loss included in the idea model includes the best and worst triplets. Using brain MRI data, this model is used to predict a four-class classification problem that helps identify and diagnose Alzheimer's disease. Authors [22] have suggested a technique for utilising medical resonance imaging (MRI) to diagnose Alzheimer's disease through adaptive learning for several classes. The suggested transfer learning model-enabled AD detection is quick and capable of handling small images without the need for manual instruments. To attain performance that is on par with or better than existing, a variety of datasets, including ADNI, can be used. And lastly, supervised and unsupervised deep learning algorithms can be used to identify multi-class Alzheimer's disease. Drawing from a variety of longitudinal multivariate modalities, including neuroimaging data, cognitive scores, CSF biomarkers, neuropsychological battery markers, and demographic data, a study presented by [23] presented a novel two-level deep learning architecture for identifying the advancement of AD. The study's initial phase effectively predicts the patient's diagnosis using a variety of classification functions, including cognitive impairment, MCI, or AD. In the second phase, the time course of change in MCI patients was estimated using a regression function. [24] developed a classification model that successfully retrieves important features using the AlexNet framework in order to identify Alzheimer's at the MCI level using MRI (Magnetic Resonance Imaging) medical photos. With the usage of over one lakh MRI images of the illness, the proposed model diagnoses Alzheimer's disease with remarkable accuracy by utilising all of the axial, sagittal, and frontal regions of the human brain. The authors [25] proposed a multiclass diagnosis structure developed from an ensemble of hybrid deep convolutional neural networks (CNNs) to distinguish individuals with MCI, AD, and cognitively normal clinical circumstances. The framework makes use of the best images derived from the three planes that are taken out of the 3D MRI data. They employ three distinct pathways to leverage richer spatial data and extract features from various MRI data views. CNN's accuracy increases with the depth of its architecture. The proposed method's usage of trained weights increases its computing efficiency.To distinguish between the course of a problem and normal ageing, early diagnosis makes use of a specialised network of autoencoders. An sufficient bias neural network performance is one of the approaches proposed by [26] that allows for a reliable diagnosis of AD. The suggested deep learning approach has outperformed traditional classifiers based on time series Resting-state Functional Magnetic Resonance Imaging (R-fMRI) data in a considerable way. The forecast model has been shown to be more accurate and dependable than traditional approaches in the best instances, as seen by the large reduction in standard deviation. Researcher [27] categorised 2182 stock photos from the ADNI collection by looking at 29 pre-trained models. The models with the highest accuracy were the EfficientNetB0 model, while the models with the best rates of sensitivity, precision, and specificity were the EfficientNetB3 and EfficientNetB2 models. To differentiate tauopathies, Researcher [28] created a DL-based approach based on digital slide pictures. They trained the You Only Look Once version 3 (YOLOv3) object recognition algorithm to identify five distinct types of tau lesions, and then used the quantitative loading of each tau lesion to generate random forest classifiers. Authors [29] propose an original MRI-based methodology that systematically integrates techniques based on regions, patches, and voxels into a coherent framework for the diagnosis of moderate cognitive impairment (MCI) and Alzheimer's disease (AD). This solution employs an ensemble method, a random subspace method, and nonlinear feature representation with DNNs to improve classification performance.[30] Their methodology yielded state-of-the-art results for four binary classification tests and one three-class classification task using the ADNI MRI dataset. A transfer learning-based method for the proficiency of deep characteristics for Alzheimer's disease stage detection was proposed by the authors [31]. The images' Clinical Dementia Ratings (CDR) were examined, and the effectiveness of handmade and deep features in identifying different stages of AD using various classifiers was compared. On augmented photographs, DenseNet demonstrated remarkable classification accuracy for all three classes, whereas a spiking neural network (SNN) demonstrated remarkable classification accuracy. As per the writers [32], In order to improve classification and prediction rates, their study assessed 13 deep neural network architectures, including Spiking neural networks, DenseNet, MobileNet, Squeezenet, ResNet, VGG, GoogLeNet, and others, utilising a variety of input sample types. On augmented pictures, DenseNet had the best classification accuracy across all three classes conducted a comparison with the latest techniques. [33] The VGG19-SVM (Visual Geometry Group) displayed fc6 (layer) features based on how well the recommended networks performed in comparing the MCI and AD classes. For CN vs. AD classes and CN vs. MCI, VGG16-SVM employed freeze-fc6 layers in a manner similar to this. The study's authors, [34], The purpose of this study was to examine the use of linguistic and auditory methods for automatic detection, Mini-Mental State Examination (MMSE) analysis, and AD prediction in a setting with limited resources. Whereas the Bidirectional Encoder Representations from Transformers (BERT) fine-tuned with automatic transcriptions from a commercial Automatic Speech Recognition (ASR) system produced the best results, the x-vector model and encoder-decoder automatic speech recognition embedding produced the best results. For the evaluation of deep features models and handcrafted feature extraction models, they have recommended evaluating the usage of several rounds of Language Model (LM) interpolation and multi-modal approaches classifiers. Deep Neural Networks (DNN), Deep Boltzmann Machines (DBM), Convolutional Neural Networks (CNN), and Deep Automatic Encoder (DA) models were employed by the authors [36] to diagnose dementia and Alzheimer's disease. The feature extraction method was applied to the data's hidden data layers. Features include cortical thickness, brain volume, hippocampal shape, and ventricular size accurately characterised the regions of structures connected to AD. As per the writings of [35], After analysing the correlations between the gathered data, the Temporal Convolutional Network (TCN) model recommended that users exclude feature vectors from the sequence of their MRI scans. There was an improvement in the accuracy of AD detection when vectors with zeros as their elements were filled with four and five residual blocks.

A. ADNI Dataset

The Alzheimer's Disease Neuroimaging Initiative (ADNI) database gathers clinical, genetic, and neuroimaging data on patients and adults with and without Alzheimer's disease. The goal of the ADNI project is to create biomarkers for early AD development identification and tracking. It includes the data of over 1,500 employees from more than 50 locations across the US and Canada in the ADNI collection. The dataset includes genetic data, assessments of cognitive function, and information from brain MRI and PET scans. This information is frequently used by scientists to explore the aetiology of Alzheimer's disease and to create novel techniques for its early identification and surveillance. The ADNI website provides access to the ADNI dataset for the general public. Academic studies on AD and its related illnesses can benefit from it. The range of data types and sample size make it an effective tool for understanding disease processes, developing new biomarkers, and improving patient outcomes.

B. OASIS Dataset

An other frequently used dataset in research on Alzheimer's disease is the Open Access Series of Imaging Studies (OASIS) dataset. It contains brain imaging and clinical data from elderly patients with Alzheimer's disease, MCI, and healthy ageing. Data from cognitive tests, MRI images, and other clinical assessments are collected. There are numerous different datasets accessible for study on Alzheimer's disease in addition to the ADNI databases, each having unique benefits and drawbacks. The investigation's objectives and available resources must be taken into account while selecting the best dataset for a particular study. The OASIS dataset has been helpful in the development of novel techniques for analyzing brain imaging data and in research on alterations in the structure and function of the brain in AD. It has also been used to construct models that forecast how a disease will progress and how well a therapy would work. Table 2 provides a thorough summary of machine learning research. Table 3 provides a thorough review of research efforts in the subject of linguistics. Last but not least, Table 4 offers details on deep learning research projects. These tables contain details about the authors, the technique, the datasets utilized, and the accuracy levels obtained in the research that are cited.

Table 1: Image database

Type of disease	AD	PD	HB
Dataset	450	450	450
Male patients data	238	340	274
Female patients data	312	210	276
Age Range	61-98	50-85	50-90

Table 2. Details of the OASIS, ADNI datasets Accuracy and Model Implemented by different Author

Model Name	Use By Author	Accuracy (Average)	Dataset
KNN	[35], [4]	97%	ADNI
ANN	[2], [1]	92%	OASIS,ADNI
Alexnet	[4]	95%	OASIS
Autoencoder	[3]	94%	ADNI
Random Forest	[5], [4]	97%	CP13
Transfer Learning	[6], [27]	92%	OASIS
RNN	[28][4]	93%	Imagenet Dataset
YOLOv3	[24] [5]	97%	CP13
TQWT	[29]	96%	SBS
BERT	[30]	84%	ADReSSo
ResNet	[31]	98%	ADNI,OASIS
CNN	[29], [22], [23], [26], [27],	95%	ADNI
SVM	[1], [2]	97%	ADNI
DNN	[23], [26]	90%	ADNI

Table 3. Summary of Deep Learning Work

Authors	Techniques	Matrices Used	Dataset
Shunsuke Koga et al. [14]	YOLOv3, Random forest	Accuracy, precision, Recall 97%	CP13 images
Serkan Savas [10]	CNN	Specificity 92.98%	ADNI
Shuangshuang Gaoa et al. [1]	CNN ResNet	Sensitivity, specificity, Accuracy 98.37	ADNI,OASIS,AIBL
Kwok Tai Chui et al. [2]	CNN,GAN,TL	Accuracy, specificity 95%	OASIS (1,2,3)
Maysam Orouskhani et al. [3]	DTN,CTN	ROC, Accuracy 99.41	OASIS
Taher M. Ghazal et al. [4]	CNN, Transfer Learning, SGDM	Accuracy, 91.70	MRI images
Shaker El-Sappagh et al. [5]	LSTM	Accuracy 93.87	ADNI
L. Sathish Kumar et al. [6]	DL Alexnet, CNN	Accuracy 90-97%	OASIS
Alejandro Puente et al. [19],[40]	ANN ResNet feature extractor with the SVM classifier	Accuracy Precision, Recall, Specificity, F1 60.30%	ADNI dataset and OASIS dataset
Bi Xiaojun et al. [37]	DCssCDBM Model	Accuracy, Confusion Matrix. ROC curve 95.04%	Beijing Easy monitor Technology dataset
Haibing Guo et al [13]	Autoencoders	Sensitivity: 94.6% Specificity: 96.7%	ADNI dataset
Eunho Lee et al. [9]	DNN	Accuracy. Sensitivity, Specificity, Recall, Precision. AUC 70-90%	ADNI Dataset
Hina Nawaz et al. [31][39]	CNN,SVM,KNNand Random Forest (RF).	Accuracy of 99.21% for a Deep feature and 92.85% for deep learning CNN	a pre-learned AlexNet network
Abida Ashraf et al. [32]	CNN,ANN and spiking neural network (SNN)	Specificity, Sensitivity accuracy :99.05%, SNN accuracy of 92%	ADNI dataset
Saeeda Naz et al. [33][36][38]	CNN, VGG19-SVM	Identification test set accuracy of 99.27% (MCI/AD), 98.89% (AD/CN) and 97.06% (MCI/CN).	ADNI dataset
Raghavendra Pappagari et al. [34]	BERT	Accuracy 84%	Interspeech 2021 ADReSSo challenge dataset

3. Experimental Results

Figure 1 visually depicts the project flow, with each block symbolizing a pivotal stage or component in the overall process.

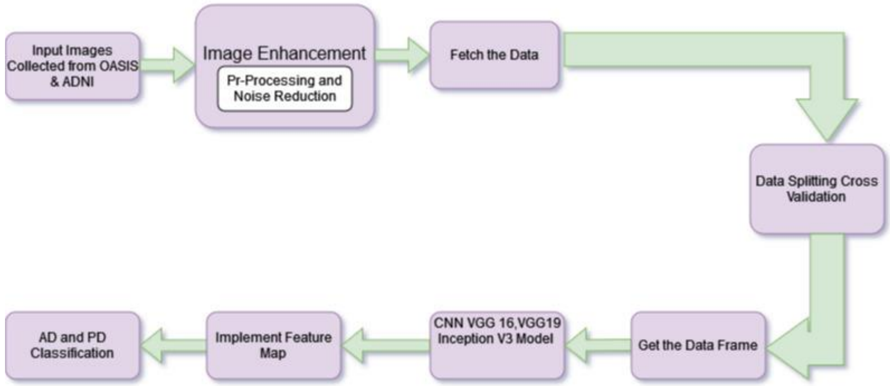

Fig. 1 Block Diagram of AD Diagnosis

We performed a comparison analysis using deep learning (DL) techniques on the ADNI and OASIS datasets. VGG16, VGG19, and InceptionV3 are the algorithms that are being examined. The following Table 5 displays the comparison's findings along with their accuracy.

Table 4 – Experimental Results

Technique	**Algorithm**	**Dataset**	**Accuracy**
Deep Learning	VGG16	ADNI	82.62%
		OASIS	93.20%
	VGG19	ADNI	82.48%
		OASIS	86.97%
	InceptionV3	ADNI	82.20%
		OASIS	95.35%

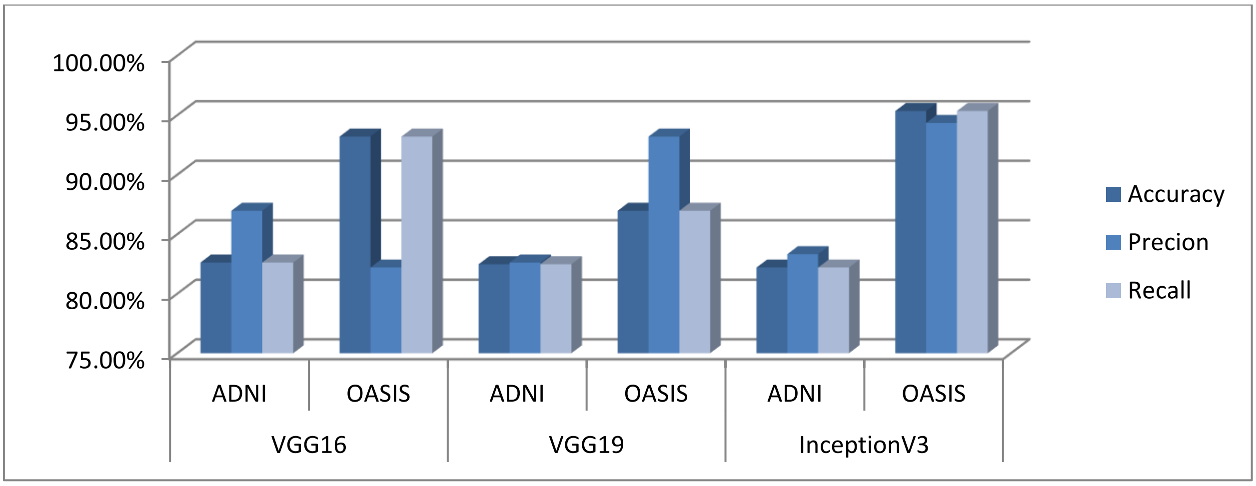

Fig. 2 Graphical Representation of all results

Table 4 and Figure 2 shows how different deep learning methods perform on the ADNI and OASIS datasets, two different datasets. VGG16, a deep learning system, produced accuracy results of 82.52% on ADNI and 90.33% on OASIS. VGG19 performed similarly, scoring 82.38% on ADNI and 86.96% on OASIS. With an astounding accuracy of 95.21% on OASIS and 82.17% on ADNI, InceptionV3 stood out for its outstanding performance. These findings highlight the need of selecting algorithms carefully in light of certain data characteristics and goals since they show how different algorithms perform differently across datasets.

4. Conclusion

The study demonstrates how well different algorithms identify Parkinson's and Alzheimer's illness in a variety of datasets. InceptionV3, a deep learning system, continuously beats its competitors and exhibits exceptional accuracy, particularly on the difficult OASIS dataset. The promise for improved Parkinson's disease and Alzheimer's disease detection is highlighted by deep learning techniques. With its remarkable accuracy, InceptionV3 offers a promising synergy to tackle the complicated datasets associated with Parkinson's and Alzheimer's disease. The results highlight how crucial it is to use algorithms that are sensitive to the subtleties of the dataset. Strong performers, InceptionV3, have the potential to advance automated and non-invasive solutions for the detection of Parkinson's and Alzheimer's disease in its early stages. To truly realize the revolutionary influence of artificial intelligence in solving the issues faced by Alzheimer's disease and Parkinson's disease, further research and optimization of these algorithms are necessary.

Reference

[1] Emre Altinkaya, Kemal Polat, “Detection of Alzheimer’s Disease and Dementia States Based on Deep Learning from MRI Images: A Comprehensive Review”, Journal of the Institute of Electronics and Computer, 2019, DOI: 10.33969/JIEC.2019.11005

[2] Bi Xiaojun , “Early Alzheimer’s disease diagnosis based on EEG spectral images using deep learning”, Elsevier, Neural Networks 114, 2019

[3] Roobaea Alroobaea, “Alzheimer's Disease Early Detection Using Machine Learning Techniques”, ResearchSquare, 2021, DOI: https://doi.org/10.21203/rs.3.rs-624520/v1

[4] Amir Ebrahimi, “Deep sequence modelling for Alzheimer’s disease detection using MRI”, Computers in Biology and Medicine,Volume 134, 2021, DOI: https://doi.org/10.1016/j.compbiomed.2021.104537

[5] Amira Ben Rabeh, “Diagnosis of Alzheimer Diseases in Early Step Using SVM (SupportVector Machine)”, 13th International Conference Computer Graphics - Imaging and Visualization, 2016

[6] Davud Asemani, Hassan Morsheddost, “Effects of ageing and Alzheimer disease on haemodynamic response function: a challenge for eventrelated fMRI”, Healthcare Technology, pp.109-114, 2017

[7] Jin Liu, Jianxin Wang, Bin Hu, “Alzheimer’s Disease Classification Based on Individual Hierarchical Networks Constructed With 3-D Texture Features”, IEEE Transactions on Nanobioscience, vol. 16, pp. 428 – 437, 2017

[8] Jun Zhang, Mingxia Liu, Le An, ,“Alzheimer’s Disease Diagnosis Using Landmark-Based Features From Longitudinal Structural MR Images”, IEEE Journal of Biomedical and Health Informatics, vol. 21, pp. 1607-1616, 2017

[9] Salim Lahmiri, , ”New approach for automatic classification of Alzheimer’s disease, mildcognitive impairment and healthy brain magnetic resonance images”, Healthcare Technology, Vol. 1, pp. 32–36, 2014

[10] Shubham Bind, Arvind Kumar Tiwari, , “A Survey of MachineLearning Based Approaches forParkinson Disease Prediction”, International Journal of Computer Science and Information Technologies, vol. 6, pp. 1648-1655, 2015

[11] Tarigoppula V.S Sriram, M. Venkateswara Rao, G V Satya Narayana ,“Intelligent Parkinson Disease Prediction Using Machine Learning Algorithms”, International Journal of Engineering and Innovative Technology, pp. 212-215, 2013

[12] Prashanth, Sumantra Dutta Roy, Pravat K. Mandal, “High-Accuracy Detection of Early Parkinson's Disease through Multimodal Features and Machine Learning”, International journal of medical informatics, vol. 90, pp. 13-21, 2016

[13] Enas Abdulhay, N. Arunkumar, “Gait and tremor investigation using machine learning techniques for the

[14] diagnosis of Parkinson disease“, Future Generation Computer Systems, vol. 83, pp. 366-373, 2018 https://doi.org/10.1016/j.future.2018.02.009

[15] Mohammad R. Salmanpour, Mojtaba Shamsaei, , “Optimized machine learning methods for prediction of cognitive outcome in Parkinson's disease”, Computers in Biology and Medicine, 2019

[16] L. Bailey, “Positron Emission Tomography”, New York: Springer Verlag, 2005

A. K. Shukla, “Positron emission tomography: An overview”, Journal of Medical Physics, vol. 31, pp. 13-21, 2006

[17] Jacobus A.K. Blokland, Petar Trindev, , “Positron emission tomography: a technical introduction for clinicians”, European Journal of Radiology, vol.44, pp. 70-75, 2002

[18] Shukla AK, , “Positron emission tomography : An overview”, J Med Phys., pp. 13–21, 2006 https://doi.org/10.4103/0971-6203.25665

[19] R. Beaulah Jeyavathana, R.Balasubramanian, A“A Survey: Analysis on Pre-processing and Segmentation Techniques for Medical Images”, International Journal of Research and Scientific Innovation, vol. 3, pp. 113- 120, 2016

[20] B. Chitradevi, “An Overview on Image ProcessingTechniques”, InternationalJournal of Innovative Research in Computer and Communication Engineering, vol.2, pp. 6466-6472, 2014

[21] Rekhil M Kumar, “A Survey on Image Feature Descriptors”, International Journal of Computer Science and Information Technologies, vol. 5, pp. 7668-7673, 2014

[22] Nancy Noella R S *et al.*, International Journal of Advanced Trends in Computer Science and Engineering, 9(4), July – August 2020, 5898 – 5905 5905

[23] Upendra Singh, “Survey paper on document classifiers and classification”, International Journal of Computer Science Trends and Technology, vol. 3, pp. 83-87,2015

[24] Saima Anwar Lashari, “A Framework for Medical Images Classification Using Soft Set”, The 4th International Conference on Electrical Engineering and Informatics, vol. 11, pp. 548-556, 2015

[25] Wen Zhu, Nancy Zeng, , “Sensitivity, Specificity, Accuracy, Associated Confidence Interval and ROC”, Analysis with Practical SAS® Implementations, Health Care and Life Sciences, 2010ea

[26] R. S. Nancy Noella “Efficient Computer- Aided Diagnosis of Alzheimer’s Disease and Parkinson’s Disease—A Survey”, Nanoelectronics, Circuits and Communication Systems, Lecture Notes in Electrical Engineering 511, pp. 53 – 64, 2019

[27] Karthikeyan B, Sujith Gollamudi, Harsha Vardhan Singamsetty, “Breast Cancer Detection Using Machine Learning”, International Journal of Advanced Trends in Computer Science and Engineering, Vol. 9, pp. 981 – 984, 2020are https://doi.org/10.30534/ijatcse/2020/12922020

[28] Dr.A.Nagarajan , “Machine Learning Approach to Predict Lung Cancer using CT scan Images”, International Journal of Advanced Trends in Computer Science and Engineering, Vol. 8, pp. 2972 – 2976, 2019ar https://doi.org/10.30534/ijatcse/2019/48862019and Life

[29] Shuangshuang Gaoa, , “A review of the application of deep learning in the detection of Alzheimer’s disease”, International Journal of Cognitive Computing in Engineering,2021,DOI: https://doi.org/10.1016/j.ijcce.2021.12.002

[30] Kwok Tai Chui , Brij B. Gupta , “An MRI Scans-Based Alzheimer’s Disease Detection via Convolutional Neural Network and Transfer Learning”, Diagnostics 2022, 12(7): 1531, DOI:https://doi.org/10.3390/diagnostics12071531

[31] Maysam Orouskhani, Chengcheng Zhu, “Alzheimer’s disease detection from structural MRI using conditional deep triplet network”, Neuroscience Informatics SAS, 2022, vol-2, DOI: https://doi.org/10.1016/j.neuri.2022.100066

[32] Taher M. Ghazal, Sagheer Abbas, Sundus Munir, M, “Alzheimer Disease Detection Empowered with Transfer Learning, Computers”, Materials & Continua, 2021, vol-70(3), DOI:https://doi.org/10.32604/cmc.2022.020866

[33] Shaker El-Sappagh, Hager Saleh, , “Two-stage deep learning model for Alzheimer’s disease detection and prediction of the mild cognitive impairment time”, Neural Computing and Applications, 2022, DOI:https://doi.org/10.1007/s00521-022-07 263-9

[34] L. Sathish Kumar, S. Hariharasitaraman, “AlexNet approach for early stage Alzheimer’s disease detection from MRI brain images”, Materials Today: Proceedings, 2022, p. 58-65, DOI:https://doi.org/10.1016/j.matpr.2021.04.415

[35] Aparna Balagopalan, Benjamin Eyre, “To BERT or Not To BERT: Comparing Speech and Language-based Approaches for Alzheimers Disease Detection”, INTERSPEECH 2020, DOI:https://doi.org/10.48550/arXiv.2008.01551

[36] Golrokh Mirzaei, “Machine learning techniques for diagnosis of alzheimer disease, mild cognitive disorder, and other types of dementia”, biomedical signal processing and control, 2022,vol-72, doi: https://doi.org/10.1016/j.bspc.2021.103293

[37] Mrs. Disha Sushant Wankhede, Dr. Selvarani Rangasamy,"REVIEW ON DEEP LEARNING APPROACH FOR BRAIN TUMOR GLIOMA ANALYSIS" Journal of Information Technology in Industry, VOL. 9 NO. 1 (2021) pp. 395 - 408 , DOI: https://doi.org/10.17762/itii.v9i1.144

[38] Disha Sushant Wankhede, R. Selvarani, Dynamic architecture based deep learning approach for glioblastoma brain tumor survival prediction, Neuroscience Informatics, Volume 2, Issue 4, 2022, 100062, ISSN 2772-5286, https://doi.org/10.1016/j.neuri.2022.100062. (https://www.sciencedirect.com/science/article/pii/S2772528622000243)

[39] Wankhede, V. Mishra, M. Karnik, A. Kekane and A. Shukla, "The Impact of the Latest Technology on Healthcare and how can it be leveraged to improve patient outcomes and reduce Healthcare costs," 2023 4th IEEE Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/GCAT59970.2023.10353516.

[40] Wankhede, D.S., Shelke, C.J. (2023). An Investigative Approach on the Prediction of Isocitrate Dehydrogenase (IDH1) Mutations and Co-deletion of 1p19q in Glioma Brain Tumors. In: Abraham, A., Pllana, S., Casalino, G., Ma, K., Bajaj, A. (eds) Intelligent Systems Design and Applications. ISDA 2022. Lecture Notes in Networks and Systems, vol 715. Springer, Cham. https://doi.org/10.1007/978-3-031-35507-3_19

[41] Wankhede, D.S., Pandit, S., Metangale, N., Patre, R., Kulkarni, S., Minaj, K.A. (2022). Survey on Analyzing Tongue Images to Predict the Organ Affected. In: Abraham, A., et al. Hybrid Intelligent Systems. HIS 2021. Lecture Notes in Networks and Systems, vol 420. Springer, Cham. https://doi.org/10.1007/978-3-030-96305-7_56