iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 **Issue:** VII **Month of publication:** July 2022

DOI: https://doi.org/10.22214/ijraset.2022.45831

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VII July 2022- Available at www.ijraset.com

Detection of Alzheimer's Disease from MRI scan using Machine Learning An Implementation Paper

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Abstract: ***Alzheimer's disease (AD) is a neurological condition that affects people 65 and older and is a leading cause of dementia. It is crucial to get an accurate and prompt diagnosis of Alzheimer's disease in order to stop the spread of this irreversible infection. This study focuses on using AI to analyze MRI data to detect Alzheimer's disease. The cerebrum's hippocampus area serves as the focal point of the suggested approach. Textural characteristics like entropy, homogeneity, energy, difference, relation, and fluctuations are eliminated from the hippocampus region using the Gray Level Co-Occurrence Matrix (GLCM). The same area that the shape highlighted are removed using the second invariant. Error-back propagation (EBP) is a technique used in artificial neural networks (ANNs) to categorize various phases of infection. The proposed framework has an 86.8% accuracy rate.***

I. INTRODUCTION

German pathologist and expert Alois Alzheimer is familiar with and knowledgeable about Alzheimer's disease (AD), an ever-evolving form of dementia marked by a progressive deterioration in memory, reasoning, and examining skills. Alzheimer's disease (AD) is a degenerative mental infection that affects memory. It is the most prevalent type of dementia and is brought on by the buildup of beta amyloid plaques in the brain. The illness is most easily recognized by its plaques and tangles. Cerebral tissue contracts as solid neurons lose their ability to carry signals and eventually pass away as plaques and problems form. The hippocampus's ability to stimulate new memories is negatively impacted by the subtly occurring neuronal death. The hippocampus is the first area of the brain to be impacted. Memory development is a mental field that only functions as a hand-off engineering between the brain and the rest of the body. Alzheimer's disease is a chronic infection with both reversible and permanent effects that follows a precise pattern of cerebrum destruction. It might go on longer. The illness develops in three stages, beginning, moderate, and extreme, each with its own set of symptoms and barriers. During the first two to four years, the person can function independently but may experience memory lapses. At a moderate level, a person might require assistance with everyday activities and might struggle with memory. This is the most advanced stage of the illness, and it can endure for two to ten years.

It can take between one and three years for the infection to reach its final stage. At this point, the patient's memory and mental faculties are impaired, and they may require uninterrupted thought because they are losing the ability to react to their surroundings. Understanding the infection as soon as feasible is essential to prevent long-term brain damage. Along with magnetic resonance imaging, non-automated techniques such as cognitive impairment testing, the Mini-Mental State Examination (MMSE), and the Clinical Dementia Rating (CDR) are used to monitor abnormal changes in the brain and study AD. These techniques include Positro Emission Tomography (PET), and single-photon emission computed tomography (SPECT). The proposed study will concentrate on using MRI scans to detect Alzheimer's disease. The hippocampus is chosen as the region of interest, and surface, region, and shape data are extracted from it using the Gray Level Co-Occurrence Matrix (GLCM) and Moment Invariant (ROI).The configuration of the attributes utilized for the shape ID is determined by the second invariant. The second GLCM request eliminates quantifiable surface data, and Moment Invariant provides a set of traits that are combined to provide identifiable evidence. The artificial neural network (ANN), which was created via an Error Back Propagation (EBP) calculation, is then utilized to organize the AD into an obscure phase using the highlights retrieved from the ROI.

II. LITERATURE SURVEY

A. Clinical Dementia Rating

The disease's last stage might endure for one to three years. At this point, the patient may require round-the-clock help as their memory and cognitive abilities continue to decrease and they become less able to adapt to their environment. Early disease detection is crucial to preventing irreversible neurological damage from occurring.

To track abnormal changes in the brain and diagnose AD, researchers currently use non-automated techniques like cognitive impairment testing, the Mini-Mental State Examination (MMSE), and the Clinical Dementia Rating (CDR), as well as imaging techniques like magnetic resonance imaging (MRI), positron emission tomography (PET), and single-photon emission computed tomography (SPECT).

B. Gray Level Co-Occurrence Matrix

An MRI scan is used in the proposed function to determine AD's diagnosis. Using moment invariants chosen as the Region of Interest and the gray-level co-accuracy matrix (GLCM), texture, area, and shape information are retrieved from the hippocampus (ROI). The collection of parameters used for moment identification of form inverters is defined by GLCM, which also extracts the second-order numerical composition attributes. On the basis of the symptoms discovered by ROI, AD is then divided into various stages. utilizing the Error Back Propagation (EBP) algorithm-trained Artificial Neural Network (ANN).

C. Hybrid Forward Sequential Selection

Hybrid Forward Sequential Selection, a feature-based method for Alzheimer's disease diagnosis, was suggested (HFS). In order to extract useful features from the MRI data in the Alzheimer's Disease Neuro Imaging Initiative (ADNI) Database, the suggested method combines filter and wrapper techniques. This method involved ranking the features and choosing the most important ones. As a classifier, the support vector machine (SVM) was employed. The proposed method, according to the authors, performs better than prior specialized selection approaches in terms of diagnostic accuracy and computing cost.

D. Advanced Local Binary Pattern Method

The Advanced Local Binary Pattern (ALBP) technique was presented. As a descriptor for 2D and 3D feature extraction, the ALBP approach was introduced. The feature was chosen using principal component analysis (PCA) and factor analysis because ALBP generates a lot of features. For multiclass classification, a support vector machine was employed. In comparison to the earlier local binary pattern (LBP) method, the authors contend that their proposed work offers greater performance and accuracy. Between 80% and 100% of the data from the hippocampus and total brain were accurate on average. With an average accuracy of 96.28 percent for multiclass categorization of the entire brain image, it is also asserted that the same rotation inverter ALBP sign magnitude lags behind other approaches. It comes to the conclusion that the extracted feature vector from large MRI brain datasets has a high dimension, needs a lot of processing power, and can be adjusted using parallel computing.

III. METHODOLOGY

1) A trained classifier that can predict classification label based on MRI scan features is the result of the training phase.
2) Accuracy, sensitivity, and specificity measures can be used to assess the trained classifier's performance.
3) The output progress is trained in a certain way to obtain the actual, validated results.
4) The data are gathered into a clinical and demographic database and are necessary for careful sample selection in later experimental designs.

IV. ARCHITECTURES

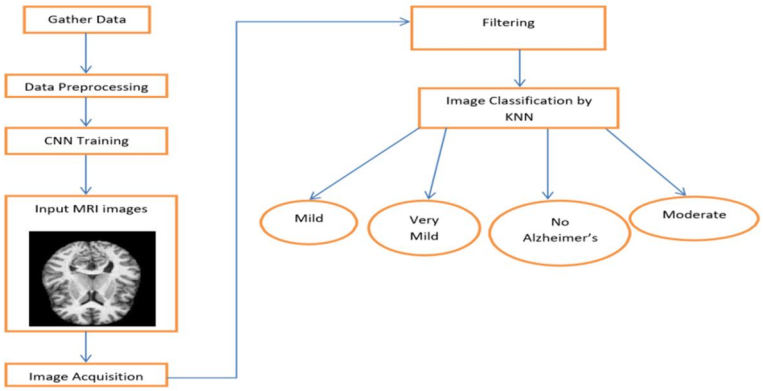

Fig 1. System Architecture

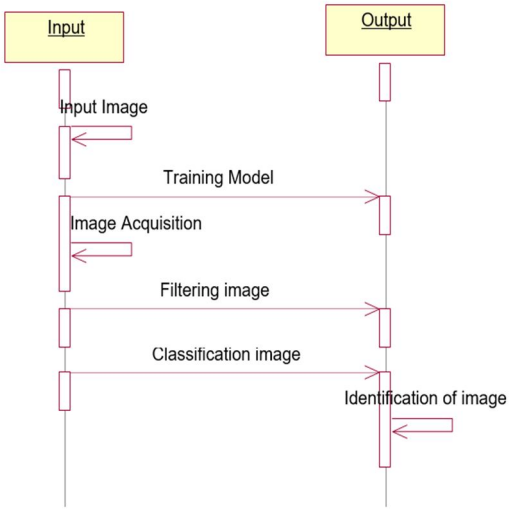

Fig 3. Sequence Diagram

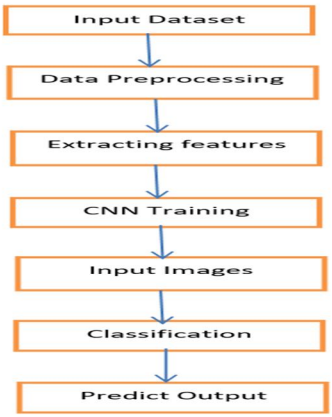

Fig 2. Data Flow Diagram

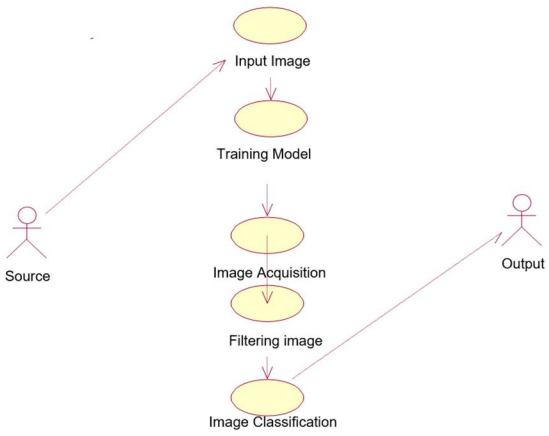

Fig 4. Use Case Diagram

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VII July 2022- Available at www.ijraset.com

V. PROPOSED SYSTEM AND EXISTING SYSTEM

A. Proposed System

An MRI scan is used in the proposed function to determine AD's diagnosis. Using moment invariants chosen as the Region of Interest and the gray-level co-accuracy matrix (GLCM), texture, area, and shape information are retrieved from the hippocampus (ROI). The collection of parameters used for moment identification of form inverters is defined by GLCM, which also extracts the second-order numerical composition attributes. On the basis of the symptoms discovered by ROI, AD is then divided into various stages. utilizing the Error Back Propagation (EBP) algorithm-trained Artificial Neural Network (ANN). “Existing system”.

B. Disadvantages

1) Some of the disease's most prominent characteristics include the plaques and tangles. There is a general shrinkage of the brain tissues as a result of the growth of plaques and tangles, which cause healthy neurons to operate less efficiently, gradually lose their ability to communicate, and eventually die.
2) The capacity to create new memories is hampered by the death of neurons, notably in the hippocampus. The first part of the brain to be impacted is the hippocampus.

C. Existing System

The disease's last stage could linger for one to three years. The patient may need round-the-clock help at this stage as their memory and cognitive abilities continue to deteriorate and their capacity to respond to their environment is lost. It is crucial to make a diagnosis of the condition as soon as possible, before irreparable neurological damage has been done.

The current non-automated techniques used to track abnormal changes in the brain and diagnose AD include Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Single-Photon Emission Computed Tomography (SPECT). These techniques also include Cognitive Impairment Testing, the Mini-Mental State Examination, and the Clinical Dementia Rating (CDR).

D. Advantages

1) Gray-level co-accuracy matrix (GLCM) and Moment Invariants are used to extract texture, area, and shape information from the hippocampus, which are then chosen as the region of interest (ROI).
2) Based on the symptoms discovered by ROI, AD is then divided into various stages. utilising the Error Back Propagation (EBP) algorithm-trained Artificial Neural Network (ANN).
3) This system proposed a feature-based method for diagnosing Alzheimer's disease called Hybrid Forward Sequential Selection (HFS). In order to extract useful features from the MRI data in the Alzheimer's Disease Neuro Imaging Initiative (ADNI) Database, the suggested method combines filter and wrapper techniques.

VI. TESTING

A. System Testing

Testing is done to look for mistakes. Testing is the process of looking for any flaws or weaknesses in a piece of work. It offers a technique to examine the operation of individual parts, subassemblies, assemblies, and/or a final good. It is the process of testing software to make sure that it satisfies user expectations and meets requirements without failing in an unacceptable way. Different test types exist. Every test type responds to a certain testing requirement.

B. Unit Testing

Designing test cases for unit testing ensures that the internal programme logic is working correctly and that programme inputs result in legitimate outputs.

It is important to verify the internal code flow and all decision branches. It is the testing of the application's separate software components. Before integration, it is done following the completion of each individual unit.

This is an invasive structural test that depends on understanding how it was built. Unit tests carry out fundamental tests at the component level and examine a particular configuration of a system, application, or business process.

Unit tests make assurance that each distinct path of a business process adheres precisely to the stated specifications and has inputs and outputs that are well-defined.

C. Integration Testing

Software components that have been merged are tested in integration tests to see if they genuinely operate as a single programme. Testing is event-driven and focuses more on the fundamental result of screens or fields. Even though the individual components were successful in unit testing, integration tests indicate that the combination of the components is accurate and consistent. Integration testing is especially designed to highlight issues that result from combining components.

D. Functional Testing

Functional tests offer methodical proof that the functions being tested are available in accordance with the technical and business requirements, system documentation, and user manuals.

Focus of functional testing is on the following areas:

1) *Valid Input:* Recognized valid input classes must be accepted.
2) *Input that is Invalid:* Defined categories of input that are Invalid must be rejected.
3) *Functions:* The assigned functions need to be used. Application outputs from the identified classes must be tested.
4) *Systems/Procedure:* It is necessary to call interacting systems or processes.

Functional tests are organized and prepared with a focus on requirements, important functions, or unique test cases. Additionally, testing must take into account systematic coverage of data fields, established procedures, and subsequent processes as well as business process flows. Additional tests are found, and the usefulness of the existing tests is assessed, before functional testing is finished.

Table 1: Summary and Critical Evaluation of techniques and limitations of different machine learning based AD studies.

	Modality	Technique	Data Set Details	Pathologically proven Data set	Accuracy	Limitation	Validation performed (No. of Folds)
(Chaves, Ramírez et al. 2013)	SPECT PET	Apriori- AR mining	SPECT: AD = 56 CTRL = 41 PET: AD = 75 CTRL = 75	No	SPECT: **96.91%** PET: 92%	Pathologically unproven data with no justification about missing values	Leave one out Cross Validation
(Klöppel, Stonnington et al. 2008)	MRI	Linear SVM	3-groups AD= 67 CTRL= 91	**Yes**	**96%**	Sample size is too small with no justification of missing values.	Leave one out Cross Validation
(Chaves, Ramírez et al. 2010)	SPECT	Apriori- AR mining	AD = 54 CTRL = 43	No	**95.87%**	Did not mention the how they limited the effect of missing values	Leave one out Cross Validation
(Chaves, Górriz et al. 2011)	SPECT	Apriori- AR mining	AD = 56 CTRL = 41	No	**94.87%**	The data may contain Missing values which will cause uncertainty	Leave one out Cross Validation
(Chaves, Ramirez et al. 2012)	FDG- PET + PiB-PET	Apriori- AR mining	AD = 19 CTRL = 84	No	**94.74%**	Unproven data with missing values	Leave one out Cross Validation
(Zhang, Wang et al. 2011)	MRI+ FDG-PET + CSF	SVM	AD = 51 CTRL = 151	No	**93.2%**	Class Imbalance and missing values	10-fold Cross Validation
(Chaves, Ramírez et al. 2012)	SPECT PET	Apriori- AR mining	SPECT: AD = 55 CTRL = 42 PET: AD = 75 CTRL = 75	No	**92.78%**	Unproven data with missing values	Leave one out Cross Validation
(Westman et al., 2012)	CSF MRI	Apriori- AR mining+ SVM	AD = 96 CTRL = 273	No	**91.8%**	Class Imbalance and missing values	7-fold Cross Validation
(Chaves, Ramírez et al. 2012)	SPECT PET	Apriori- AR mining for feature selection PCA, SVM	SPECT: AD = 56 CTRL = 41 PET: AD = 75 CTRL = 75	No	**91.75%**	Unproven data with missing values	Leave one out Cross Validation
A. Veeramuthu et al. (2014)	PET	AR mining	Not Given	No	**91.33%**	No dataset details, missing values or any preprocessing steps highlighted	No
Robi Polikar et al. (2010)	EEG + MRI + PET	Ensemble based decision fusion	AD = 37 CTRL = 36	No	**85.55%**	Unproven data with missing values	5-fold Cross Validation

VII. RESULTS

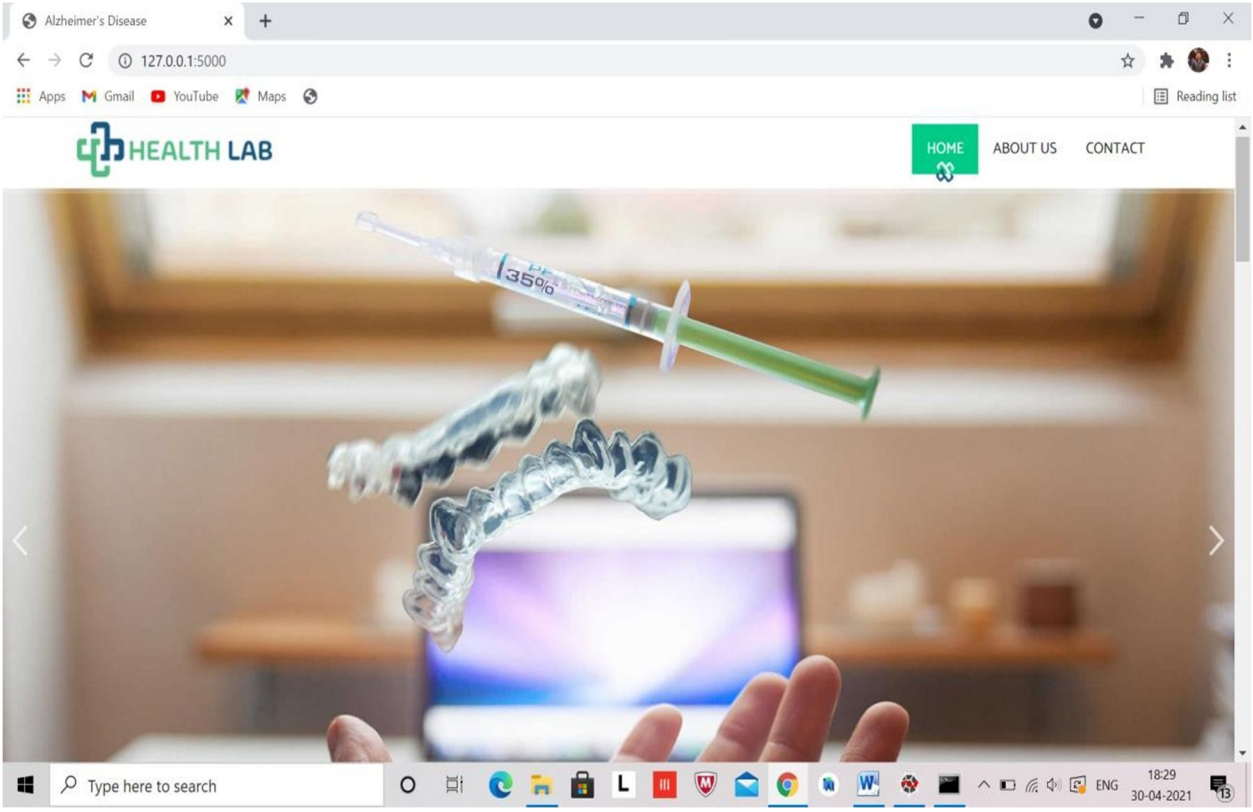

Fig 5. Home Page

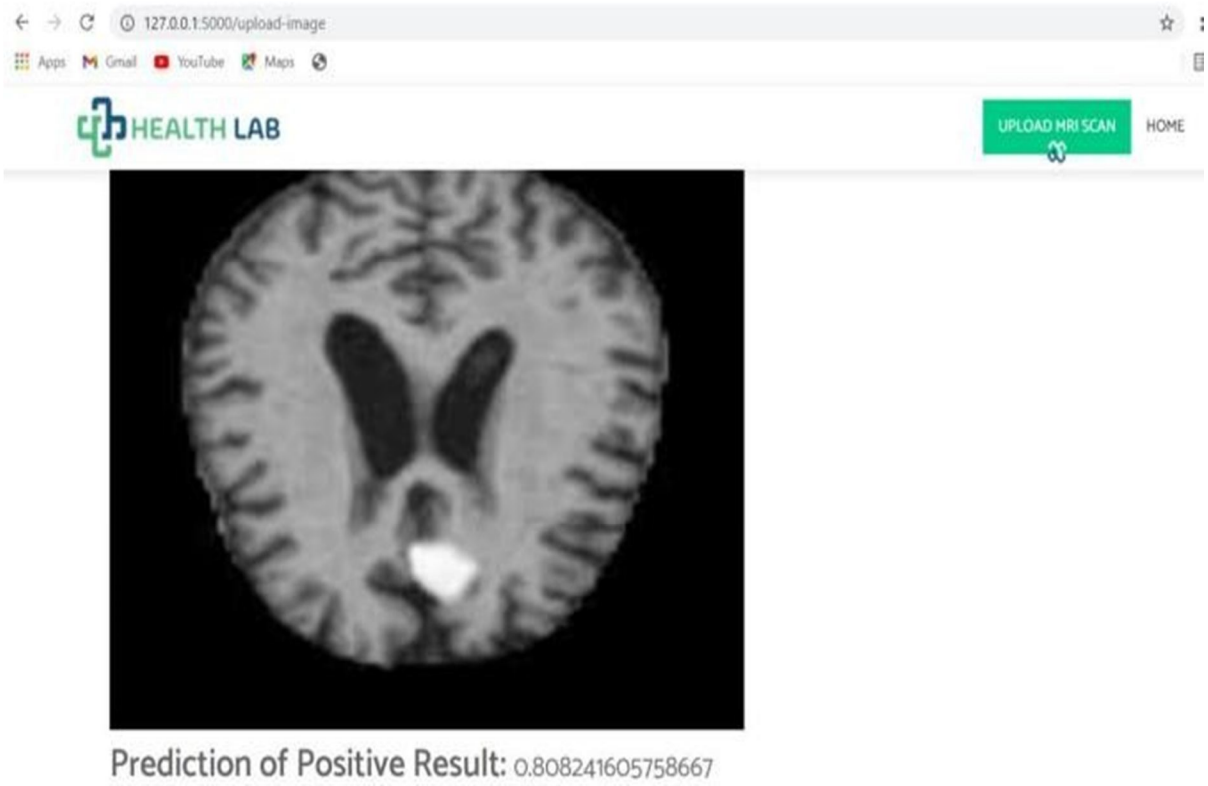

Fig 6. Final result page

VIII. CONCLUSIONS

The foundation of this study is a comparison and evaluation of previous work in machine learning algorithms and Alzheimer's disease prediction. There is little doubt that contemporary machine learning trends have been introduced, including the types of data employed and the potency of these methods for early Alzheimer's disease prediction. It goes without saying that machine learning increases prediction accuracy, especially when compared to conventional statistical tools. The review found that the clinical diagnosis was not entirely accurate since pathological recognition was lacking, which led to uncertainty in the anticipated results. The suggested strategy is based on one method to save on the extra cost of computing and combining many methods. We anticipate that pathologically validated data will enhance classification accuracy and validity and support balanced class classifiers in producing reliable results. This model has the potential to assist doctors in improving their predicting accuracy while resolving the challenges noted in earlier studies.

In this study, a machine learning-based method for diagnosing Alzheimer's disease is proposed. The OASIS dataset was used in experiments. The hippocampus region's composition, area, and shape characteristics are extracted from the MRI scan. Additionally, OASIS text features were retrieved. Through error-back propagation, these properties were used to train the network for categorization. The proposed system's average accuracy is 86.8%.

IX. FUTURE ENHANCEMENTS

There is a race to develop novel, inexpensive, non-invasive techniques for early Alzheimer's disease diagnosis. The use of brain MRIs, or magnetic resonance imaging, has been the subject of some of the most current studies. Alzheimer's is typically identified when symptoms appear, but by then the illness has already progressed.

According to a team of academics, their predictive model depends on obtaining an MRI using a typical 1.5 Tesla scanner used for basic scans. They modified a classification system for cancer tumours. They assigned various traits to each of the 115 regions they created in the brain. They developed the algorithm to determine which traits could alter in a way that would properly indicate the presence of Alzheimer's disease. More than 400 individuals with early-stage and late-stage Alzheimer's disease and other neurological diseases' brain scans were used by the researchers to evaluate its methodology. The data from more than 80 persons who were having testing to diagnose Alzheimer's was also used by the researchers to test it.

The use of a novel quantitative gradient echo (qGRE) MRI technique is another method for identifying brain regions that are no longer functional due to the loss of healthy neurons.

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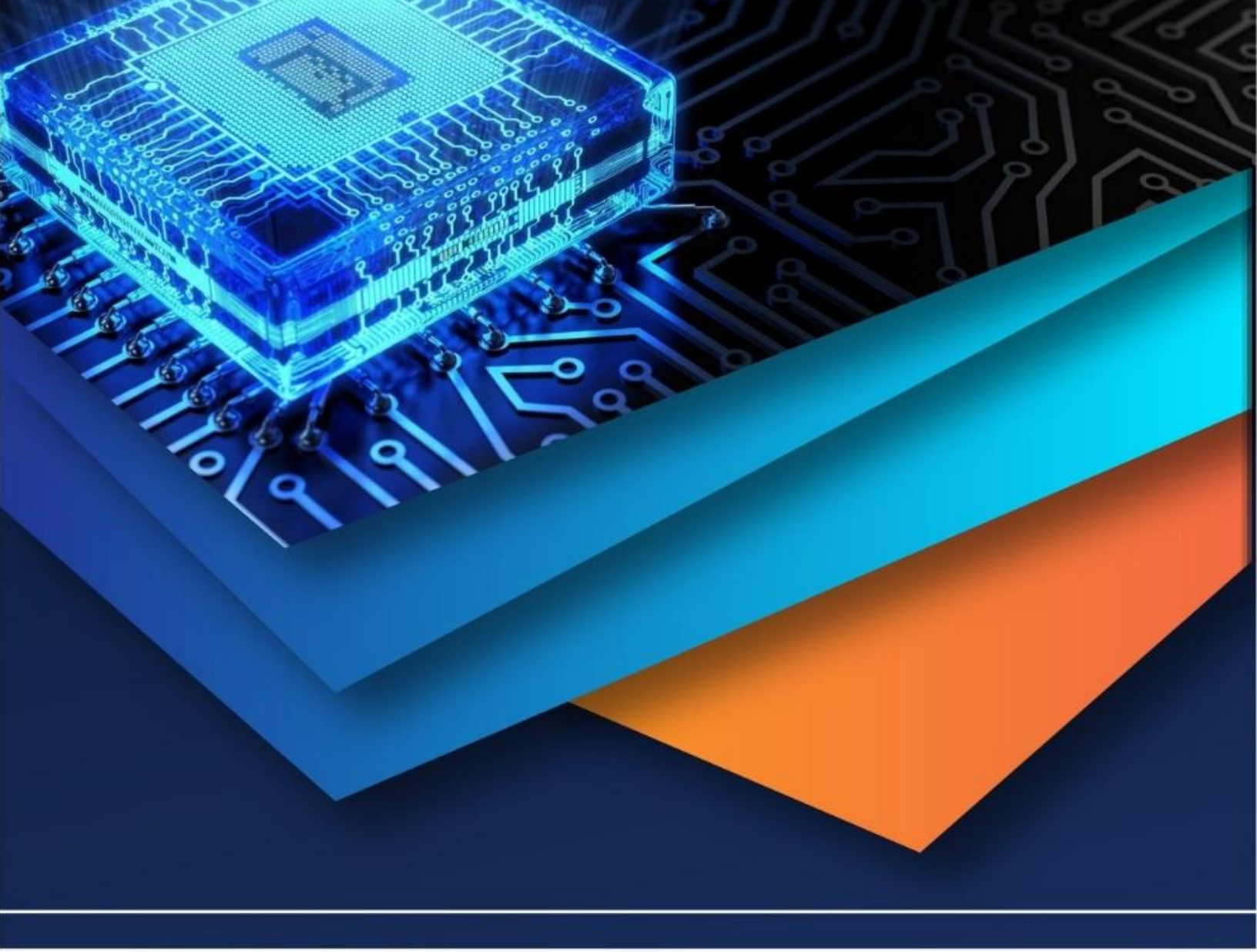

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