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A Comprehensive Analysis on Neuro-Degenerative Disorders using Machine Learning Techniques

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Abstract

A class of illnesses known as neurodegenerative diseases mainly impacts the brain and nervous system's structure and function over time. Deterioration of nerve cells, brought on by these diseases, leads to a loss of cognitive function, malfunction of the motor systems, and, in extreme situations, substantial difficulty with everyday tasks. Amyotrophic lateral sclerosis (ALS), Parkinson's disease, Alzheimer's disease, Retinal and Huntington's disease are among the most common neurodegenerative illnesses. Many variables, including heredity, the environment, and aging, contribute to the development of these illnesses. In this review, we look at automated retinal layer segmentation methods, discussing their uses and recent developments as they pertain to different types of neurodegenerative diseases. With the increasing frequency of these ailments, non-invasive imaging techniques, especially those that target the retina, are vital for the early identification and tracking of these conditions. Automatic retinal layer segmentation in various neurodegenerative situations is covered in this review, along with state-of-the-art algorithms, techniques, and technology. This survey paper reviews 42 research papers for neurodegenerative disorders detection and explores the potential of computer-assisted methods for neurodegenerative disorders and staging. The survey's goal is to shed light on the present state of this dynamic area by analyzing it thoroughly and drawing attention to noteworthy developments, obstacles, and possible future research directions. Contributing to the continuous efforts to improve diagnosis accuracy and patient care for neurodegenerative diseases, the collected data helps provide light on the strengths and weaknesses of current automated segmentation methods.

Keywords: *Alzheimer's disease, Amyotrophic lateral sclerosis, Parkinson's disease, Neurodegenerative disorders, Retina imaging.*

1. INTRODUCTION

The term "neurodegenerative disorders" refers to a collection of illnesses that affect the brain, spinal cord, and other parts of the central nervous system and cause the slow death of nerve cells [1–5]. Despite their differences in presentation, the underlying processes of neuronal death and the buildup of aberrant protein aggregates are comparable to many renowned diseases, including amyotrophic lateral sclerosis, Huntington's disease, Parkinson's disease, and Alzheimer's disease [6-9]. Cognitive function, motor abilities, and general daily functioning are all impacted by these illnesses, which appear in varied ways. There are many variables that contribute to the start of these conditions, including aging,

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but there are also genetic, environmental, and lifestyle components [10–13]. Effective solutions continue to elude researchers, and the medicines available today mostly aim at symptom management and disease progression slowing [14–17]. In order to alleviate the severe effects that neurodegenerative diseases have on sufferers and their loved ones, researchers are actively looking into the underlying molecular and cellular mechanisms, finding ways to detect them early, and creating new treatments [18-21].

Because they are progressive and currently have no treatment, neurodegenerative illnesses, which include diseases like Alzheimer's, Parkinson's, Huntington's, and amyotrophic lateral sclerosis (ALS), provide enormous difficulties to healthcare systems across the world. To implement appropriate interventions and develop successful therapies, it is essential to recognize and accurately monitor these diseases early on [22–26]. Emerging as potential tools for early diagnosis and disease progression monitoring, non-invasive imaging methods, especially those focusing on the retina, have made a remarkable comeback in recent years. The purpose of this review is to investigate the state of the art in automated retinal layer segmentation methods and how they have been applied to different neurodegenerative diseases [27-32]. Because it is an outgrowth of the brain, the retina provides a rare opportunity to study the structural alterations brought on by various diseases. Automated retinal layer segmentation allows for quantitative and accurate examination, which sheds light on changes caused by diseases [33–37]. We will explore several neurodegenerative situations and the state-of-the-art techniques and approaches used for automated retinal layer segmentation. We hope to contribute to the current efforts to improve diagnosis accuracy and track disease development in neurodegenerative illnesses [38-41] by learning about the successes, failures, and possible innovations in this area. Our approach to these complicated and debilitating illnesses might be revolutionized by the convergence of cutting-edge imaging technologies and computational approaches [42].

2. BACKGROUND STUDY

2.1 Survey on Neurodegenerative Diseases AD

An, N. et al. (2020) These authors goal was to develop a more effective outcome prediction mode for primary care by combining the knowledge of specialists with multisource data and overcoming the difficulty of AD categorization. In order to classify AD, this research suggests DELearning, a three-layer architecture that employs deep learning ensemble at each layer. Using NACC UDS's clinical data, the author evaluated DELearning alongside six other ensemble learning modalities. According to the findings of the experiments, DELearning achieves the highest level of accuracy when it comes to AD categorization. It offers a data-driven approach to support primary care for AD, which was particularly useful in areas with limited access to AD specialists.

Castro, A. et al. (2020) when compared to earlier efforts using traditional horizontal plane MRI, the experimental findings demonstrate that the model performs well, particularly when identifying the early stages of AD. Because of the treatment's higher effectiveness in the early stages and the low phenotypic expression, these phases were the most challenging to identify. This opens the door for further inquiry by demonstrating that the issue may be tackled from the sagittal plane. TL enables Data Augmentation and experimentation with little data. The use of TL eliminates the possibility of producing implausible examples or those that reproduce labeling mistakes, in contrast to this method.

Cheng, Y.-W. Et al. (2020) These authors results point to the possibility that dyslipidemia and hypertension play distinct roles in the neurodegenerative diseases that characterize mild cognitive impairment. To further understand how vascular disease interacts with Alzheimer's pathology, more research was required. Randomized controlled studies should be conducted to confirm the possible positive benefit of statin medication for dyslipidemia when it was treated before the stage of MCI. Another potential treatment for Alzheimer's disease could be found by learning how vascular pathology contributes to neurodegeneration.

Commins, S., & Kirby, B. P. (2019) Because of their utility in assessing the effects of potential therapeutic agents, identifying underlying pathological mechanisms, and learning about the effects of genetic modification, animal models have greatly enhanced these authors knowledge of neurodegenerative disorders, especially Alzheimer's disease. Positive pre-clinical outcomes have not yet been transferred to the clinic, and their value was restricted since they cannot recreate all elements of the complicated neurodegenerative alterations.

Jo, T. et al. (2020) Tau PET pictures from Alzheimer's disease patients compared to controls may be classified using deep learning. Applying this classifier to scans from elderly patients with mild cognitive impairment also allows it to rank the tau distribution according to how similar it was to Alzheimer's disease. One potential utility of a deep learning-derived AD-like tau deposition pattern was individualized early illness diagnosis in the prodromal or even preclinical phases of Alzheimer's disease. More advancement in predictive modeling, together with the incorporation of multi-modality data sets and bigger samples, were anticipated to contribute to the development of precise precision medicine tools for Alzheimer's disease and associated neurodegenerative illnesses.

Martinez-Murcia, F. J. et al. (2019) The global prevalence of Alzheimer's disease surpasses that of any other neurological illness. Although the author were getting a better grasp on its mechanisms, novel approaches were required to shed light on the illness and its diagnosis. Many automated diagnostic techniques were available, and image biomarkers play an important role in modern clinical practice. New resources made possible by the deep learning revolution allow us to automatically extract picture attributes without assuming anything about the process itself.

Matej, R. et al. (2019) The overlapping of neurodegenerative illnesses may lead to accelerated development or, in a large number of cases, a very unusual presentation. This highlights the critical need of conducting comprehensive neuropathological brain exams and establishing clinical-pathological correlations to determine the impact of various co-occurring diseases on the ultimate illness presentation. Improving prognosis accuracy in neurodegenerative dementias and influencing innovative therapy choices and outcomes may be the goal of this final analysis. A detailed description of the clinical picture of these deficits was still absent, and recently identified neuropathological entities associated with aging, such as ARTAG and PART, were more frequent than anticipated.

Table 1: Comparison table for existing work

Author	Year	Methodology	Advantage	Limitation	Accuracy
Choi, H. et al.	2019	Deep learning	There were several ways in which the deep learning model discussed here can improve neuroimaging and cognitive assessment for the purpose of differentiating between AD and NCs and foretelling cognitive	The stated deep learning model has some good features, but it may also have some bad ones. This model does not adequately reflect the different populations impacted by neurodegenerative illnesses since it was too dependent on data from the	81.00

			outcomes in MCI and PD patients.	Alzheimer's Disease Neuroimaging Initiative (ADNI) database, which increases the possibility of bias.	
Karapinar Senturk, Z.	2020	SVM	Early detection of non-motor symptoms that may precede the appearance of motor symptoms was a particular benefit of the machine learning-based diagnosis of Parkinson's disease that was reported in this work.	The difficulty of feature selection and the fact that various approaches may work differently on different patient groups was one possible drawback of machine learning-based diagnostics.	93.84
Marzban, E. et al.	2020	Deep Learning	This study uses deep convolutional autoencoders to sift through MRI scans for signs of Alzheimer's disease (AD), which has the distinct benefit of being able to extract abstract, high-level information on the spot.	The interpretability of the generated features was a possible restriction of using deep convolutional autoencoders in this exploratory data analysis.	80.00
Sivaranjini, S., & Sujatha, C. M.	2019	ANN	A major benefit in the context of Parkinson's disease diagnosis was the development of two neural network-based models, Voice Impairment Classifier for voice recordings and	The reliance on massive datasets for training and testing was a possible shortcoming of neural network-based algorithms.	89.15

			VGFR Spectrogram Detector for gait data. This allows for early-stage identification.		

2.2 Survey on Neurodegenerative Diseases PD

Chiu, S.-I. et al. (2019) these authors research introduces several methods for visualizing and classifying neurodegenerative illnesses that rely on machine learning. First, to make sure no important data was lost, the author utilize MICE to fill in missing information. Afterwards, the author use LDA to decrease the dimensionality, allowing for the visualization of the data to be enhanced using 2D or 3D scatter plots. In addition, the author used multiple classifications to achieve varying degrees of performance, and the author specified numerous critical classification jobs that doctors can understand and use. For these kinds of classification jobs, the author proposes a number of classifiers that work better.

Grover, S. et al. (2018) the author presents the results of using a deep neural network to foretell how bad Parkinson's would go. With respect to accuracy, the suggested DNN model outperformed the state-of-the-art methods. The author can also infer that motor UPDRS score classification was a superior measure for Severity Prediction than total UPDRS score classification since it outperforms total UPDRS score classification.

Karapinar Senturk, Z. (2020) these authors research aimed to construct a decision support system based on FS that might detect early signs of Parkinson's disease by analyzing speech signals from both healthy individuals and those with the disease. The xperiments made use of a variety of FS and categorization approaches. The main goal in doing so was to decrease the computing cost of the classification job while simultaneously improving the model's performance and accuracy. After comparing classification technique accuracy with and without FS, it became clear that FS had a significant impact. When working with voice signals, which include hundreds of phonetic parameters, the findings show that FS approaches in conjunction with classification methods was very beneficial.

Quan, C. et al. (2021) Using voice data, this study proposed a deep learning-based technique for PD identification. The proposed method ingeniously combines the Bidirectional LSTM model with dynamic articulation transition features to capture time-series characteristics of continuous speech data. Compared to traditional machine learning models that use static characteristics for PD identification, the proposed technique performs much better in experiments that use 10-fold Cross Validation (CV) and dataset splitting without samples overlap of one person.

Sivaranjini, S., & Sujatha, C. M. (2019) Neuroimaging assessment of pathophysiological alterations was critical for the diagnosis of Parkinson's disease. In recent years, magnetic resonance imaging (MRI) has become more important in the study of degenerative diseases. Using magnetic resonance imaging to detect structural changes allowed researchers to follow the progression of Parkinson's disease. The detection of these anomalies and the differentiation between PD and HC are accomplished by the use of several deep learning and machine learning algorithms in image analysis. To classify magnetic resonance images of patients with HC and PD, the author here use deep learning architecture. The images that were used for classification were obtained from the publicly available PPMI database. The magnetic resonance images are normalized in pre-processing before a Gaussian filter is applied to them.

2.3 Survey on Retinal Layers in Multiple Neurodegenerative Disorder

Anoop, B. N. et al. (2020) the author provide a deep ensemble learning-based automated approach to segmenting retinal layers from Optical Coherence Tomography (OCT) pictures. The author used a predictor block and four foundation models that adhere to the DilatedReLayNet architecture to construct the ensemble based architecture. Compared to other state-of-the-art approaches and the standalone single DilatedReLayNet model, experimental findings on a typical benchmark dataset demonstrate that the suggested architecture enhanced the segmentation accuracy.

Kashani, A. H. et al. (2021) In order to determine the temporal link and causation of retinal imaging results in the disorders the author have examined, longitudinal studies were greatly needed, as the author have said several times throughout this text. Besides this, there were a lot of caveats to retinal imaging that should be addressed in future research since they have a major influence on the conclusions that may be drawn about neurological processes from this imaging technique and the retina itself. The author will talk about future research' opportunities to improve their methods in light of these constraints in the section that follows.

Myszczynska, M. et al. (2020) Unlike humans, machine learning algorithms were able to sift through mountains of multidimensional data, identify patterns, and draw new conclusions. Nevertheless, machine learning's use to improve diagnostics, prognosis, and treatment development was very new. With the use of medical records, molecular profiles, imaging data, and the potential discovery of more targeted diagnostic biomarkers, machine learning has the potential to one day allow for the earlier and more accurate detection of neurodegenerative disorders.

Sarkar, S. R., & Banerjee, S. (2019) A vast, dynamic, and intricate microbial population resides in the human intestines. Important functions performed by the gut microbiota include digesting, immunopotentiation, microvilli formation stimulation, dietary fiber fermentation, and pathogen colonization prevention. Animal and observational research point to gut microbiota as a key player in the neuropathogenesis of central nervous system illnesses via changes in Gut-Brain-Axis function. An increase in inflammatory cytokines and bacterial metabolites, brought on by dysbiosis, may change the permeability of the stomach and the blood-brain barrier, leading to neuroinflammation.

Sweeney, M. D. et al. (2018) It was now well acknowledged that optimal brain functioning depends on healthy blood vessels, thanks to the growing significance of brain vasculature in the etiology of human neurodegenerative illnesses, including AD. A significant conceptual advance7 has been the use of single-cell transcriptomics to study A-V vascular zonation in mouse models; this method sheds light on biological processes occurring at various vascular tree and BBB levels.

3. Popular methods

3.1 Popular methods

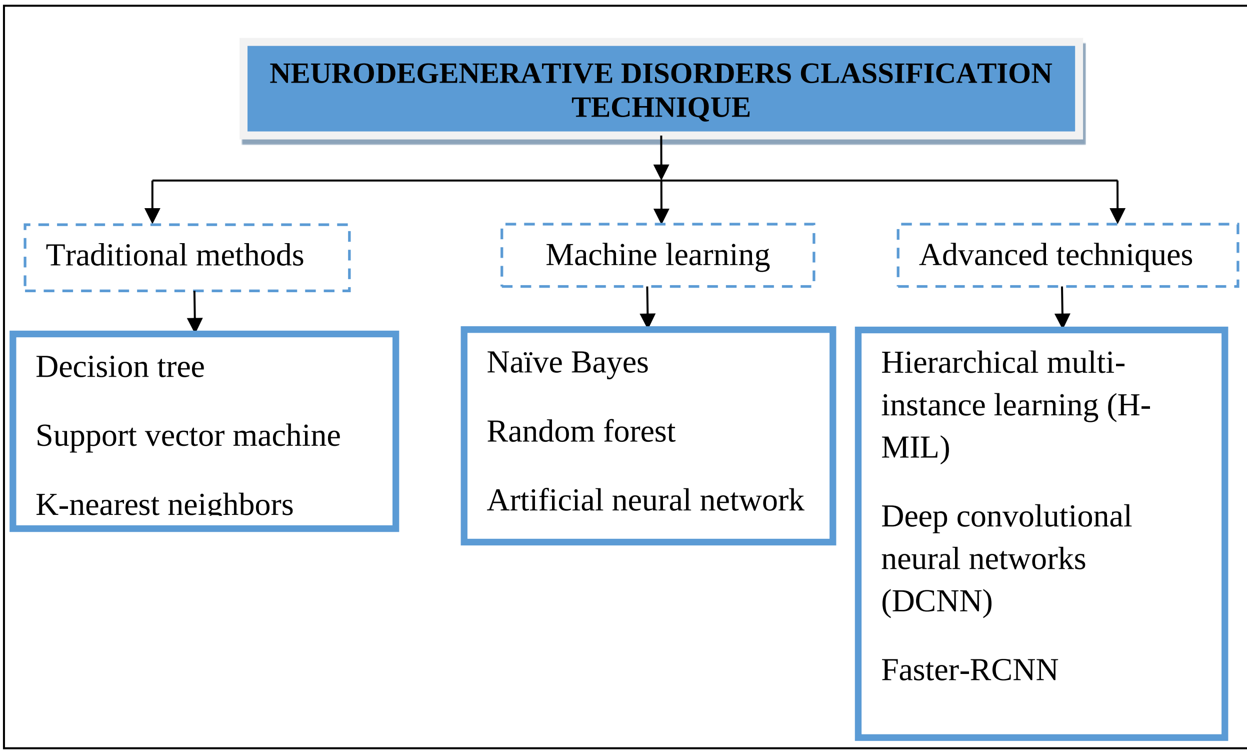

Figure 1: Methods for Neurodegenerative Disorders Classification

Table 2: comparison table for existing methods Merits and Demerits

Algorithm	Merits	Demerits
CNN	Because of their superior accuracy in picture categorization and their inherent capacity to acquire hierarchical features automatically, convolutional neural networks (CNNs) are ideal for detecting subtle differences and patterns in medical pictures linked to neurodegenerative diseases.	Because they are data-hungry models, CNNs may need massive datasets for training before they can generalize to the wide variety of patterns seen in neurodegenerative diseases. Particularly for medical photos with detailed annotations, acquiring such datasets may be a daunting task.
SVM	For the analysis of intricate patterns and correlations in neurodegenerative disease-related medical imaging data, support vector machines (SVMs) work well in high-dimensional feature spaces.	Margin of separation in support vector machines (SVMs) makes sense in two-dimensional spaces, but it becomes confusing and hard to see in three-dimensional ones. Classification aspects might be difficult to understand.
DT	Final Call Trees provide a straightforward route to decision-making since they	Final Call When a deep tree takes in noise from the training data, it becomes

	are intrinsically interpretable. Clinicians benefit from this openness since it clarifies the thinking underlying the categorization of neurodegenerative diseases.	more likely to overfit the model. To reduce the likelihood of overfitting, methods like pruning and establishing minimum sample size requirements for node splitting are essential.
RCNN	When it comes to medical imaging for neurodegenerative diseases, RCNNs' ability to spatially localize areas of interest within the input picture is vital.	In particular, RCNN training may be computationally demanding. When computing resources are limited, this intricacy might become an issue.

3.2 Improved CNN

By using Improved Convolutional Neural Networks (I-CNNs), an improved version of the classic CNN architecture, the categorization of neurodegenerative diseases has made great strides forward. By implementing a number of improvements, this upgraded model aims to make illness categorization more accurate and efficient. Automatically learning detailed characteristics from complex medical imaging data linked with neurodegenerative illnesses is a strong suit of the Improved CNN, which makes use of sophisticated convolutional layers, adaptive pooling approaches, and new activation functions. A notable asset is its improved capacity to detect minute picture patterns and alterations, which allows for a more detailed and accurate diagnosis of many diseases. Improving the model allowed it to better capture local and global characteristics, which are critical for identifying particular biomarkers of different neurodegenerative diseases. Incorporating attention processes also allows for a more targeted examination of important areas in the photos, which improves the model's decision-making even more.

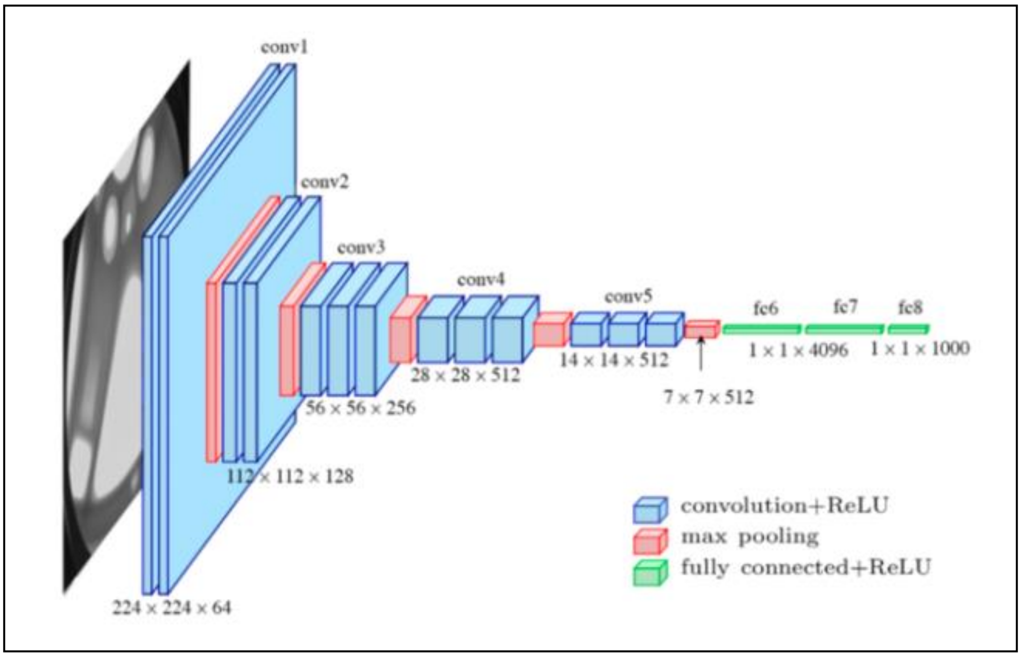

Figure 2: Improved CNN architecture

3.3 Improved SVM

Applying an Improved Support Vector Machine (SVM) method has brought a new degree of accuracy to the categorization of neurodegenerative diseases. This improved model builds on the strong base of classic SVMs by adding cutting-edge methods and optimizations designed for the complexities of neuroimaging data. By using revised kernel architecture, the Improved SVM is able to grasp complicated feature spaces linked to neurodegenerative diseases and their intricate, non-linear interactions. The capacity of the Improved SVM to adjust to different levels of data complexity is one of its standout features. The model does a fine balancing act by means of hyperparameter adjustment and careful regularization, thereby reducing the risk of overfitting on small datasets without sacrificing generalizability. In the field of medical imaging, where datasets often display intrinsic variety, this flexibility is very advantageous. To further highlight the importance of identifying the most useful biomarkers within neuroimaging data, the Improved SVM incorporates feature selection techniques. The model becomes more interpretable by zeroing down on these important traits, which in turn provide light on the elements that really matter for making classification judgments. When it comes to healthcare, this interpretability is crucial, since it allows for better model-clinician cooperation in confirming diagnostic results.

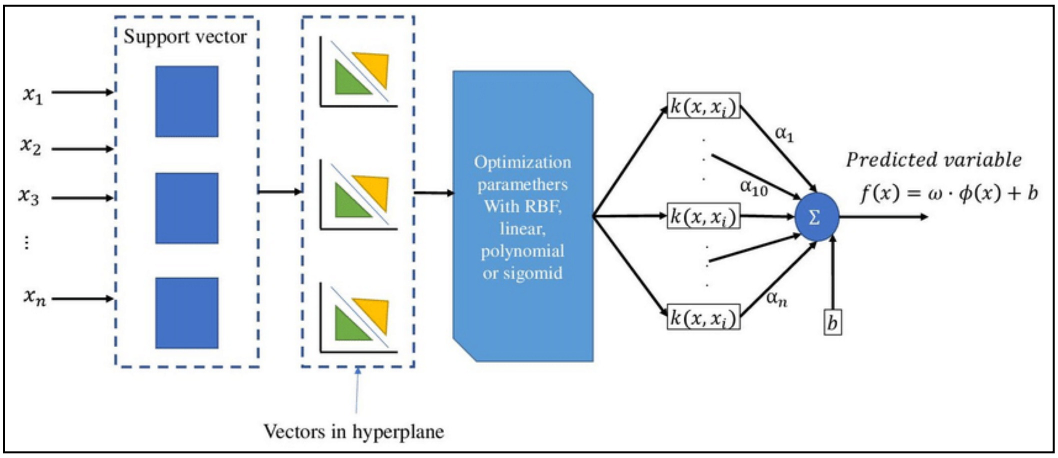

Figure 3: Improved SVM architecture

3.4 VGG 19

Application of the VGG-19 architecture, a strong CNN known for its depth and ability to recognize complex patterns within medical imaging data, has significantly improved and refined the categorization of neurodegenerative diseases. Because of its 19 layers, VGG-19 excels in extracting hierarchical features from large neuroimaging datasets, which allows for a thorough examination of structural anomalies that may indicate different neurodegenerative diseases. The capacity of VGG-19 to learn and express more abstract properties automatically is one of its major advantages, thanks to its deep design. This is of the utmost importance when it comes to neurodegenerative diseases, since precise diagnosis relies heavily on detecting even minute differences in brain patterns and structures. A more complete picture of the underlying disease may be achieved because to the model's ability to stack convolutional layers, which successfully capture both fine-grained and coarse-grained information. The ability to fine-tune VGG-19 to particular neuroimaging datasets and the subtleties of various illnesses is further demonstration of its superiority. Even when dealing with sparse medical imaging data, the model is able to generalize robustly thanks to transfer learning, which makes use of pre-trained weights on large-scale datasets.

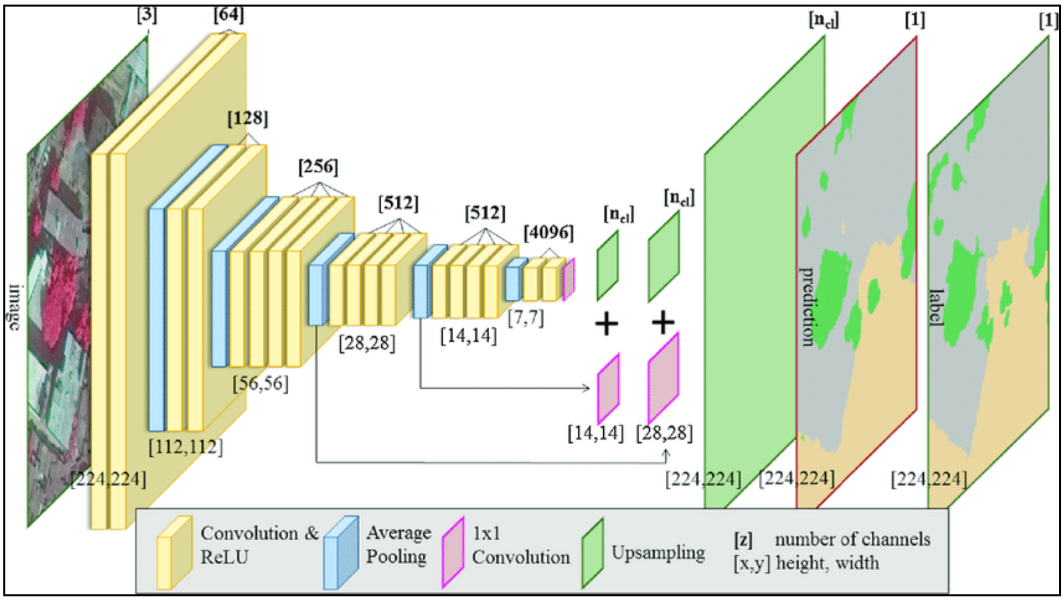

Figure 4: VGG-19 architecture

4. DISCUSSION

This all-encompassing review starts with a brief description of neurodegenerative diseases, a focus on how they gradually affect the neurological system and brain, and an examination of the complex etiology that includes elements linked to heredity, the environment, and aging. With little break in continuity, the story moves on to the meat of the survey, which is methods for automated retinal layer segmentation as they pertain to neurodegenerative diseases. This change in emphasis highlights the need of non-invasive imaging techniques, especially those that target the retina, for the early diagnosis and tracking of these conditions, which are on the rise. The survey promises to explore state-of-the-art algorithms, techniques, and technologies used for automated segmentation, with the goals of illuminating the present state of affairs, resolving obstacles, highlighting successes, and outlining possible avenues for further study. Improving patient treatment in the field of neurodegenerative illnesses is the goal of the survey, which is why it places equal focus on learning about skills and limits.

Table 3: Existing author's accuracy comparison chart

Author	Method used	Accuracy
Choi, H. et al.	CNN -AD	81.00
Karapinar Senturk, Z.	SVM-PD	93.84
Marzban, E. et al.	Deep learning-AD	80.00
Sivaranjini, S., & Sujatha, C. M.	ANN-PD	89.15

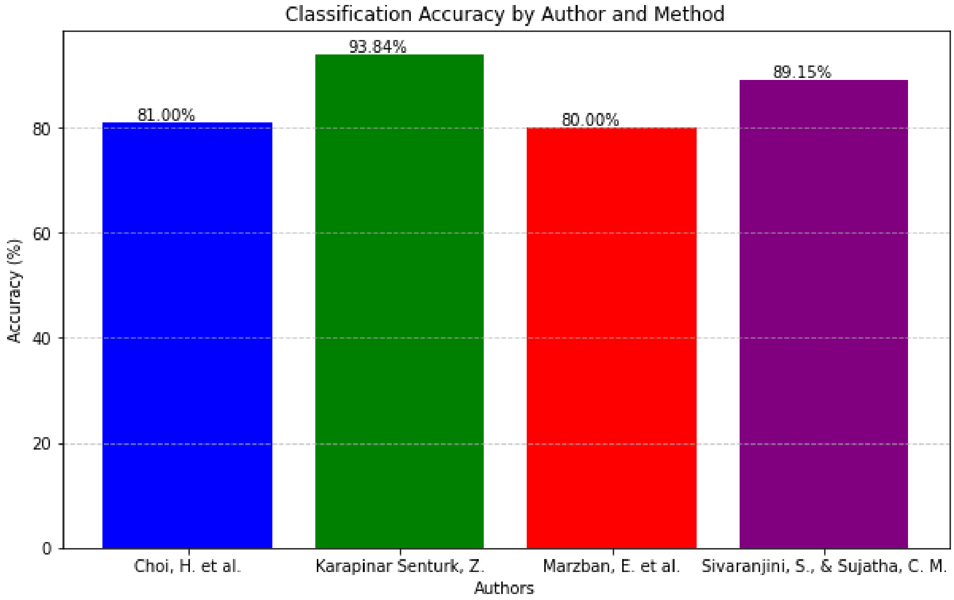

Figure 5: Classification accuracy comparison chart

The accuracy ratings acquired by different writers using different techniques for neurodegenerative condition categorization are compared in Table 3 and picture 5. With the use of CNNs, Choi, H. et al. were able to achieve an accuracy rate of 81.00%. Among the writers on the list, Karapinar Senturk, Z.'s 93.84% accuracy using Support Vector Machines (SVM) stands out. An accuracy of 80.00% was attained by Marzban, E. et al. via the use of Deep Learning algorithms. Finally, Sivaranjini, S., and Sujatha, C. M., using ANN, achieved an accuracy of 89.15%. The accuracy metrics illustrate how well several approaches were used to automate the categorization of neurodegenerative illnesses. SVM performed quite well, whereas CNN, Deep Learning, and ANN all had varied strengths in this area.

5. CONCLUSION

Finally, this review has covered all the bases when it comes to neurodegenerative diseases, illuminating their murky origins and the critical need for new diagnostic tools. This study has looked at how neuroscience and state-of-the-art technology meet via automated retinal layer segmentation methods. The integration of cutting-edge algorithms, techniques, and technologies in this field has highlighted the importance of non-invasive imaging, especially in the retinal setting, and has shown new possibilities for early diagnosis and monitoring. The results of this study will help researchers better grasp the current state of automated segmentation methods, the obstacles they face, and the revolutionary effects they may have on patient treatment, which is particularly important given the rising incidence of neurodegenerative illnesses. The poll concludes that moving ahead, research should continue to tackle the issues highlighted, build upon previous successes, and investigate potential new directions for study. The purpose of this poll is to help increase diagnosis accuracy, which in turn will lead to better outcomes and a higher quality of life for those living with neurodegenerative diseases, by encouraging healthcare providers and technology companies to work together.

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