

Alzheimer's Disease Based on Machine Learning Algorithms and Mind Maps: Review

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Abstract

Alzheimer's disease (AD) is a complex neurological illness that has several deep reasons. According to recent research, the use of machine learning techniques (ML) on MRI images can assist in identify the brain regions and the connections between them that are implicated in dementia. The study aims to review literature from 2017 to 2023 on the use of machine learning algorithms to identifying and categorize AD. The precision of each machine learning model is assessed, and mind map models are employed to illustrate the study and compare the outcomes.

Keywords—Machin-Learning Algorithms, Dementia and Alzheimer's Classifications, Mind maps models.

I. INTRODUCTION

The most common kind of dementia, Alzheimer's disease, can cause significant memory loss. It weakens the essential processes of neurons, including metabolism, communication, repair, and regeneration inside body. Cognitive functions including thinking, reasoning, and memory are impacted by AD. Mild Cognitive Impairment (MCI), the precast of AD, causes progressive memory loss and behavioral problems. Around 15-20% of older people (65 years of age or older) have MCI, and 30–40% of them get AD within five to six years. According to the article medical imaging plays a critical part in the early detection and diagnosis of various neurodegenerative diseases, such as Alzheimer's Disease [2]. As cutting-edge technologies like deep learning (DL) and machine learning have emerged, there is a growing interest in leveraging these techniques for the analysis of medical images to identify potential biomarkers and patterns associated with neurodegenerative conditions. By utilizing these biometrics, healthcare professionals can extract features from brain MRI images, allowing for more precise and detailed analysis for the detection of dementia. Fig1 shows MRI images during the three phases of the disease.

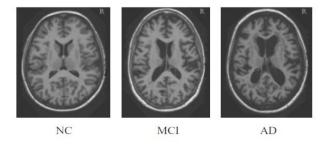


Fig. 1.Magnetic Reasoning Images(MRI) shows Alzheimer's phases[1]

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A.Stages of Alzheimer Disease

Three classifications are utilized to categorize the phases of Alzheimer's disease: mild, moderate, and severe levels as shown in Table I. Consider that because stages of the disease might overlap, it may be challenging to categorize an individual with Alzheimer's.

| Stage | The initial symptoms |
|---------------------------------|-------------------------------------------------------------|
| Mild, or initial Phase | moderate indications and overall forgetfulness |
| Moderate, or intermediate Phase | incapacitating symptoms; additional attention is required |
| Severe, or final Phase | notable alterations in behavior and personality, absence of |
| | awareness |

TABLE I. THE THREE MAIN STAGES OF ALZHEIMER

In this context, the integration of ML and DL algorithms into medical imaging has presented promising results for risk assessment, early detection, and prognosis of diseases like Alzheimer. However, further investigation is required to fully understand the complexities of AD, as the particular biochemical processes behind the illness remain unknown[3].

B.Types of Dementia disease

The word "dementia" refers to a broad range of symptoms resulting from brain abnormalities that impact behavior, thought, memory, and emotion. Alzheimer's disease, vascular dementia, Lewy body dementia, frontotemporal dementia, and other secondary dementias with diverse etiologies are among the several forms of dementia. Of all the dementias, Alzheimer's disease is the most prevalent and the size of the hippocampus and amyloid plugs are indicators of what happens in the human brain which appears clearly in MRI, accounting for 50–60% of dementia cases. Approximately 20%–30% of cases are vascular dementia, roughly 10%–25% are Lewy body, and 10%–15% are frontotemporal. There are further secondary dementias with different etiologies. Given that different varieties of dementia have different symptoms and may need different treatments, it is critical to make an accurate diagnosis[4]. The next figure shows many instances of dementia.

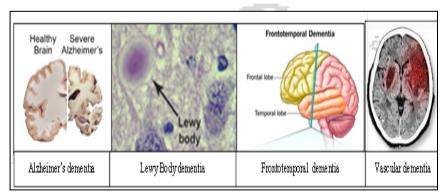


Fig. 2. Alzheimer and lewy bodys and frontotemporal kindes of demintia (google leNet)

C.Alzheimer Biomarkers

The Common imaging techniques used include structural neuroimaging, functional imaging and hybrid imaging [5]. The structural imaging consists of two main types MRI (works under radio waves) and CT related to X-ray while the functional imaging such as fMRI, PET, and SPECTS.

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Hybrid images include more than one type of image to raise the precision and quality of it as shown in Fig3.

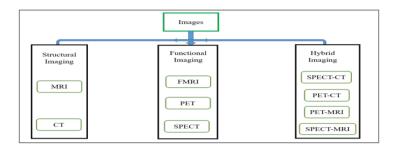


Fig.3. The three main types of Alzheimer's biometrics

D.Machin Learning Techniques

Although there are significant differences in how machine learning algorithms are defined, in general, they can be categorized based on their intended use. The primary categories are as follows: supervised Knowledge, unsupervised Knowledge, Simi-supervised knowledge, and reinforcement knowledge[6]. This research work will measure the accuracy of each algorithm used in classification and detection that is applied on Alzheimer's disease.

1.Supervised learning Algorithms

In this instance, human specialists serve as the teacher, providing the computer with training data that includes input and predictors and demonstrating the right responses (output). The computer should be able to identify patterns in the data. To predict values of the results for new data based on associations learned from prior data sets, Modeling the relationships and connections between the properties of the input and the desired projected output is the aim of supervised learning techniques. Regression and classification issues are the two primary categories of supervised learning challenges. There are several algorithms that work under supervision learning Table2 shows the common types used to classification and detection[7].

2. Unsupervised Learning Algorithms

Represent a set of machine learning algorithms that are primarily employed in descriptive modeling and pattern recognition. That is, the algorithm cannot attempt to model relationships based on either labels or output categories. In an effort to provide consumers with more meaningful insights and a clearer explanation of the data, these algorithms attempt to apply techniques on the input data to mine for rules, identify patterns, summarize, and categorize the data sets. Clustering algorithms and association rule learning algorithms are the two primary categories of unsupervised learning algorithms.

3. Semi-Supervised Learning

In the first two categories, either every observation in the dataset has a label or every observation in the dataset has a label. In between the two is semi-supervised learning. In many real-world scenarios, labeling comes at a significant expense because it takes knowledgeable human experts to complete. Therefore, semi-supervised algorithms are the best options for developing models when labels are present in a small percentage of data but absent from the rest. These techniques take advantage of the notion that unlabeled data contains valuable information about the group parameters even while the group memberships of the data are unknown.

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4. Reinforsment Learning

As a subset of machine learning, reinforcement learning falls under the umbrella of artificial intelligence. It enables devices and software agents to autonomously ascertain the best course of action in each situation to optimize performance. The reinforcement signal is the simple reward feedback that is needed for the agent to learn its behavior. The common algorithms related to this type are Q-learning, Temporal Difference (TD) and Deep Adversarial Network.

| Algorithm | Learning Type |
|-----------------------------------------------------------------------------------------------------------------------------------|----------------------------------|
| Nearest Neighbor (KNN), Nave Byse, and Disision Tree Linear and logestic Reggresion, Support Vector Mation, Neural Network. | Supervision Machin learning |
| K. means Clustring and Association Rules | Unsupervision Machin learning |
| ALZheimer-NET model[8] | Semi-supervisued Machin learning |
| Q-learning, Temporal Difference, and Deep Adversarial Network | Reinforsment Machin learning |

Mindmapes and its theory Behind

A mind map has the power to transform a large list of boring facts into a visually appealing, memorable, and well-organized graphic that follows your brain's natural processes. To aid in analysis and memory, it enables you to graphically organize your thoughts. An intuitive framework can be built by the user around a central concept by using a mind map, which is a non-linear graphical representation of tasks, words, concepts, or other items related to and arranged around a central concept or subject. Fig 4 represents types of machine learning algorithms as example to utilizing these maps[9].

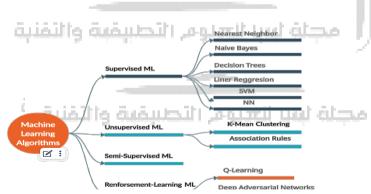


Fig.4. Types of Machine learning Algorithms

The aim and objective part, the challenge section, the literature review section, the methodology portion, the results section, the conclusion paragraph, and the references are the order in which the review research is organized.

I. AIM AND OBJECTIVES

The aim is to clarify the precision of learning from machine algorithms applied to AD visually. To achieve this aim, two important objectives should be pursued: reviewing and evaluating the

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literature on machine learning approaches relevant to AD and applying common visual models suitable for displaying the outcomes attractively.

II. THE CHALLENGES

Analyze the accuracy of each MI technique using the collected papers with varying values for the same model. These variations in the algorithm's accuracy scores are the outcome of several elements supporting the accuracy. For example: Dataset Size, Dataset Type, Greyscale or Color images (when the dataset is based on images), Data Extracted, and Pre-processing. Consequently, the accuracy is extremely relying on the data's quality and amount of these data in one hand and in other hand the preprocessing and the steps of feature extraction.

| Effected Factores | Constrants |
|--------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Dataset Size | Long-term dataset(longitudinal) |
| Dataset Type | MRI |
| Imaging type | Grey -Scale |
| Data-extracted, Pre-processing and other factors | The accuracy of each technique will be measured as range between Lowest value per percentage and to highest value per percentage, where, these processes will consider all the other different factor. |
| Molel type | Classifyer |

III. METHODOLOGY AND CONSTRANTS

The proposed methodology in this review paper consists of four major phases: Gathering, Filtering, Analysis, and Displaying phases. Furthermore, many constraints should consider applying the methodology with greater precision and control. Table 5 shows the factors affect to accuracy of each algorithm applied to AD and the constraints that will be applied during the methodology.

The figure below presents the mechanism of suggested methodology.

| | and the second se | | |
|----------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------|--|
| Phase1: Gathering 38 research paper Related AD | | | |
| Phase2: filtering 20 paper documente | ed | Rejected paper: -for Dementia in general nor AD specifically -Accuracy not mentioned -Ambiguity paper | |
| Phase3: Analysis Phase4: Results display using mind maps | | Comparing and get max and min value of algorithm | |
| | | | |

Fig.5. the methodology Mechanism

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IV. LETTERITURE RIVIEW

The literature has expressed criticism of the use of machine learning algorithms for both Alzheimer's and dementia disease identification. Some studies have pointed out that most research in this area has focused on using machine learning for the classification and prediction of different cognitive diseases and states, rather than specifically identifying risk factors associated with dementia or AD [6]. Additionally, the use of complete case analysis in previous studies has limited the inclusion of cases with missing data, potentially affecting the accuracy of the results [2]. Furthermore, while machine learning approaches have been used to select risk factors and predict dementia status, there is still a need for dedicated machine learning methods that combine deep learning and reinforcement learning for early diagnosis of Alzheimer's illness [10]. Overall, Additional research is required, and improvement in machine learning algorithms for the detection of dementia and Alzheimer's. Furthermore, Machine learning algorithms have been criticized for their limitations in diagnosing and predicting the disease because of the complexity of the disease and the lack of definitive diagnostic tools, which makes it challenging for machine learning algorithms to accurately detect the disease [11]. Another criticism is the need for large datasets to train the algorithms effectively [7]. Additionally, there is a concern about the interpretability of machine learning models, because they frequently serve as "black boxes," making it challenging to decipher the underlying logic behind their forecasts. Furthermore, the time required for training certain algorithms, for example, NN's algorithms, capable of significantly longer compared to other models[8]. Despite these criticisms, machine learning algorithms have shown promise in assisting and improving

Alzheimer's disease diagnosis, achieving high accuracy rates in predicting the disease. From recent literature reviews, there is a need to clarify the overall performance of machine learning algorithms on this illness to assess the accuracy of each one. Tables from

IV to VI illustrate a survey of 20 related research paper worked on AD by using machine learning techniques from 2017 to 2023.

| References | work | Authors | year |
|------------|------|------------------------|------|
| [12] | LR1 | Abdulmunem and et il | 2022 |
| [13] | LR2 | Patel, and et il | 2023 |
| [14] | LR3 | Singh, and et il | 2023 |
| [15] | LR4 | Qiao and Hanquan | 2021 |
| [16] | LR5 | El-Latif, and et il | 2023 |
| [17] | LR6 | Farouk, and et il | 2020 |
| [5] | LR7 | Ahmed, and et il | 2018 |
| [18] | LR8 | Altinkaya, and et il. | 2020 |
| [19] | LR9 | Chandra, and et il | 2023 |
| [20] | LR10 | Hojjati, and et il | 2019 |
| [21] | LR11 | Wang, and et il | 2019 |
| [22] | LR12 | Kumariand et il | 2022 |
| [13] | LR13 | Patel, Richa and et il | 2023 |
| [23] | LR14 | Mahjabeen, and et il | 2023 |
| [24] | LR15 | Cui, Ruoxuan and et il | 2019 |
| [25] | LR16 | Ebrahimi, and etil | 2021 |
| [26] | LR17 | Kaur, and etil | 2023 |
| [27] | LR18 | Basaia, and etil | 2018 |
| [22] | LR19 | Kumari, and et il | 2022 |
| [28] | LR20 | Kim, and etil | 2021 |

TABLE III. THE LITERTURE RIVIEWS (LR) BETWEEN 2017 AND 2023

TABLE IV.

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TABLE V. THE RESEARCH TITLE AND THE CONFERENCE/JOURNAL

| work | Title of research | Conference/journal name | |
|------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|
| LR1 | Brain MR Images Classification for Alzheimer's Disease | Iraq Journal of Science | |
| LR2 | A Logistic Regression and Decision Tree Based Hybrid Approach to | 2023 International Conference on Computational Intelligence | |
| | Predict Alzheimer's Disease | and Sustainable Engineering Solutions (CISES) | |
| LR3 | IHDNA: Identical Hybrid Deep Neural Networks for Alzheimer's | 2023 3rd International Conference on Intelligent | |
| | Detection using MRI Dataset | Communication and Computational Techniques (ICCT) | |
| LR4 | Using K-Means Algorithm and Convolutional Neural Networks to | Journal of Physics: Conference Series | |
| | Identify Alzheimer's Disease in Coronal Brain Scans | | |
| LR5 | Accurate Detection of Alzheimer's Disease Using Lightweight Deep | Diagnostics | |
| | Learning Model on MRI Data | | |
| LR6 | Early diagnosis of alzheimer's disease using unsupervised clustering | International Journal of Intelligent Computing and Information | |
| | | Sciences | |
| LR7 | Neuroimaging and machine learning for dementia diagnosis: recent | IEEE reviews in biomedical engineering | |
| | advancements and prospects | | |
| LR8 Detection of Alzheimer's disease and dementia states based on deep | | Journal of the Institute of Electronics and Computer | |
| | learning from MRI images: a comprehensive review | | |
| LR9 | Novel Method for Detection of Alzheimer's Disease using Gini | 2023 10th International Conference on Signal Processing and | |
| 1.5.4.0 | Impurity based Decision Tree Model | Integrated Networks (SPIN) | |
| LR10 | Identification of the early stage of Alzheimer's disease using structural | Frontiers in neurology | |
| 1011 | MRI and resting-state fMRI | | |
| LR11 | Functional magnetic resonance imaging classification based on | 2019 International Conference on Image and Video Processing, | |
| 1.0.10 | random forest algorithm in Alzheimer's disease | and Artificial Intelligence 2022 IEEE 21st Mediterranean Electrotechnical Conference | |
| LR12 | Using SVM for Alzheimer's Disease detection from 3D T1-MRI | | |
| LR13 | | (MELECON) | |
| LR13 | A Logistic Regression and Decision Tree Based Hybrid Approach to Predict Alzheimer's Disease | 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES) | |
| | Predict Alzheimer's Disease | and Sustainable Engineering Solutions (CISES) | |
| LR14 | Early Prediction and Analysis of DTI and MRI-Based Alzheimer's | Springer | |
| LICI4 | Disease Through Machine Learning Techniques | springer | |
| LR15 | RNN-based longitudinal analysis for diagnosis of Alzheimer's disease | Computerized Medical Imaging and Graphics | |
| LR16 | Convolutional neural networks for Alzheimer's disease detection on | Journal of Medical Imaging | |
| LKIU | MRI images | Journal of Wedear Imaging | |
| LR17 | Utilizing the Random Forest Algorithm to Enhance Alzheimer's | 2023 Third International Conference on Artificial Intelligence | |
| LICI / | disease Diagnosis | and Smart Energy (ICAIS) | |
| LR18 | Automated classification of Alzheimer's disease and mild cognitive | Neuroimaging: Clinical | |
| | impairment using a single MRI and deep neural networks | and a second secon | |
| LR19 | Using SVM for Alzheimer's Disease detection from 3D T1MRI | 2022 IEEE 21st Mediterranean Electrotechnical Conference | |
| | | (MELECON) | |
| LR20 | Development of random forest algorithm based prediction model of | Psychiatry Investigation | |
| | Alzheimer's disease using neurodegeneration pattern | , , , , , , , , , , , , , , , , , , , , | |

Table V shows the main algorithms of ML that applied on AD using common long-term datasets.

| Work | Algorithms | Dataset | Accuracy |
|------|---------------------|-------------------------------------------|------------|
| LR1 | DBN Classifier | ADNI | 98.46% |
| LR2 | Logistic Regression | OASIS | 96% |
| LR3 | CatBoost | ADNI | 95.41% |
| LR4 | K-means | ADNI | 75% |
| LR5 | Logistic Regression | ADNI | 97.87% |
| LR6 | K-means | ADNI | 78% |
| LR7 | CatBoost | OASIS | 92-96% |
| LR8 | CNN | ADNI | 99.9 |
| LR9 | SVM | ADNI | 99.78% |
| LR10 | Association Rule | ADNI | 97 % |
| LR11 | Random forest | ADNI | 90.68% |
| LR12 | SVM | ADNI, and MRI images from 202 subjects | 98.71% |
| LR13 | Decision Tree | Long-term Dataset | 96% |
| LR14 | Nave Bayes | ADNI | 96.92% |
| LR15 | RNN | ADNI | 70% to 90% |
| LR16 | CNN | ADNI | 86.88% |
| LR17 | Decision Tree | ADNI | 95% |
| LR18 | CNN | ADNI | 99% |
| LR19 | SVM | Kaggle dataset | 99.77% |
| LR20 | Random Forest | ADNI | 93.5% |

TABLE VI. ML CLASSIFIERS AND THEIR ACCURACY AND DATASETS

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THE RESULTS

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As it was noticed all algorithms mentioned in Table V explained accuracy algorithms of machine learning based on Supervision learning also, they deal with classification dataset. Other type of techniques are Semi-supervised machine learning which work as mixed ML techniques that are relevant to the prediction such as ALzhiemerNET model[29]. Furthermore, Forecasting learning algorithms deal with sensors, devices so, the input data depends on time series. Table V's results from significant research papers will be represented utilizing a mind map model. Additionally, each classifier's accuracy is measured as a range between a high and low accuracy value as shows in Fig 6,7,8, and 9.

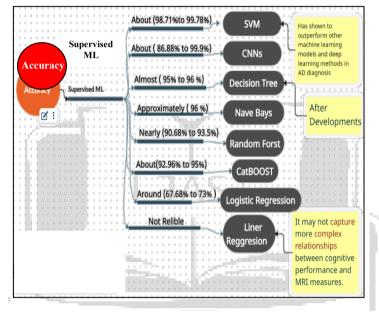


Fig.6 the acuracy of supervised machine learning that applied on Alzheimer's disease

The illustration below shows how accurate unsupervised machine learning techniques can be.

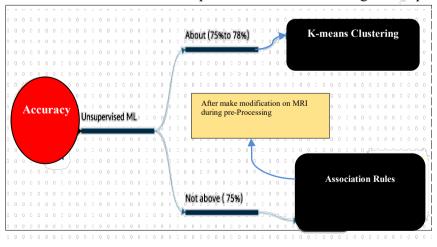


Fig.7 the acuracy of unsupervised machine learning that applied on Alzheimer's disease

The figure below demonstrates the accuracy of semi-supervised machine learning methods.

LJAST Volume 12 Issue 01 Libyan Journal of Applied June 2024 Science and Technology **ISSN 2958-6119** مجلة ليبيا للعلوم التطبيقية والتقنية لسا للسلوم التطبيق Alzheimer's NET missionervised MI (85 95%) **CNNs**, Transfer CNNs , Transf 2: using pre-trai like VGG19 an learning using pretrained models like has been em VGG19 and ResNet50 classify diff the disease Fig.8 the acuracy of semi-supervised machine learning that applied on

Alzheimer's disease

Lastly, Fig.9 illustrates the final section of the machine learning model, known as reinforcement machine learning, which is not included in this study for the previously stated reasons.

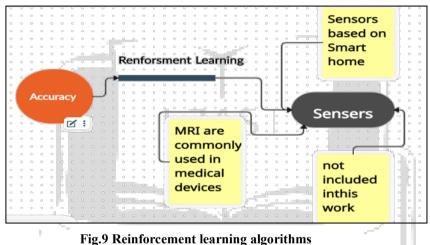


Fig.9 Kennorcement learning algorithms

v. Conclusion مصلة لسيا للسلوم. التصليقية والتقنية

Research that used machine learning techniques to classify and identify AD was reviewed. Every Machin Learning model was assessed for accuracy. Furthermore, mind map models were used to illustrate the comparison and research outcomes.

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VI. FUTURE WORK

In the future, early illness detection will be achieved by the application of reinforcement machine learning. and more investigation into the potential applications of machine learning to discover a treatment plan that can halt or stop the progression of the illness.

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