Section A-Research paper
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A Systematic Review Analysis of Different Alzheimer's Disease Diagnostic Approaches

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Abstract:
There was a huge population of people suffering from mental diseases all across the world. The primary need was to conduct experiments with an adequate examination of the brain disease. Dementia has been the primary factor of brain disease. Trauma or merely becoming older could cause a decline in cognitive abilities including learning, remembering, and problem-solving. "Alzheimer's Disease (AD)" proved to be the most widespread type of dementia. AD has been linked to cognitive impairment in 60-80% of cases. There is currently no effective therapy for this condition. Even though the early diagnosis of AD proved to be very beneficial for those living with this condition. As a branch of "Artificial Intelligence (AI)", "Machine Learning (ML)" approaches use a wide range of statistical and optimizing procedures to enable machines to acquire knowledge from large and complicated data sources. As a result, researchers all across the globe are increasingly turning to ML to identify the earliest stages of AD through "Computerized AD Detection (CADD)". The research attempts to provide a review of the several methods used to diagnose AD based on neurology and cognitive examination of the brain. In an attempt to further accurately identify AD mostly prior, it has been recommended here to investigate and analyze the evaluation of continuing techniques. While certain methods are effective at identifying AD, these have been evaluated using data from a wide variety of neuroimaging modalities, which collectively pose valid concerns about the reliability of the data used. Several studies using neuroimaging modalities for AD detection might assist from this reviewed article.

Keywords: *Dementia, Alzheimer's disease, Artificial Intelligence, Machine learning, Neuroimaging.*

1. Introduction

The term "Dementia" is used to describe a group of disorders that might affect a person's daily life. These symptoms are employed to distinguish between different kinds of illness, such as AD and "Parkinson's disease (PD)". Whereas AD is primarily a disorder of the elderly, its frequency has increased in recent years. Dementia cases in its earliest stages, including those affecting people younger than 65, have been rising in prevalence in numerous countries. AD accounts for between 50 and 70 % of all instances of illness in patients [1]. Other symptoms, such as altered confusion, attitude, and actions, tend to become more noticeable as the illness worsens. It's possible that their day-to-day routine, schedule, and place of residence could require some clarification. Figure 1 from the "World Health Organization (WHO)" estimates that by 2030, AD and various kinds of dementia will account for 1.36 % of the total mortality worldwide.

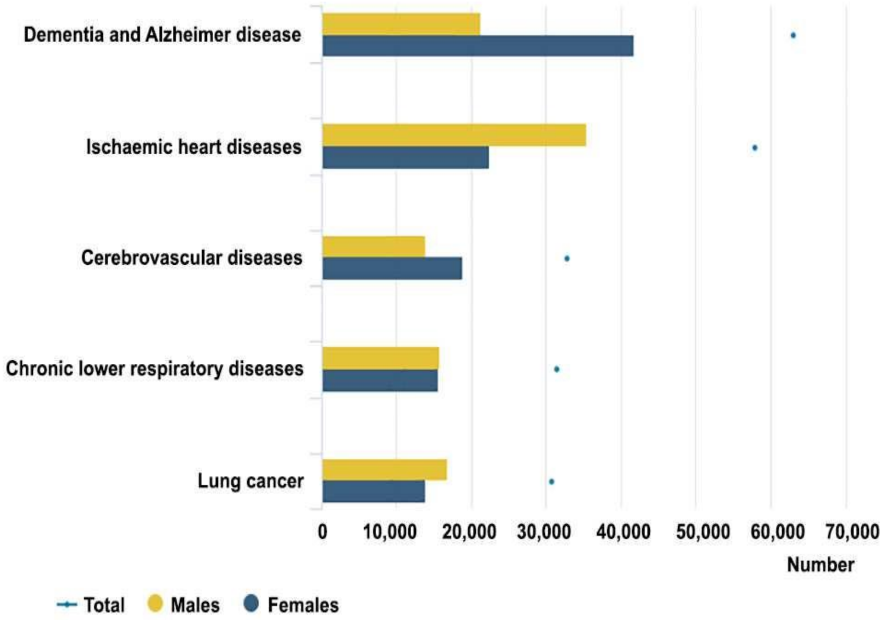

Figure 1. Statistics from "WHO"

A person with mild dementia could anticipate living another 8 years, on average. The loss of synaptic activity occurs in sufficient numbers and makes the illness long-lasting as AD becomes apparent. Impairment can't be normal because surviving neurons are unable to divide and substitute dead ones in the exact way that the remaining cells function. Early diagnosis of dementia continues to be essential to minimizing the rate of impairment. Costs associated with dementia are a further concern to address. The current worldwide expense associated with dementia is estimated to be "819 billion US dollars", but is expected to rise to a trillion US dollars by 2028 [2].

In 2024, the cost of dementia was estimated to reach 26.2 billion pounds worldwide. Dementia has been identified in around 84 million people, and its occurrence was estimated at 4.2 billion inside hospitals. Alzheimer's is becoming more expensive to treat, hence effective diagnostics and assistance tools must be created at a reasonable price. Pharmaceutical cost reduction and improved access to medical resources are central to many of the ideas put forth [3].

Investigation of the consequences of ADs is necessary for either improving the effectiveness of existing therapies or creating new, simpler, and cheaper ways to identify the disease. Diagnostic methods for AD are divided into two categories, "Invasive", and "Non-Invasive" [4].

Using "Invasive" methods requires access to information obtained within the body of the patient, which includes a "Lumbar Puncture" or "Blood Collection". The goal of these techniques is to locate possible biomarkers which function as precise indicators of AD. The levels of "beta-amyloid" and "tau" in the cerebrovascular fluid are only two of the many biomarkers established as measurements of AD. Because of the difficulty and expense of using established biomarkers, researchers are always looking for less stringent as well as cheaper solutions. Yet although some of these checks may not be safe and soothing, others might be impossible to implement [5].

Non-invasive analysis, on the contrary, presents no risks to the patient and may be performed with ease throughout therapy. "Neuroimaging", "Behavioral", "Psychological Assessment", and "Cognitively Interference" are merely a few of the "Non-Invasive" methods employed for early AD diagnosis.

Due to the latest technology by online tools and datasets in the present generation, enormous information is progressively extending and is progressing exponentially [6]. This is for the most part evident in clinically large text information and also with tested imaging data. Consequently, the concern of such information opens up the idea of the neuroimaging and intensity of the enormous information for researchers. Analysts in the medication field, particularly "Magnetic Resonance Imaging (MRI)" analyzed the enormous information with huge dimensionality data were examined.

Initial identification of AD needs the exact data from cases/patients, for example, illness history, neuro-based records, and so on. Due to time limitations for treating AD, it is a must to detect it in early-stage to stop its progress from mild to severe. Due to the above reason, scientists have put forth numerous attempts to give a framework that can find the component and reason for the infection and stops its advancement beyond what many would consider possible. The investigation of different neurological-based imaging modalities to analyze AD are follows [7].

PET "Positron Emission Tomography"

It was another type of imaging modality method that gives a portrayal of a given metabolic procedure through the recognition of a "Positron Emitting Isotope" that is bound to a "Biologically Active Molecule (BAM)". Based on the metabolic procedure in which these molecules were included, a particular change was predicted. But this method isn't as generally accessible as MRI scans which was a high cost also it includes an infusion of a radioactive tracer. For identifying AD this was an alternate methodology in experiments. While comparing with the MRI it had the advantage to produce the hidden damages that occur in the brain. This methodology is accessible in a few openly accessible organization that supports research on Alzheimer's cases. It's an analysis of assessing the glucose level. Since glucose is the primary energy source of the brain. With the decrease in the level of glucose, the metabolism weakens the capacity of the brain. For Alzheimer's cases, hypometabolism is essentially found in the "Back Cingulate Gyri", "Precuneus", and "Parietotemporal Affiliation Cortices" which were shown in Figure 2. "Regional Hypometabolism" isn't a pathophysiological marker for Alzheimer's, however, it was checked to analyze the level of the degeneration. ***The main drawback of PET was a costly method for***

analyzing and it isn't broadly accessible, at present for the most part for PET to diagnose AD is in the researching stage only. Many ML-based techniques are needed to provide the results as TruePositive. Since only considering the PET images the analysts can't conclude the AD cases.

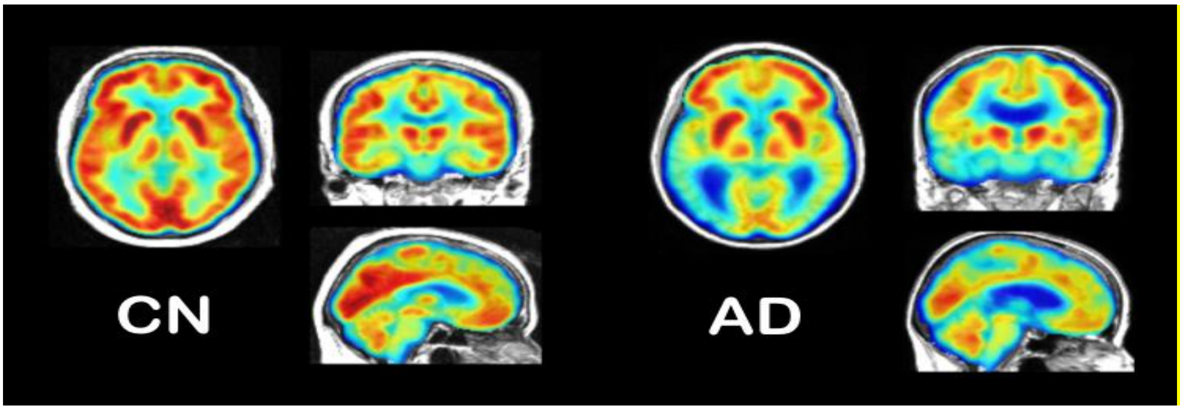

Figure 2. PET for Cognitive Normal (CN) patient and Alzheimer’s disease patient

dMRI "Diffusion Based MRI"

This method quantifies the dispersion of water along axons and can give a portrayal of the brain's "White Matter Fiber Bindles (WMFB)".This was very sensitive for analyzing the damages at the microstructural level that might be available in the WMFBwhich provides various results to predict the cases. The dMRI shows the level of the injuries that occur in the brain in WhiteMatter areas for recognizing Alzheimer'scases which were shown in Figure 3.

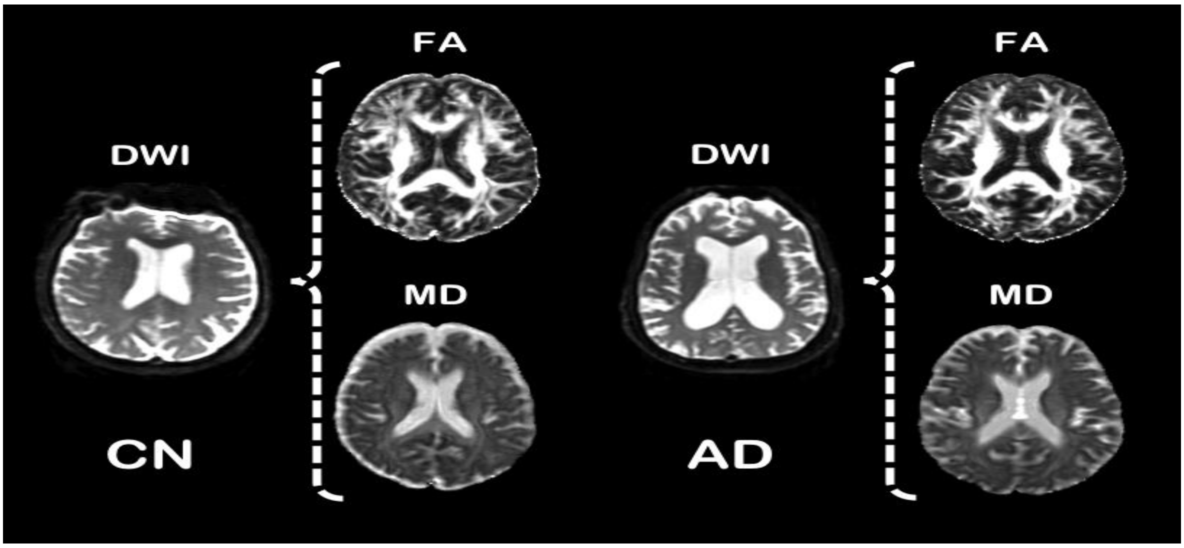

Figure 3. Diffusion MRI for Cognitive Normal (CN) patient and Alzheimer’s disease patient

During progression in MCIstage, it differentiates the cases with the "brain's para Hippocampal Gyrus, Temporal White Matter, Spleniumof Corpus Callosum as well as Posterior Cingulum". But in the case of the progressed AD stage, the regions on both the frontal and backside were severely damaged. While using the ML methods in dMRI the accuracy of the classification ranges from 75% to 80% for classifying the subject as CN and AD.

fMRI "Functional Based MRI"

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This method gives a proportion for the changes of level in the blood oxygen,the activity of the neuronal can be predicted by this method.It was formally tested while any psychological assignments or during a "resting state (rs-fMRI)" for the cases. The Functional connection between various cerebrum areas could be observedwhich was shown in Figure 4. Specifically, different examinations dependent on rs-fMRI have confirmed modifications in the brain termed "Default Mode Network" while analyzing the MCI and AD cases. Besides, the availability changes such as connectivity within the cerebrum region are very useful in analyzing AD cases to predict the plaque's deposition level.

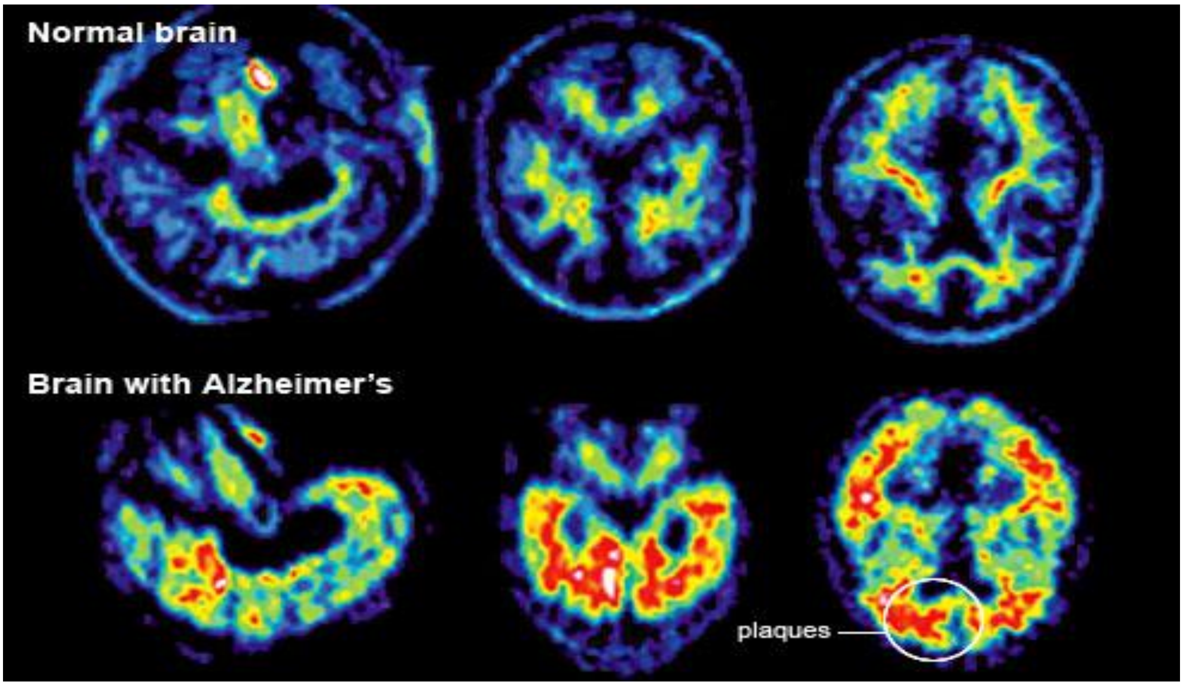

Figure 4. fMRI for Cognitive Normal (CN) patient and Alzheimer's disease patient

sMRI "structural MRI"

The MRI scans with T1-weighted give a structural perspective on the cerebrum. As of now, MRI devices have a higher clarity which displays various types of tissues in the brain accurately. By using sMRI the losses or harm in the tissues are possible to evaluate. This was a phenomenal strategy to calculate the level of damage that occurs in the brain which was given in Figure 5.

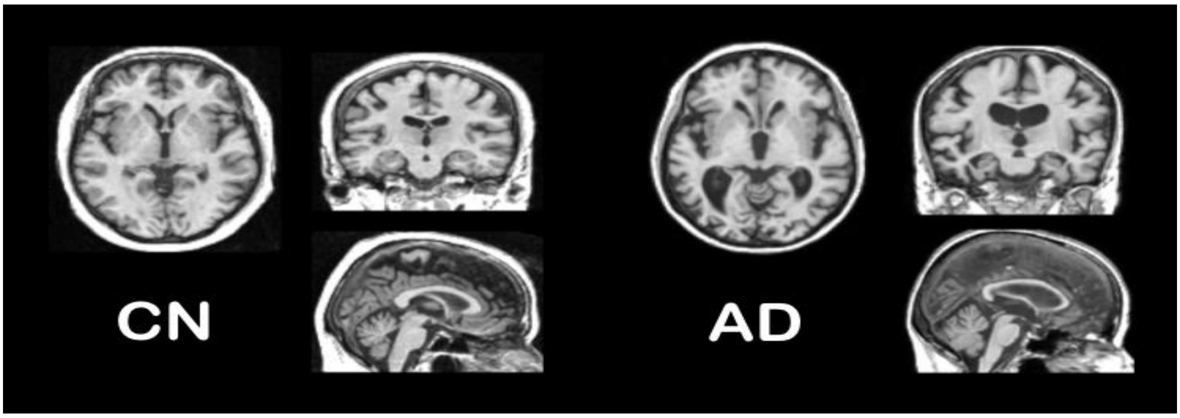

Figure 5. sMRI images for Cognitive Normal (CN) patient and Alzheimer's disease patient

ISSN 2063-5346

The decay in the brain was represented as a proportion of the neurodegeneration. Which was a correlation between the deposition of the tau as well as psychological shortfalls. The sMRI shows the graduation of the cases affected by AD. It covers the area from the "Medial Temporal Lobe" to the "Temporal Neocortex" with its coordinating "Parietal Regions" and also the region of the frontal part. Then again, visual and essential sensorimotor cortices remain moderately saved until late in the illness course.***Utilizing the sMRI which was broadly accessible also a "Non Invasive" method which means taken externally from the human body. This was cost-effective when contrasted with different methodologies. The prediction of AD using sMRI is good but for MCI conditions it needs good ML techniques for providing better accuracy.***

Through this, we came to know that imaging modality is the best way to identify AD in the software field. In that imaging modality, the sMRI plays an efficient role to estimate the affected parts in the given MRI images. With the advancement of ML techniques in the recent generation, many well-versed learning classifiers are available in different fields [8]. By applying the best classifier models in the prediction of AD cases using sMRI we can achieve better classification results while comparing with other modalities.

Problem Statement: To address the "Big-Data's Dimensional issue in Alzheimer's Disease Health-Care Application", this review paper presents a broad overview of the relevant literature. The sMRI dataset was typical of a larger dimensionality, which caused processing difficulties. Large-scale examination of data using a minimum-effort assessment for exploring a cerebrum-based method of imaging proved to be a challenging effort. The methods currently used in this regard could be sorted down further into a few distinct categories, such as reduction of dimensionality and selection of features. There existed several recommended approaches to reduce the image's dimensions [9]. However, methods for reducing data dimensions result in significant feature loss during data import. The methods for choosing the features don't give preference to a single ideal characteristic for use in classifying instances.

In light of the rapid development of ML approaches for AD categorization during the last several years, the ***goal of this study*** is to assess such advancements. Classification issues in the beginning stages of AD could be resolved by the use of ML approaches in diagnosing. Since algorithms tricks on ML have currently become widespread, particularly for the analysis of MRI as well as PET imagery, this has served as an essential and beneficial aspect for evaluating various types of imaging [10].

Paper Contribution: This article's contribution has been an in-depth review of the many different approaches used in CADD, divided into its distinct modules. These include "Preprocessing" to remove noise from the sMRI image, "Segmentation" for separating the hippocampus as a whole area, "Feature Extraction" for obtaining cerebral structure features, "Feature Selection" to choose the most suitable features coming from the array of features, and "Classification" for classifying each person as having either "Cognitive Normal (CN)", "MildCognitiveImpairment (MCI)", or "Alzheimer Disease (AD)".

Paper Organization: Section 1 provides an overview of Alzheimer's disease and discusses its consequences, indications, and diagnostic procedures; Section 2 provides a bibliography of recent studies on AD categorization; Section 3 describes the CADD methodology modules and the various techniques used in them; Section 4 discusses the investigated work; and Section 5 it concludes the entire paper and discusses its potential applications.

2. Related Works

The researchers of [11] developed a cutting-edge "Multi-Task" method for choosing features to keep extra data across phases. Limiting the size of the features chosen across all modalities led to defining the formation of an "Inter Modality Relationship" to be an independent operation. To combine the information from the various categorization techniques, a "Multi-kernel Support Vector Machine (SVM)" was used. PET and MRI referencing images of participants having "94.37% Precision with an Area of 0.9724 under the ROC-Curve for AD recognition" and "78.80% Accuracy with an Area of 0.8284 under the ROC-Curve for MCI recognition" were obtained from the "Alzheimer's Disease Neuroimaging Initiative (ADNI)" dataset.

The researchers of [12] presented a "Gene-Selection" method that combines "Genetic Algorithm (GA)" with SVM to improve classification accuracy. The GA-SVM approach has been employed to select numerous "gene subsets" from diverse sets of training data with the highest level of specificity. Using the technique demonstrated achieved "100% Precision in just 15 genes", demonstrating its efficacy in choosing and categorization. Biochemically stated, "Alzheimer's Genes" have been linked to a minimum of "53% cases". The genes are additionally leveraged to simulate diseases and find "Candidate-Genes" associated with certain disorders.

The researchers of [13] developed a novel method of employing MRIs in the early detection of MCI and AD. There are two primary phases to the framework, and they are the selection of features and feature categorization. The greatest outcomes are achieved by using several types of monthly changes. The framework used in this research outperformed previous research in terms of "Accuracy, Adaptability, and Precision". There is a promising opportunity in the approach they suggested for making early forecasts of a person's MCI to AD transformations, as demonstrated by the study's findings.

According to researchers in [14], "MRI-Preprocessing, extraction of features, selecting optimal feature subset, and finally classification" are the first steps in using SVM to analyze MRI data from brain scans for early detection and alternative classification of AD. Biomarker extraction and verification methods were linked to MRI. In their study, they looked at the primary benefits and drawbacks of many different methods. The characteristics linked with healthy and unhealthy aging were clarified based on the findings of the study's categorization findings and biomarker outcomes. The paper concluded by highlighting open questions and potential future steps.

An initial MRI diagnostics framework for "MCI-AD" transformation has been examined by researchers in [15]. The 2 primary phases of this paradigm are functional accumulation and categorization. At the initial stage, they took an algorithm for searching for varying regions that demonstrate the greatest number of reliable features for classifying data. The features were then classified using Linear-SVM in the subsequent stage. A total of "1435 cases" were examined throughout 8 different weeks, and researchers examined a total of "226

Section A-Research paper
ISSN 2063-5346

ADNI database features". The most accurate forecasts were obtained by using various permutations of the months. The suggested framework provided outcomes that had greater "Precision", "Sensitivity", and "Specificity" than was previously shown in the prior studies. According to the findings, the framework has a high likelihood of predicting and detecting premature transformation from "MCI to AD".

3. Methodologies

Understanding exactly such a widespread disease in individuals leads to AD as time passes are crucial. Some kind of standard, universal architecture is required. The course of developing into the subsequent phase of an illness is now being studied, as well as the development and migration of the term are used to describe this progression. The CN represents the beginning of the phase. A person with CN does not show any signs of intellectual dysfunction. The diagnosis of CN is amended to "Mild Cognitive Impairment (MCI)" whenever the person has cognitive problems wholly or partially significant for the patient or others surrounding her or him to look at however not sufficient to affect the person's daily activities. MCI is a common symptom of AD's later stages. Those with MCI pose a greater chance of developing AD. The specimens of those with MCI have been determined to be in the advanced AD phase. The emphasis of the present research revolves around a critical analysis of existing ML approaches toward AD identification. As a result of training, a large pool of samples is produced. Each given instance could consist of a data item and a desired outcome or the label. For AD identification, the individual's medical history serves as a reference object, with a prognosis shifting towards AD as time progresses. The learning-capable method examines the sample information and creates a model that can be used to assign a grade to any given input. As a result, the method may make previously inaccessible data very easy to extract from the set used for training. Figure 6 depicts the AD-oriented CADD methodology modules as a whole.

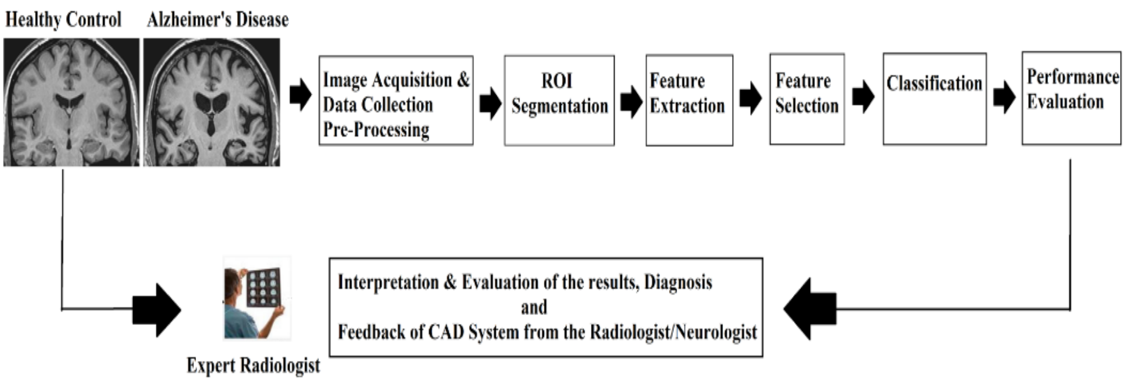

Figure 6. Processes for Classifying AD and Its Methodologies

3.1. sMRI Brain-Image Data Collection

Researchers could obtain publicly accessible information on AD through the "ADNI", and "KAGGLE" databases. The "T1 images of CN, MCI, and AD" that make up these databases are combined with other similar "Fast-Field MRI Echo Images" to provide a more complete depiction of those medical conditions. These images were acquired using "In-plan resolution 0.94 * 0.94 mm2, coronary contiguous slices with 160-170, TE = 4.6ms, matrix dimension = 256 = 256 cm2, TR = 2300 ms, Field-Of-View (FOV) = 256-260 = 240 cm2,

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thickness = 1.2 mm, and the flip angle = 8-9°" according to the throughout the two-year uniformity of "3T-Philips" clinical imaging systems. Nearly 2000 images are included within those databases.

3.2. Brain's sMRI-Image Preprocessing

Numerous different permutations regarding details, like values that are missing and data that is redundant, could be present in databases, all of which might influence erroneous findings. As a result, the accuracy of the information has to be increased before any sort of evaluation can be performed. Once ADNI and KAGGLE databases have been acquired. The sMRI images can potentially be preprocessed using a range of filtration techniques, including the "Discrete Cosine Transform (DCT)", "Discrete Wavelet Transform (DWT)", and the "Median Filter (MF)". The "Smoothing" and "Normalization" had been prominent processes throughout the preprocessing phase. The brain's area was estimated by taking the "head size intracranial, including the brain cortex, white-matter, 3rd and 4th-valve, lower side ventricle, laterum ventricle, cerebellum cortex, cauthane, putamen, pallidum, white-matter brain, hippocampus, and amygdala" assessment. Preprocessing represents the starting point in CADD, where it transforms images in multiple manners to enhance data quality, get rid of unnecessary or distracting errors, and increase attributes. The "Peak-Signal-to-Noise Ratio (PSNR)" constitutes a statistic generated by filtering methods after they have processed the input data. The refined PSNR method result is headed to the next stage of segmentation.

3.3. Segmenting Hippocampus

Hippocampus segmenting comprises a form of separating the area of the hippocampus in a preprocessed sMRI image. The approaches of segmenting images may serve as a stepping stone on the path to more advanced image analysis. The hippocampus has been taken from the sMRI scan of the brain and separated into open regions that correspond to clusters of pixels sharing similar features. Segmentation techniques could be employed according to the relative pixel brightness or the relative location of the pixels. Pixel orientation may be inferred from a series of pixels by determining the distance between them. Non-contextual techniques, also known as thresholding techniques, have been employed for segmentation within such cases since they are not affected by the pixel's position. The threshold methods, although fail in conditions of uneven intensity. Segmentation techniques are often classified as "Similarity" or "Discontinuity" approaches. Intensity values are used to split the sMRI images at the edges into distinct regions during the process of segmentation in edge modeling. This is because every sMRI image has several distortions of varying intensities. The term "Region Segmentation" describes the process wherein similar pixels are clustered together to form distinct objects. The process of "Threshold Segmentation" is one such example. Some of the segmentation methods for segmenting the hippocampus region from the sMRI image are based on "Edge", "Region", and "Clustering".

3.4. Extraction of Hippocampus Features

In an attempt to evaluate or transform the segmented sMRI information, it is necessary to obtain the features that are required. The subsequent procedures are used for extracting features. Both computing technology "Automation" and approaches based on human interpretations had been used. Features that rely on determination, which means colors and choosing the best statistical representation, are put through vigorous testing in an in-depth interpreting process. The system-centered approach provides a soft computation structure that allows the extraction of this type of feature value. Some of the feature extracting methods for extracting useful features from the segmented sMRI image is based on "Texture", "Histogram", "Intensity Histogram", and "Second-Order Statistical Features".

3.5. Selection of Optimal Features

Each sMRI sequence commonly consists of a multitude of features that together contribute to a wealth of data, hence numerous sMRI data are presented in 3D design.Therefore, it is crucial to restrict the volume of data employed during the feature-extracting procedure. It is generally known that the curse of dimensionality arises when the number of individuals who need to be examined is far more than the amount of space available.Therefore, in particular situations, a method of features getting chosen has been employed to get around it. It is common knowledge that the appropriate picking of features may improve AD categorization performance and speed out iterative testing phases. There are two primary guidelines for progress in picking features: "Feature Subset Selection" and "Feature Grading". Identifying a particular group of features to focus on while ignoring the remainder is the focus of the learning approach. Desirable features are given a better grade, whereas non-relevant ones get an inferior one.Some of the feature selection methods for selecting optimal features from the feature vectors are based on "Filtering", "Wrappers", and "Embedded".

3.6. AD Classification Based on ML Approaches

To classify the subject as CN, MCI, and AD many researchers used different methodologies that were described above. In an earlier period for diagnosing they used basic probabilistic methods. The role of ML methods is booming nowadays. By using these techniques the researchers succeeded in predicting Alzheimer's cases. In this article, we took an examination of the current state of AD classification using popular ML techniques.

3.6.1. LR "Logistic Regression"

This model is completely based on a regression type that utilizes a logistic based distributional procedure. Identifyingthe output from the given input variable implies the probability prediction method. The method was very simple. The main drawback of this technique depends on the size of the dataset, in the case of a large-level dataset the accuracy level will get deviation. It works based on calculating the "Region Of Interest (ROI)" for the given input. For a comparative study with other traditional algorithms, this method works moderatelywith AD versus CN (Specificity at 89% and Sensitivity at 61%). But produce minimal for sMCI vs pMCI (Specificity as 82% andSensitivity as 24%). For use in high measurements, various kinds of thresholds could be appended for LR. The common threshold settings range from 11 to produce a normal solution and 12 for producing the expected solution.In any case, depending on the need they can use two threshold settings also to form the proper structure [16].

3.6.2. SVM "Support Vector Machine"

One of the classical techniques which can provide effective solutions in any kind of application. It was expected to locate an ideal isolating hyperplane that augments the edge between points of various classes. The methodology is known to be powerful in higher-dimensional datasets. It can be utilized with various kinds of kernels. The best kernel for SVM is linear based kernels and for non-linear types, RadialBasis kernels can be used. For example, while the size of the dataset dimensionality is high it can opt to go for a linear based kernel. In this circumstance, opting for a non-linear based kernel means it increases the size of the dataset.

Many researchers had applied this ML method for classifying AD, MCI, and CN [17]. While applying they get outcomes for classifying the AD and CN to obtain outcomes effectively which range (Specificity as 91% andSensitivity as 69%)but in the case of sMCI vs pMCI outcomes deviated (Specificity as 80% andSensitivity as 65%).For MRI images the researchers used "Graph Kernel" to classify the AD subjects.

3.6.3. EL "Ensemble Learning"

This method is developed by the combination of similar methods by its various advantages in forming a proper EL method. The structure is designed by a collection of classifiers that were learned from the given input datasets. The basic principle of this method to produce the outcome was to combine the weighted outputs from each classifier from its combination set. For the given dataset it predicts the weighted votes from each class. Thus it was very suitable in the present day's large-scale applications.

One of the best EL methods was "Random Forest (RF)". This operates by forming a single decision tree from different classes of trees. The major advantage of this method can be applied to higher-dimensional datasets. This technique was recently applied to detecting AD cases [18]. They applied it for structural-based MRI and achieved good accuracy results while comparing it with traditional methods such as SVM and LR-based approaches. Here the outcomes they achieved were (Specificity at 93% andSensitivity at 76%) for classifying Alzheimer's subjects.

4. Discussion of the Study

Here we discussed only the ML methodology's performance since the other methodology's advantages and disadvantages are already mentioned in their section itself. In machine learning methods we analyzed three types of methods for classifying AD and Normal from MRI images. The authors [16,17,18] had taken the datasets from the ADNI community open-source database in that they had implemented their models for classifying the subjects. Based on their outcome the specificity and sensitivity were shown in Table 1 and Figure 7. In that given result the ensemble learning method performs better when compared with Logical Regression and Support Vector Machine in both sensitivity and specificity.

Table 1. Metrics Comparision

Parameters	Logistic Regression	Support Vector Machines	Ensemble Learning
SPECIFICITY	89	91	93
SENSITIVITY	61	69	76

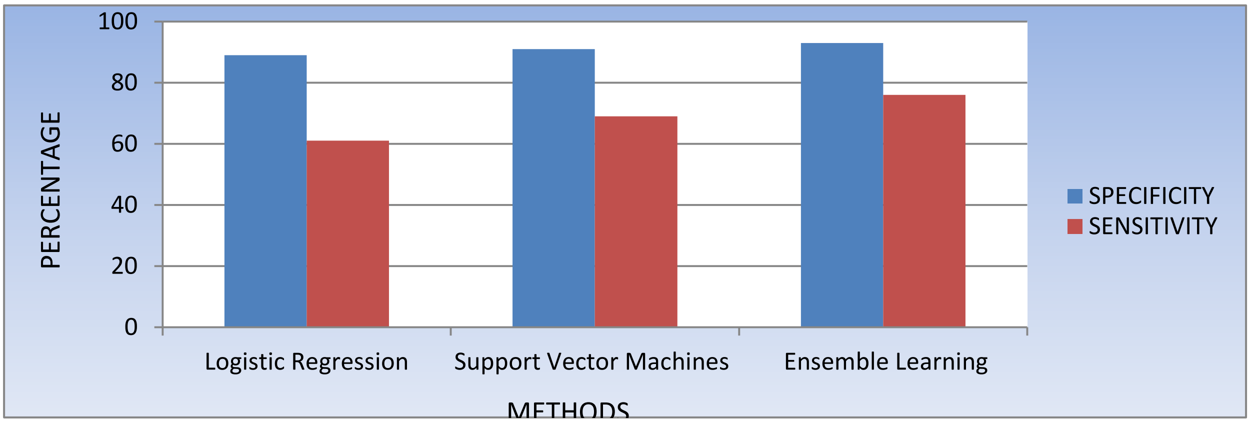

Figure 7. Metrics Comparision

We discovered that the aforementioned techniques give some interesting insights into well-executed research focused on ML for AD categorization. Many other captivating studies with equally impressive findings appear to exist. Many studies have shown that evaluation and characterization of outcomes are necessary, especially in AD evaluation and identification. People who conduct or evaluate studies as well as individuals who aim to employ ML techniques need to possess the capacity to identify problems with sMRI dataset intake, sample planning, identification, or implementation.

Compared to the surveys we looked at, the size of inputs (huge dataset), feature processing, and validation are among the most common problems. Due to their ease of use and superior precision with smaller sets of data, such techniques are unable to handle a large population of input. This had been defined as having a large data collection that has several advantages for dependability, accuracy, and regularity, even though lesser numbers of samples could result in redundant learning.

Since the analyzed methods were able to accomplish an accuracy of 93% at most, the reliability of the model has been challenged because of its size and use of unofficial data. Much of the study's findings rely on information that hasn't been proven pathologically, and this could introduce errors in the results. Although this kind of data could be gathered from hospitals, researchers have had no reason to consider including it in their studies. While surveying different methodologies for classifying the AD and normal subjects, we came to know that "structural MRI (sMRI)" with an ML algorithm is efficient in producing better results.

5. Conclusion

Dementia is one of the huge medical problems that has tested well-being specialists around the world. What's more, it generally occurred in more elder individuals above 50 age. But yet now no legitimate medications are available to cure this ailment. It is dangerous by influencing the individual's memory aptitudes and lesseningtheir thinking capacity. It will spoil their day-to-day life. Numerous medicinal services experts and software researchers were performing research exercises on this issue forthe most recent two decades. By considering all the modalities still, there is a requirement for identifying the cases in the early stage itself. Here we surveyed predicting ADcases in a software-based approach by analyzing different methodologies. The purpose of this study aimed to investigate how the "Class

Imbalance" and "Over Training" problems are addressed, as well as to assess publications that include clinically established evidence. This study reveals that efforts to reduce costs lead to many models being built on a single modality instead of combining numerous modalities. We anticipate that anatomy verification could boost the speed and accuracy of the discoveries, while a "Balanced Class" could end up in more accurate categorization. According to the survey's conclusions, it is suggested that an improved CADD system could have been constructed by paying attention to each component, including "Preprocessing", "Segmentation", "Feature Extraction", "Feature Selection", and lastly "Classification" for categorizing individuals for "CN", "MCI", and "AD" regarding sMRI brain-image databases for more accurate classification.

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