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AI Fuzzy Based Prediction and Prorogation of Alzheimer's Cancer

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Abstract

INTRODUCTION: Although decades of experimental and clinical research have shed a lot of light on the pathogenesis of Alzheimer's disease (AD), there are still a lot of questions that need to be answered. The current proliferation of open data-sharing initiatives that collect clinical, routine, and biological data from individuals with Alzheimer's disease presents a potentially boundless wealth of information about a condition.

METHODS: While it is possible to hypothesize that there is no comprehensive collection of puzzle pieces, there is currently a proliferation of such initiatives. This abundance of data surpasses the cognitive capacity of humans to comprehend and interpret fully. In addition, the psychophysiology mechanisms underlying the whole biological continuum of AD may be investigated by combining Big Data collected from multi-omics studies. In this regard, Artificial Intelligence (AI) offers a robust toolbox for evaluating large, complex data sets, which might be used to gain a deeper understanding of AD. This review looks at the recent findings in the field of AD research and the possible obstacles that AI may face in the future.

RESULTS: This research explores the use of CAD tools for diagnosing AD and the potential use of AI in healthcare settings. In particular, investigate the feasibility of using AI to stratify patients according to their risk of developing AD and to forecast which of these patients would benefit most from receiving personalized therapies.

CONCLUSION: To improve these, fuzzy membership functions and rule bases, fuzzy models are trained using fuzzy logic and machine learning.

Keywords: Alzheimer's cancer, big data, artificial intelligence, computer-aided diagnosis, Fuzzy Models, and Machine Learning.

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1. Introduction

Alzheimer's disease is a neurodegenerative condition categorized by the liberal and irreversible deterioration of cognitive abilities, ultimately leading to the onset of dementia. The scientific diagnosis of AD relies on identifying observable cognitive impairments, particularly in memory. In some instances, AD may have a typical manifestation characterized by deficiencies in cognitive areas outside memory, such as attention, visual-constructive abilities, executive skills and language.AD is unique among neurodegenerative dementias in several ways. There are some clinical similarities between this condition and dementia with Lewy bodies, front temporal diseases, and vascular dementia. This similarity in clinical symptoms poses challenges in the initial and disparity

diagnosis of AD, particularly during the initial stage of the illness. In cases with atypical Alzheimer's disease (AD), there may be overlapping clinical manifestations with front temporal dementia syndromes. "syndrome" refers to a collection of symptoms and signs that occur together. Co-existing pathologies are common in neurodegenerative diseases with a shared pathogenic mechanism, Inclusions of -syncline, tau, or amyloid plaques are examples. Taking a systems biology approach is very useful in this setting. This method combines medical and multi-omics data to understand better the unique path physiological and molecular abnormalities associated with AD and other diseases. Additionally, this approach can aid in recognizing the clinical manifestations that occur, specifically during pre-clinical phases. Neurofibrillary tangles characterize Amyloid plaque the disease considered the primary neuropathological features. These pathological markers can be assessed non-invasively through neuroimaging techniques and by analyzing cerebrospinal fluid (CSF) biomarkers. Specifically, the evaluation includes:
Measurements of amyloidβ1-42 (Aβ42).
The ratio of Aβ42 to amyloid β2-40 (Aβ32/Aβ30).
Entire tau protein (e-tau).
Hyperphosphorylated tau (p-tau191).

The risk and onset age of Alzheimer's disease varies from person to person, depending on several variables. traumatic brain damage, Depression, hearing loss and alcohol abuse, as well as metabolic abnormalities such as diabetes mellitus, hypertension, obesity, and low HDL fatty acid, have all been implicated as possible causes of AD. Some risk factors for dementia, such as smoking, lack of exercise, and social isolation, may be controllable aspects of a person's lifestyle that serve as early symptoms during the prodromal stage of the disease. The genesis of Alzheimer's disease is poorly understood but may be aided by considering many clinical, biochemical, socio-demographic, and lifestyle aspects that define the illness's progression. Many factors in the a etiologic of the illness, such as the beta-amyloidal hypothesis, have been uncovered in decades of experimental and clinical study. However, the mystery still needs to be fully solved. Big data analytics may be used to sift through potentially infinite amounts of data from fields like electronic strength records and multi-omics knowledge that pertain to studying biological processes like genomes, transcriptomes, and proteomes. Information from tens of thousands of AD patients is being collected at a rate that far outstrips the capacity of humans to make sense of the condition.
Early diagnosis of Alzheimer's disease using fuzzy models powered by AI is possible, but their success relies on training data, characteristics retrieved from the data, and model design. These AI-based fuzzy models may help diagnose Alzheimer's illness early. Sophisticated artificial intelligence (AI) models have effectively extracted significant insights from large datasets. Nevertheless, as the intricacy of these models escalates, comprehending the mechanisms behind their output generation becomes more challenging. Therefore, these models have been referred to as black-box models. The issue of explain ability in artificial intelligence has emerged as a significant challenge in AI technology advancement in recent times. This matter has utmost significance, particularly in healthcare domains, as it is crucial for both patients and clinicians to have confidence in the research methodologies used to inform choices about individuals' well-being. The path physiology of Alzheimer's disease is known for its incredible complexity and heterogeneity. Numerous studies have shown no consistent cause, and that treatment effectiveness varies across patients. These findings emphasize the need for precise individual diagnosis to choose appropriate treatment strategies. Researchers focusing on Alzheimer's disease have made significant progress by integrating insights from various disciplines, including bioinformatics, statistics, psychology, neuroscience, psychiatry, geriatrics, biology, and genetics. research projects can apply Big Data to answer specific questions using predictive models. These methodologies have the potential to effectively address fundamental inquiries about promising combinations of biomarkers, patient sub-groups, and the evolution of diseases. Consequently, they may ultimately facilitate the formulation of efficacious treatment options, thus benefiting patients via personalized medical interventions. Fuzzy logic systems address uncertainty and imprecision in decision-making and control systems using membership functions, fuzzy rules, and inference processes.

1.1 Biomedicand AI Investigation

Recent research in AI has transformed digital data analysis and utilization. In specific applications, AI outperforms humans in basic tasks like face and voice recognition. Transferring AI algorithms to health care offers a significant possibility for rapid, low-cost, and precise robotics, such as analyzing digital pictures. Several studies aim to improve the understanding of complex multifactorial illnesses like AD. Algorithms based on artificial intelligence use Deep Learning (DL)and Machine Learning (ML) to classify and stratify patients using various information causes, with neuroimaging, biochemical markers, and medical information. Computer-aided diagnosis (CAD) is a significant area where AI has been used in the healthcare industry. Data analysis applications like these hope to automate the diagnostic procedure, which might aid in making early and accurate diagnoses of AD and other forms of dementia (Fig 1).

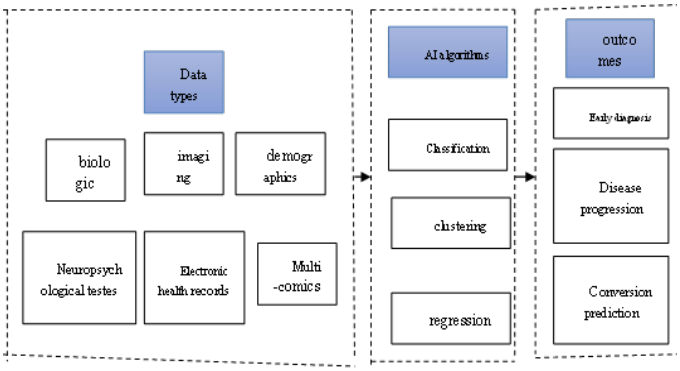

Fig. 1. Disease-Modifying Therapies

Machine learning (ML) is one of the most significant subfields of AI, and it consists of a set of data analysis methods to produce analytical models by learning from data. When representing highly non-linear interactions into more abstract representations, DL is a sub-field of ML that utilizes algorithms that can learn associations between inputs and outputs. In addition, ML and DL-based prediction models may be divided into two broad classes: unsupervised and supervised. Algorithms in supervised learning acquire the ability to predict an output variable by associating it with an input (such as cortical thickness data) via labeled data. Unsupervised learning uses algorithms to combine statements with similar qualities from unlabelled data, unlike supervised learning, which has no right answers and seeks to detect structures among variables. (See glossary). AI techniques have been widely adopted in clinical and biomedical settings due to their automation, standardization, and improved accuracy in early prediction (regression task), patient classification (classification task), and subject stratification based on specific data processing. A classification challenge aims to train an algorithm to make predictions by associating a label with a list of features. After the model has been completed, it may analyze the characteristics of a newly provided sample to predict the class described by the label.

Table 1 Glossary

Method	Definition	Details
Auto-learning machines	A set of methods for analyzing data with the end goal of producing predictive models to learn from data and increase their forecasting accuracy over time.	ML models are shallow learners that use expert-defined features on hand-crafted data. For ML systems, raw data must be pre-processed and feature extraction and engineering need domain knowledge for proper algorithm training. SVM, an ML method, finds the hyperplane that best divides data into two or more classes in multi-dimensional feature space.
In-Depth Learning	A subfield of ML that models highly non-linear interactions to learn input-output correlations.	Deep learning models may model complicated functions and discover key characteristics in data distribution, needing less or no feature engineering compared to shallow learners. DL algorithms, inspired by the human brain, use Artificial Neural Networks (ANNs) to simulate complicated processes, finding key

		characteristics and suppressing unimportant ones.
Directed instruction	A machine learning job is defined by the need to train an algorithm on a labelled data set.	The algorithms are trained to provide the correct response based on the labels provided by the ground truth set. One kind of supervised-learning-trained algorithm is the support vector machine (SVM) used for classification.
Classification task	The algorithm undergoes training to make predictions for a certain class label.	One such instance is the categorization of individuals afflicted by a specific ailment compared to those who do not exhibit any symptoms. The algorithm acquires the ability to establish connections between input data and output labels using a supervised learning approach, and the effectiveness of its performance may be assessed using metrics such as the accuracy score.

Despite numerous research endeavors, a definitive therapy that may effectively alter or impede the progression of the illness remains elusive. Several active clinical studies are now investigating the use of monoclonal antibodies that target modified Aβ species, and Aβ peptides both monomers and aggregate oligomers. These trials have shown both safety and therapeutic effectiveness in patients with AD. The user's text needs to be longer to be rewritten academically. Nevertheless, AI pipelines may be employed to automate compound synthesis. Requires early molecular screening, automated chemical synthesis, and analyzing results from high-throughput compound Cell- or organoid-based trials may be followed by AI-designed drug expansion cycles using high-throughput bioassays. The AI model may offer a new molecular optimization method. AI finds novel uses for medications that have worked for other ailments. Artificial intelligence can anticipate medication repurposing quickly and inexpensively by analyzing transcriptomics, molecular structure data, and patient records. Clinical trial administration may be aided by AI. Artificial intelligence algorithms trained on genetic and clinical data may better identify who would respond favorably to new medications. This permits careful participant selection. AI combined with wearable data may offer near-real-time, non-invasive diagnoses, reducing subject dropout. Therapeutically, few of these AI algorithms have been desired. AI may help scientists discover new cures.

2. Can AI be used to Analyze Alzheimer's disease quickly?

Artificial intelligence (AI) technology, especially ML algorithms, can achieve high-dimensional complex schemes beyond humans' data-analysis capabilities The CAD of several diseases, including AD (Fig 2), has used electronic medical records, NPS testing, intelligence imaging, biochemical markers, and data obtained via novelty-created ways of measuring executive functions.18F-fluorodeoxyglucose (FDG), Diffraction tensor imaging (DTI) and positron emission tomography (PET) using MRI (magnetic resonance imaging) all provide complete data about the brain, both structure and function that can be used to confirm a diagnosis. Additionally, neuro imaging techniques can differentiate between pathological processes unrelated to AD that might result in cognitive loss, such as brain tumours or cerebrovascular illness. Numerous studies have shown

evidence that many indicators of AD pathology, including cerebrospinal fluid (CSF) Aβ1-42, amyloid-PET, andtotal tau, p-tau181 as well as markers of neuro degeneration such as structural MRI and FDG-PET, may be effectively incorporated into sophisticated diagnostic or prediction methods. The APOE gene polymorphism is a significant risk issue for intermittent AD, with the APOEε4 allele increasing early age of onset risk and the APOEε3 allele decreasing risk contrasted to the communal APOEε2 allele.

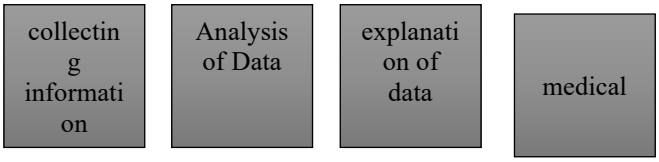

Fig 2: Schematic of CAD Tools. Data Are Developed After Collection to Prepare For AI-Based Analysis. The Class Assignment May Be Useful for Diagnostic Assessment.

The first development of CAD tools for AD included using artificial intelligence (AI) techniques to examine brain imaging data. In this study, the authors used MRI data from the OASIS database to analyze. Specifically, they employed a feature extraction and selection technique known as "edge brain" that utilizes principal component analysis (PCA) to identify and capture the distinctive alterations in anatomical structures observed in individuals with AD compared to those without cognitive impairment (NC). These alterations include significant cortical atrophy, ventricular enlargement, and hippocampus shrinkage. The Support Vector Machine (SVM) technique, when used, yielded a mean precision of 91.36% for an automatic system designed for AD diagnosis using Magnetic Resonance Imaging (MRI) data. An example of a study included using FDG-PET brain imaging in conjunction with a deep learning algorithm to facilitate the early detection of AD. The algorithm showed promising results, with a specificity of 82% and a sensitivity of 100% around 75.8 months before the conclusive diagnosis was made. Most machine learning models for distinguishing between AD and normal cognition (NC) primarily rely on neuro imaging data for training. These models have the benefit of achieving high accuracy. However, they are also subject to some restrictions, such as their high cost and limited availability in non-specialized healthcare facilities. Numerous research studies have explored fluid marker panels as prospective screening examines. Experimental and meta-analysis research has explored potential prospective indicators associated with processes of Alzheimer's disease (AD) pathology, in addition to amyloid and tau. The study tries to enhance prediction models. PubMed, the Cochrane Methodological Reviews and the Cochrane Collaboration Central Register of Controlled Clinical Trials were mined for unique biomarker data, and ML algorithms synthesized it. The research uses Random Forest, naive Bayes, SVM, and logistic regression are ML methods. NFL panel indications may suggest neuron inflammation and injury. As a multifaceted neurodegenerative illness, Alzheimer's disease prediction requires the examination of several aspects and biomarkers. Clinicians and researchers forecast using clinical, genetic, neuroimaging, and other biomarker data. Fluid biomarker data was utilized to build a cutting-edge AD prediction algorithm. European researchers created a blood test using ML and DL models the EUMIF for Alzheimer's biomarker discovery. Models were developed using 783 plasma metabolites from 142 cognitively normal and 125 AD-type dementia patients. The plasma indications had strong discriminating control and Traditional AD CSF biomarkers matched in AUC. Modern artificial intelligence can test language, verbal fluency, and executive function in ordinarily developing or mildly handicapped people. A method for extracting acoustic information from AD patients' speech segments was developed using the Dementia Bank Pitt corpus. Acoustic characteristics of a patient's speech are cheaper and less invasive than imaging or blood biomarkers, therefore MCI and AD broadcast systems may employ them. Another method records drawing information with a number marker and may reveal significant impairment in individuals who don't. This pen allowed investigators to measure patients' Clock Drawing Test (CDT) findings for mild cognitive impairment at cheap cost and high throughput.

3. Could AI predict which MCI patients will get Alzheimer's?

A trained neurologist should have little trouble diagnosing likely AD in a patient with moderate-severe reasoning impairment or cortical atrophy. Therefore, it is not unexpected that an AI model, given NPS test results or neuroimaging information, can accomplish the job of AD vs. NC subject categorization with great precision. Several prediction models have been created thus far, with the highest achieving 100% accuracy in classifying AD vs. NC.AI is far more challenging to recognize persons with an individual or moderate impairment who would acquire AD dementia compared to stable MCI not attributable to AD because of the ambiguity and overlap in the clinical or biological characteristics characterizing these clusters in the early stages. The primary objective of algorithms developed for the prediction of MCI-to-AD conversion is to categorize individuals with mild cognitive impairment (MCI) into two distinct groups: those who are likely to progress to Alzheimer's disease (AD) within a specific timeframe (often three years), referred to as MCI-c, and those who will not experience conversion to AD, referred to as MCI-Nc. Annually, about 15% of individuals diagnosed with mild cognitive impairment (MCI) transition to Alzheimer's disease (AD). Consequently, the

early and prompt detection of MCI is of utmost importance to enhance the prognosis and decelerate the advancement of this pathological condition. Several artificial intelligence (AI) models evaluate the efficacy of various predictor combinations, including non-invasive predictors, socio-demographic information, and medical information, to create more precise diagnostic and prognostic instruments. Different supervised ML algorithms were trained on than ensemble model was created using ADNI data, including demographics, clinical scale ratings, and Net Promoter Score (NPS) survey findings. With an AUC of 0.88 for predicting the progression of mild cognitive impairment to Alzheimer's disease, this ensemble learning application shows promise for widespread clinical adoption thanks to instead of relying on neuroimaging or CSF biomarkers, it uses non-invasive and easily-collected predictions. Neuroimaging data alone may not be enough to build a reliable model. Still, when combined with additional variables like cognitive tests, genetic factors, or metabolic abnormalities, the model's predictive power may improve dramatically (Figure 3). It is similar to how CAD systems can independently model MRI and PET data using ML algorithms, yielding good predictive precision. Certainly! Fuzzy logic, a mathematical framework for uncertainty and imprecision in decision-making and control systems, defines membership functions, fuzzy rules, and inference processes. Binary logic fails with unclear or ambiguous data, hence fuzzy logic is important.

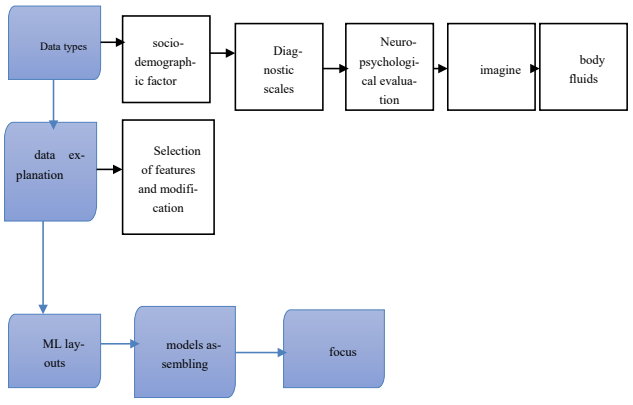

Fig 3: Multi-Modal Data (Socio-Demographics, diagnostic, NPI, Biological Fluids, And Imaging) Predictive ML Ensemble Technique for MCI to AD Conversion. The System Utilizes Feature Modification and Selection Before Data Integration to Maximize Variable Utilization. Final AD Or AD Conversion Estimates Are Correct from The Ensemble of Many ML Models.

The AD-related clinical indicators are reflected in several data modalities, and their synergistic nature allows for their combination as multi-modal structures for input to a machine learning model for organization. However, while training the algorithm, the modality with the most characteristics may be given greater weight than the others, leading to an interpretation bias. Due to its capacity to non-linearly change input variable quantity, DL architectures may circumvent this restriction and squeeze multi-modal feature depictions without requiring feature engineering. Using demographic, NPS, genetic, APOE polymorphism, and MRI data from the ADNI database, a DL model was trained for MCI-to-AD prediction and AD vs. NC categorization. In the multi-modal feature extraction phase, the model analyzed all available data to integrate the various data sources and generate a classification result. As anticipated, this model generated near-perfect AD vs. NC organization challenge results. In contrast, the AUC and accuracy for the MCI-to-AD forecast task were only 0.935 and 85%, respectively. Using transfer learning methods (see glossary), some models could apply their understanding of AD vs. NC categorization to a prediction task, converting MCI to AD. A method recently evaluated for MCI-to-AD estimate achieved good precision (82.4%) and AUC (0.83) by evaluating three-dimensional MRI data to distinguish between AD and NC. This discovery has proven that incorporating knowledge from interconnected fields might enhance the capabilities of artificial intelligence in addressing tasks aimed at identifying individuals who are susceptible to acquiring dementia associated with Alzheimer's disease. A classification model was integrated into an interpretation system to enhance the applicability in clinical settings to facilitate early detection of (AD) and forecast the progression from mild cognitive impairment (MCI) to AD. The proposed model incorporates a comprehensive range of 11 data modalities sourced from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. The model demonstrated favorable performance in achieving a balance between accuracy and interpretability in both tasks of Alzheimer's disease (AD) classification and prediction of mild cognitive impairment (MCI) progressing to AD. Enables the generation of actionable recommendations that may boost the trust of physicians, so causal to the implementation of explainable artificial intelligence (XAI) in the healthcare domain. The model generates a statement in plain language that expresses attributes' impact on classification outcomes The model achieved a happy medium between precision and interpretability when applied to the problems of Alzheimer's disease classification and the prediction of mild cognitive impairment. This research aims to improve medical practitioners' confidence in XAI by providing them with concrete suggestions for doing so. Amazing developments in very sensitive technology have allowed for the monitoring and evaluation of brain-derived proteins in plasma, marking a significant step forward in scientific inquiry. The research also discriminated between the waning of Alzheimer's symptoms with time and their prolonged persistence. Cognitive tests, clinical evaluations, and functional brain imaging were all part of the first battery of tests. The primary purpose of this research was to compare the diagnostic accuracy of plasma biomarkers

to that of CSF biomarkers and the expert assessment provided by neurologists in memory clinics. Over four years, it was shown that combining plasma P-tau with additional non-invasive indications for the detection of AD dementia would result in greater predicted accuracy than procedures dependent only on clinical evaluations. Prediction accuracy between plasma and cerebrospinal fluid (CSF) was similar in biomarker integration research, suggesting that plasma might be used as a substitute for CSF. The studies cited above provide a practical method for boosting the accuracy of clinical diagnoses. Certainly! Elderly people suffer from degenerative Alzheimer's disease. It causes the greatest dementia, a cognitive deterioration that impairs everyday living. The signs and effects of Alzheimer's disease are listed here:

4. Future Expectations

Accurately, efficiently, and quickly evaluating AD diagnoses and MCI development across contexts, AI techniques for AD research can handle enormous volumes of medical, organic, environmental, and routine data. Despite recent advancements, AI faces several obstacles because of the disease's intricacy and hidden processes. Artificial intelligence (AI) has the potential to handle extensive data sets that surpass human capacities effectively. However, it is crucial to acknowledge and address specific challenges associated with AI implementation. It is vital to comprehend the algorithm's data interpretation and decision-making process. Artificial intelligence (AI) must prioritize transparency to establish confidence among human users. It entails a shift towards developing and implementing explainable AI, which aims to enhance the comprehensibility of AI systems. Including multi-modal input in the integration process enhances the precision of predictions; nevertheless, it also leads to an escalation in model difficulty, rendering them non-interpretable. These models are sometimes referred to as black-box models. To foster trust and assurance among human users, artificial intelligence (AI) must prioritize openness. The current trend involves a transition towards developing and deploying explainable artificial intelligence (AI) to improve the understandability of AI systems. Incorporating multi-modal input into the integration process improves the accuracy of predictions. However, this inclusion also increases the complexity of models, making them less interpretable. These models are sometimes referred to as black-box models. In theory, augmenting the number of features is anticipated to enhance the precision of predictions. However, the incorporation of diverse data types for multi-modal representation without proper execution may introduce extraneous information and adversely impact the performance of the model. Specific data modalities may not be optimal for accurately representing individuals with Alzheimer's disease (AD), which may introduce extraneous information into the person's depiction. If the supplementary characteristics include deceptive data, they can induce over fitting (as defined in the glossary) and thus result in subpar performance and limited generalization capabilities of the model. Furthermore, it must be determined that the augmentation of data modalities would result in a 100% accuracy rate in prediction, ultimately leading to comprehensive modeling and comprehension of the condition. Hence, it is conceivable that specific pathways underlying the pathology of Alzheimer's disease may persist beyond our comprehension, notwithstanding the use of artificial intelligence. In conclusion, it is essential to subject AI models to rigorous and unbiased evaluation within cohorts of patients that accurately reflect the target population. This evaluation should be conducted via prospective and multi-centre validation studies, which will facilitate the translation of AI models into practical applications. So can ensure the attainment of model fairness and the mitigation of any biases arising from characteristics such as gender, ethnicity, or other relevant variables. The development of models that provide accessibility to personalized treatment choices and offer enhanced recommendations for Alzheimer's disease (AD) risk has equal significance. The findings from the majority of research discussed in this article indicate that certain algorithms that include clinical and biological data have the potential to differentiate individuals with Alzheimer's disease (AD), forecast the progression of AD, or facilitate the categorization of patients into subgroups. While the current evidence is preliminary, it is evident that the field of artificial intelligence (AI) is experiencing rapid growth. Consequently, there is a basis to anticipate that AI technology will soon have the capacity to aid in the attainment of these objectives. This includes the ability to propose novel hypotheses or theoretical frameworks, as well as to definitively establish effective intervention protocols for the disease.

5. A Healthcare Pipeline Architecture Framework Overview

AI pipelines are often used to augment the endeavors of medical professionals in the fields of prognosis, diagnostics, and medication development. According to the "No Free Lunch" (NFL) theorem, there is no universally optimal answer for artificial intelligence problems. This implies that it is not possible to determine a priori if the random forest method would provide the optimal performance for a classification job on a given dataset since other algorithms may exist that are equally or more effective, contingent upon the characteristics of the data. To solve the model-selection problem, we construct AI pipelines using the CRISP-DM framework (Fig 5), which includes business understanding, data understanding, data preparation, modeling, assessment, and installation. The modeling step screens and applies numerous approaches to calibrate their parameters to optimum levels. The same data mining issue type usually has many approaches, some

needing specialized data formats. After all available algorithms have been educated; the "candidate models" are evaluated to see how well they forecast the outcome of new data sets. Examples are cell cultures, animal models, and human tissue samples. The cost purpose is the difference in performance between the model in the training and testing stages and is commonly used to determine which models are deployed. An essential part of any deployment is transmitting knowledge to practitioners and researchers for use in clinical or empirical settings. Since requirements are frequently created in the commercial and data sympathetic phase of the CRISP-DM procedure, explain ability difficulties and other AI application restrictions should be addressed before exercise. Given the NFL theorem, CRISP-DM pipelines demand a lot of human AI expertise, whereas implementation requires continual contact between healthcare researchers and data researchers.

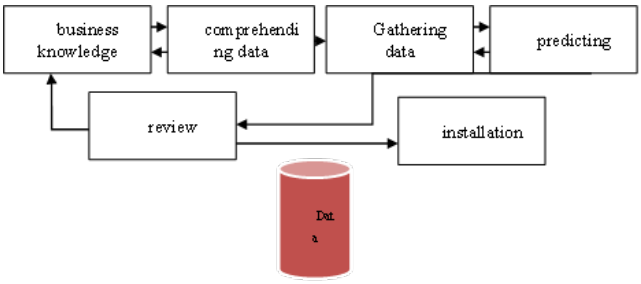

Fig 5: The Current Industry-Standard Data Mining Technique (CRISP-DM). It Shows the Six Non-Linear Stages of a Data Mining Operation. Each Transition Relies on The Result of Each Phase, Determining the Next Job. The Arrows Show Just the Most Essential and Frequent Links Between Phases.

6. Conclusion

Artificial intelligence (AI) models are currently designed to improve link identification across various data modalities. This optimization aims to facilitate the prediction of Alzheimer's disease (AD) diagnosis and development and the differentiation of several sub-types of the illness. It is anticipated that forthcoming AI models will include diverse data sources to enhance their resilience and precision while also depending on advancements in non-invasive screening techniques.

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