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Computational intelligence-based classification system for the diagnosis of memory impairment in psychoactive substance users

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Abstract

Computational intelligence techniques have emerged as a promising approach for diagnosing various medical conditions, including memory impairment. Increased abuse of psychoactive drugs poses a global public health burden, as repeated exposure to these substances can cause neurodegeneration, premature aging, and negatively affect memory impairment. Many studies in the literature relied on statistical studies, but they remained inaccurate. Some studies relied on physical data because the time factor was not considered, until Artificial Intelligence (AI) techniques came along that proved their worth in this diagnosis. The variable deep neural network method was used to adapt to the intermediate results and re-process the intermediate in case the result is undesirable. Computational intelligence was used in this study to classify a brain image from MRI or CT scans and to show the effectiveness of the dose ratio on health with treatment time, and to diagnose memory impairment in users of psychoactive substances. Understanding the neurotoxic profiles of psychoactive substances and the underlying pathways is hypothesized to be of great importance in improving the risk assessment and treatment of substance use disorders. The results proved the worth of the proposed method in terms of the accuracy of recognition rate as well as the possibility of diagnosis. It can be concluded that the diagnostic efficiency is increased by increasing the number of hidden layers in the neural network and controlling the weights and variables that control the deep learning algorithm. Thus, we conclude that good classification in this field may save human life or early detection of memory impairment.

Keywords Deep Learning, Machine Learning, Memory Impairment, Psychoactive Substance, Brain Image, Medical Image

Introduction

Memory impairment is a significant public health concern, with millions of people worldwide experiencing memory loss that affects their daily lives. Accurate diagnosis of memory impairment is crucial for effective treatment and management of the condition. Unfortunately, current diagnostic methods are often inadequate, and patients may go undiagnosed or misdiagnosed for years [1]. However, recent developments in computational intelligence-based classification systems offer the potential to revolutionize the way memory impairment is diagnosed. By leveraging the power of advanced algorithms and artificial intelligence, these systems offer a more accurate and personalized approach to diagnosis, improving patient outcomes and helping healthcare professionals provide better care and support [2].

As a result of the pressures of life and the difficult conditions that societies go through, the phenomenon of

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drugs and narcotic substances that negatively affect the human brain has spread. This phenomenon is not limited to a specific age or gender, but has taken its toll on society in general. From this point of view, it has become important to study a specific system for diagnosing memory impairment in people who abuse narcotic and psychoactive substances, which are common in our time [3].

The effect of these substances is examined through their effect on the brain and the side effects they cause from actions during temporary and permanent memory loss. The tomography of the brain gives an accurate visualization of the changes in the brain cells that the brain is going through. Artificial intelligence algorithms are used to diagnose diseases of the brain that come from medical images. One of the most famous artificial intelligence algorithms is the deep learning algorithm, which depends on extracting features from the medical image and then classifying those features to find results in a very accurate manner.

Computational intelligence techniques have emerged as a promising approach to the diagnosis of various medical conditions, including memory impairment. With the increasing abuse of psychoactive drugs presenting a global public health burden, there is an urgent need for effective methods to diagnose and treat memory impairment in substance users [4].

Repeated exposure to psychoactive substances can cause neurodegeneration, premature aging, and negatively affect memory impairment. Although the basis for these neurotoxic effects has not been fully elucidated, compelling evidence has shown that dysregulation of neurotransmission, disruption of mitochondrial function and dynamics, impairment of neuroimmunomodulation, and epigenetic changes result from many psychoactive substances, such as alcohol, cannabis, opiates, amphetamines, and cocaine [5].

In this study, we propose the use of AI techniques to classify brain images from MRI or CT scans and show the effectiveness of dose ratio on health with time of treatment, in the diagnosis of memory impairment in psychoactive substance users. The aim of this research is to improve risk assessment and treatment of substance use disorders by understanding the neurotoxic profiles of psychoactive substances and the underlying pathways. Memory impairment arises from diverse factors such as aging, trauma, disease, and genetics. Yet, pinpointing its exact cause remains tricky due to variable and overlapping symptoms. Present diagnostic approaches combine medical history, physical exams, and neurological tests [6], but subjectivity and time constraints limit their effectiveness, missing subtle brain function changes. The absence of a uniform diagnostic process further complicates matters, with varying criteria across healthcare professionals causing inconsistent diagnoses and treatments [7]. Moreover, the lag between symptom onset and diagnosis leads to delayed management. computational intelligence-based systems can analyze data in real-time, providing more immediate diagnosis and treatment options [8]. Most of the systems uses advanced algorithms and artificial intelligence to identify patterns and trends in data, allowing healthcare professionals to make more accurate and personalized diagnoses [9]. computational intelligence-based classification systems can detect subtle changes in brain function that may be missed by traditional diagnostic methods [10, 11]. By using a standardized algorithm to analyze data, healthcare professionals can ensure that patients are diagnosed consistently and accurately, leading to more effective treatment and management of the condition [12]. researchers have developed algorithms that can accurately diagnose Alzheimer's disease based on data from brain imaging and cognitive tests [13]. There are concerns about the ethical implications of using artificial intelligence in medical diagnosis [14, 15]. For example, there is a risk that algorithms may perpetuate biases or discriminate against certain patient groups.

To achieve this, we analyzed brain diagrams and their effects on drug-induced cellular and molecular mechanisms. Our research indicates that computational intelligence techniques can be used to classify the brain, leading to early detection of memory impairment and potentially saving human lives**.** Objectives in this study comes from answering the following questions in detail:

- How can memory impairment be diagnosed using artificial intelligence technology?
- What is the effect of the duration of abuse of psychoactive substances on the accurate diagnosis?
- What is the benefit of deep learning technique in diagnosing memory impairment?

Related work

Memory impairment is a known consequence of substance abuse, affecting both short-term and long-term memory. In recent years, developments in artificial intelligence (AI) have provided new opportunities to explore the nature and extent of these cognitive deficits [16]. Using AI, researchers can analyze large datasets to identify patterns and trends in the relationship between substance use and memory impairment [17]. Such AI-related work has successfully identified specific substances that are more likely to cause memory impairment, as well as the dosage levels and frequency of use that lead to more severe cognitive deficits. Moreover, AI has proven useful in predicting which individuals are more likely to experience memory impairment as a result of substance use based on various factors such as genetic predisposition, lifestyle choices, and co-occurring mental health conditions. These findings have important implications for the development of personalized interventions and strategies to mitigate cognitive deficits among those struggling with substance abuse [18].

The use of AI in analyzing large datasets has provided researchers with new opportunities to identify patterns and trends related to substance abuse and memory impairment, including the specific substances, dosage levels, and frequency of use that lead to more severe cognitive deficits. Additionally, AI has helped in predicting which individuals are at a higher risk of memory impairment as a result of substance use, based on factors such as genetics [19].

Research on the relationship between psychoactive substance use and memory impairment is a growing field, and recent studies have explored the potential of artificial intelligence (AI) techniques for identifying patterns and predicting outcomes related to substance abuse and cognitive deficits. For example, a study by Pan, Dan, et al. (2020) used a deep neural network to analyze magnetic resonance imaging (MRI) data from individuals with a history of substance abuse and identified specific patterns of brain activity associated with cognitive deficits [20]. Another study by Barenholtz, & Hahn, W. E (2020) utilized machine learning algorithms to predict which individuals with substance use disorders were at higher risk for cognitive impairment and found that a combination of demographic, clinical, and behavioral factors increased the likelihood of memory deficits [21]. In addition, studies by [22] and [23] utilized machine learning algorithms to assess the impact of different substances, including alcohol and marijuana, on memory and other cognitive functions. Together, these studies suggest that AI techniques have the potential to improve our understanding of the relationship between substance abuse and memory impairment, and may assist in the development of targeted interventions to mitigate these cognitive deficits.

Research studies revealing the impact of psychoactive substance use on memory impairment have witnessed a steady growth in recent years. Moreover, researchers have started exploring the potential of artificial intelligence (AI) techniques for identifying various patterns and predicting outcomes related to substance abuse and cognitive deficits [24]. For instance, [25] utilized a deep neural network to process the MRI data of substance abusers and illustrated specific patterns of brain activity associated with cognitive deficits. Additionally, [26] employed machine learning algorithms to predict individuals with substance use disorders at higher risk for cognitive impairment with a combination of demographic, clinical, and behavioral factors. Furthermore, [27] deployed machine learning algorithms to assess the impact of different substances, including alcohol and marijuana, on memory as well as other cognitive functions. The above-mentioned studies, among others, suggest that AI techniques have the potential to enhance our knowledge of the relationship between substance abuse and memory impairment. Furthermore, these techniques could prove valuable in the development of customized interventions to mitigate these cognitive deficits in substance users. Although challenges in this domain, including the need for reliable data.

Deep learning

Deep learning is a promising technique in the field of artificial intelligence that involves the use of artificial neural networks to perform various tasks. It is a subfield of machine learning and has been widely applied in many domains, including medical imaging.

In medical imaging, deep learning algorithms are trained on large datasets of medical images to learn the underlying patterns and relationships between the images and the conditions they depict. Convolutional neural networks (CNNs) are one of the most commonly used deep learning techniques in medical imaging [28, 29], and they have been applied in a variety of applications, such as detecting cancers, classifying medical images, and segmenting structures within images. The power of deep learning lies in its ability to automatically learn complex patterns and relationships within the data. This makes it a highly effective tool for medical imaging analysis and diagnosis. Furthermore, deep learning algorithms are capable of handling large amounts of data, making them well suited for processing the large datasets commonly encountered in medical imaging. However, despite its many benefits, deep learning in medical imaging is still in its early stages, and much research is still needed to improve its accuracy and reliability [30]. There is also a need to address some of the technical challenges associated with deep learning, such as the need for large amounts of training data and the risk of overfitting. Despite these challenges, the continued development of deep learning techniques is expected to have a significant impact on the field of medical imaging. With ongoing research and innovation, deep learning has the potential to revolutionize the way medical images are analyzed and processed, leading to improved diagnoses and treatments for a wide range of medical conditions.

Types of deep learning

There are several types of deep learning techniques [31], including:

Convolutional Neural Networks (CNNs): Used primarily for image classification and object recognition tasks.
Recurrent Neural Networks (RNNs): Used for sequence data, such as time series data or natural language processing.
Generative Adversarial Networks (GANs): Used for generative tasks, such as image generation or style transfer.
Autoencoders: Used for dimensionality reduction, feature learning, and anomaly detection.
Long Short-Term Memory Networks (LSTMs): A type of RNN that is designed to handle the vanishing gradient problem and handle long-term dependencies.
Transfer Learning: A technique that involves using a pre-trained network on a large dataset and fine-tuning it for a specific task.
Deep Belief Networks (DBNs): A generative probabilistic model that is trained using unsupervised learning and then fine-tuned using supervised learning.

These are some of the most commonly used deep learning techniques, and the choice of which to use depends on the specific task and data being analyzed. It is also common to use combinations of these techniques to solve complex problems.

Different between DL and ML

Deep learning and machine learning are related subfields of artificial intelligence, but there are some key differences between them [32]:

- Depth of architecture: Deep learning algorithms have many layers, with each layer learning to extract increasingly complex features from the data. In contrast, machine learning algorithms typically have fewer layers and focus on simpler, rule-based feature extraction.
- Data representation: Deep learning algorithms can automatically learn a hierarchical representation of the data, whereas machine learning algorithms rely on manual feature engineering.
- Scale of data: Deep learning algorithms are well suited for processing large amounts of data, whereas machine learning algorithms may struggle with the same amount of data.
- Use of labeled data: Deep learning algorithms are typically trained on large amounts of labeled data, while machine learning algorithms can also be trained on smaller amounts of data, or even on unstructured or unlabeled data.
- End-to-end learning: Deep learning algorithms can learn to perform a task end-to-end, without the need for manual feature engineering, whereas machine learning algorithms often require hand-designed features.

Overall, deep learning is a more advanced and sophisticated technique that is well suited for complex, data-rich problems, while machine learning is a more general-purpose technique that can be used for a wider range of problems as shown in Fig. 1.

Using DL in medical image

Deep learning has become a significant player in the field of medical imaging, contributing to a number of different tasks and applications. This includes:

- Image classification: In this task, deep learning algorithms are used to classify medical images into vari-

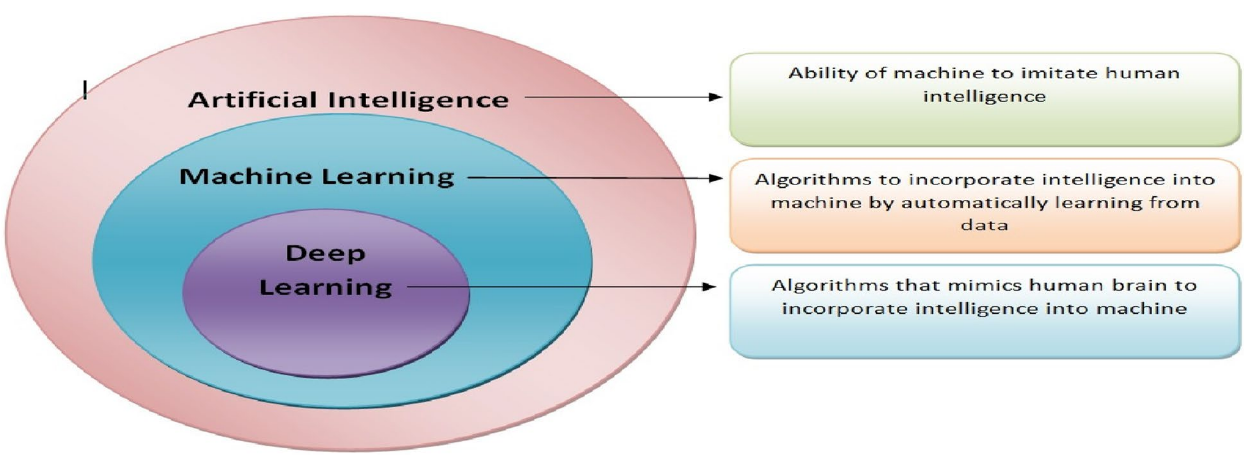

Fig. 1 Relation between Machine Learning and Deep Learning

ous diagnostic categories, such as identifying the presence of cancer or abnormal tissue. The algorithms are trained on large amounts of labeled medical images, allowing them to learn complex patterns and features in the data that can be used for accurate classification [33].
- Object detection and segmentation: Deep learning algorithms are also used to detect and segment objects within medical images, such as tumors or organs. This is an important task as it allows medical professionals to more accurately assess the size, shape, and location of the objects in question, which can be critical in making a diagnosis or planning a treatment [34].
- Image generation and reconstruction: Another important application of deep learning in medical imaging is the generation of new medical images or the reconstruction of existing images with improved resolution or reduced noise. This can be particularly useful for applications such as improving the quality of low-resolution images or for creating synthetic images for use in training and validation of other algorithms [35].
- Image registration and alignment: In many cases, medical images are taken at different times or from different angles, making it difficult to compare and analyze them accurately. Deep learning algorithms are being used to align and register medical images, allowing for more precise comparison and analysis over time.
- Automated diagnosis: One of the most exciting applications of deep learning in medical imaging is the support or automation of the diagnostic process. By using deep learning algorithms to analyze medical images, medical professionals can make more efficient and accurate diagnoses, leading to improved patient outcomes [36].

In conclusion, the use of deep learning in medical imaging is an ever-evolving field, with new and innovative ways being explored to leverage its capabilities. The potential benefits of deep learning in medical imaging are numerous and include improved accuracy, efficiency, and cost-effectiveness, making it a valuable tool for medical professionals.

Proposed method

The proposed classification system utilizes a dataset of 100 subjects, including 50 psychoactive substance users with memory impairment and 50 without memory impairment. The dataset was collected from a psychiatric hospital, these percentage according to the standard dataset and the research used for benchmarking). The inclusion criteria for the memory impairment group were individuals who reported memory problems as a consequence of psychoactive substance use, and who scored below the 25th percentile on a standardized neuropsychological memory test. The exclusion criteria were individuals with a history of neurological or psychiatric disorders, traumatic brain injury, or a current substance use disorder other than the one being studied. The inclusion criteria for the control group were individuals without a history of substance use or any cognitive impairment. The exclusion criteria were the same as those for the memory impairment group.

The dataset was divided into a training set and a testing set, with 80% of the subjects used for training and 20% for testing. The training set was used to train two machine learning algorithms: an artificial neural network and a support vector machine. Both algorithms were implemented using the Python programming language and the scikit-learn library.

The artificial neural network consisted of three layers: an input layer, a hidden layer, and an output layer. The input layer had 10 nodes, representing 10 neuropsychological tests that were used as features. The hidden layer had 15 nodes, and the output layer had 2 nodes, representing the two classes: memory impairment and no memory impairment. The network was trained using the backpropagation algorithm with a learning rate of 0.01 and a momentum of 0.9. The training was performed for 100 epochs.

Neuropsychological memory tests

Standardized neuropsychological memory tests are assessment tools designed primarily to investigate memory function in a structured manner. These tests are part of the clinical and research settings, as well as have a role in identifying memory defects and knowing the extent of cognitive impairment. The tests are either verbal memory, visual memory, immediate recall, or delayed recall. There are protocols used to measure different aspects of memory, such as Wechsler Memory Scale, California Verbal Learning Test, and Rey Complex Figure Test, and they depend on strict administrative procedures with high accuracy. Doctors can evaluate the condition through this test and evaluate strengths and weaknesses. This strategy can be very useful in our proposed method.

Here are the tests included in the this study:

- Wechsler Memory Scale (WMS): This widely accepted assessment evaluates diverse memory facets, encompassing immediate and delayed recall, recognition memory, and working memory. It delivers separate measures for verbal and visual memory domains, enabling a comprehensive evaluation.

- California Verbal Learning Test (CVLT): The CVLT appraises verbal memory by presenting a list of words to the examinee. It gauges a range of memory aspects, including learning, short and long-term retrieval, and recognition of the presented words.
- Rey Complex Figure Test (RCFT): This test scrutinizes visual memory and organizational capabilities. Participants replicate a complex figure and later recollect it after a pause, shedding light on their aptitude to remember intricate visual information.

The proposed method consists of several stages starting with segmentation and data extraction, in the absence of noise in the image. This study relied on high-quality, noise-free images that were collected from a standard database, and in order for the system to be standard and optimal, a phase of noise removal from the image must be added. After extracting the features, they are stored in a special vector in order to be used in the next stage, which is classification. One of the most important methods of artificial intelligence is used here, which is the deep learning algorithm, which depends on multiple and variable layers according to the input and data returned from the previous and subsequent stages. After that, the stage of evaluating the resulting data takes place in order for the system to function in an integrated manner. As shown in Fig. 2.

Extracting good features is the basis for building a deep neural network system, which takes information from vectors that contain the extracted features, and thus is based on the data. The deep neural network depends on updating the layers and nodes that are the basis for the correct conclusion in the system and thus predicting the most accurate results. The deep neural network differs from the traditional neural network in terms of re-feedback and deducing features automatically, according to the requirements of the desired result, as in the Fig. 3.

Good features come from good segmentation, which is effective in some images and less effective in others. Among the most important features that have been taken into consideration are the area of color change in parts of the image, the color contrast in the segmented image areas, the extent of proximity or distance of the subtractive areas from the medical image, and other important features, as shown in the Fig. 4.

The incidence of the disease is proportional to the period of time in which sedatives or drugs that affect the psychological state were taken. Among these statistics, which reflected the development of the disease over a period of time and a sample, and its reflection on the CT images of the brain, which clearly shows the effect of these medications, analgesics, and sedatives on the memory centers in the brain. This is reflected in the Fig. 5, which shows the development in the case of injury.

Once the brain has been segmented, various features can be extracted from each segment to analyze and understand different aspects of brain structure and function. Here are some commonly extracted features from segmented brain images used in this study:

Volume: The volume of each segmented brain region provides information about the size and relative importance of that particular structure.
Surface Area: The surface area of segmented regions can be calculated, which gives insights into the extent of cortical folding and complexity issue.
Thickness: The thickness of the cortical regions measured, providing information about the integrity and health of the brain.
Shape Descriptors: Various geometric features like curvature, gyrification index, or fractal dimensions extracted for describing the shape features of segmented brain regions.
Intensity Statistics: Statistical measures of the intensity values within each segmented region, such as mean, standard deviation, or histogram-based features, which based on pixel intensity and gray value.

Through work, the study also showed that the effect of drugs on the brain is not only the only influencing factor, but age also has an effect on the incidence of memory loss. Age has a negative effect on memory loss in certain proportions, and this percentage increases in the case of taking drugs and according to the ratios. In the case of taking these drugs for the same period at younger ages, the effect will be much greater than on more advanced ages. This is due to the fact that the brain tissues in the initial stages are ready to build through nutritional metabolism, so any symptom that limits this construction has a significant impact on poor construction and thus the long loss of memory. This is what is diagnosed in our proposed system, as shown in the Fig. 6.

Which consists of several stages in the formation of the hidden layers of the neural network and the feedback process that allows reprogramming each of the hidden layers according to the infectiousness of each iteration. The well-known standard neural network components are the main parts such as the input layer, the hidden layer, and the output layer. Deep learning contributes and interferes with the components of the hidden layer depending on the input layer, which here is the main interest of the work. Several parameters control the deep neural network, some of them are variables that can be changed according to the desired result this will reflected in RIW (Region Iteration Weight) rule, and some are fixed parameters that can only be changed by changing the structure of the certain layer in the neural network. These parameters will illustrate in

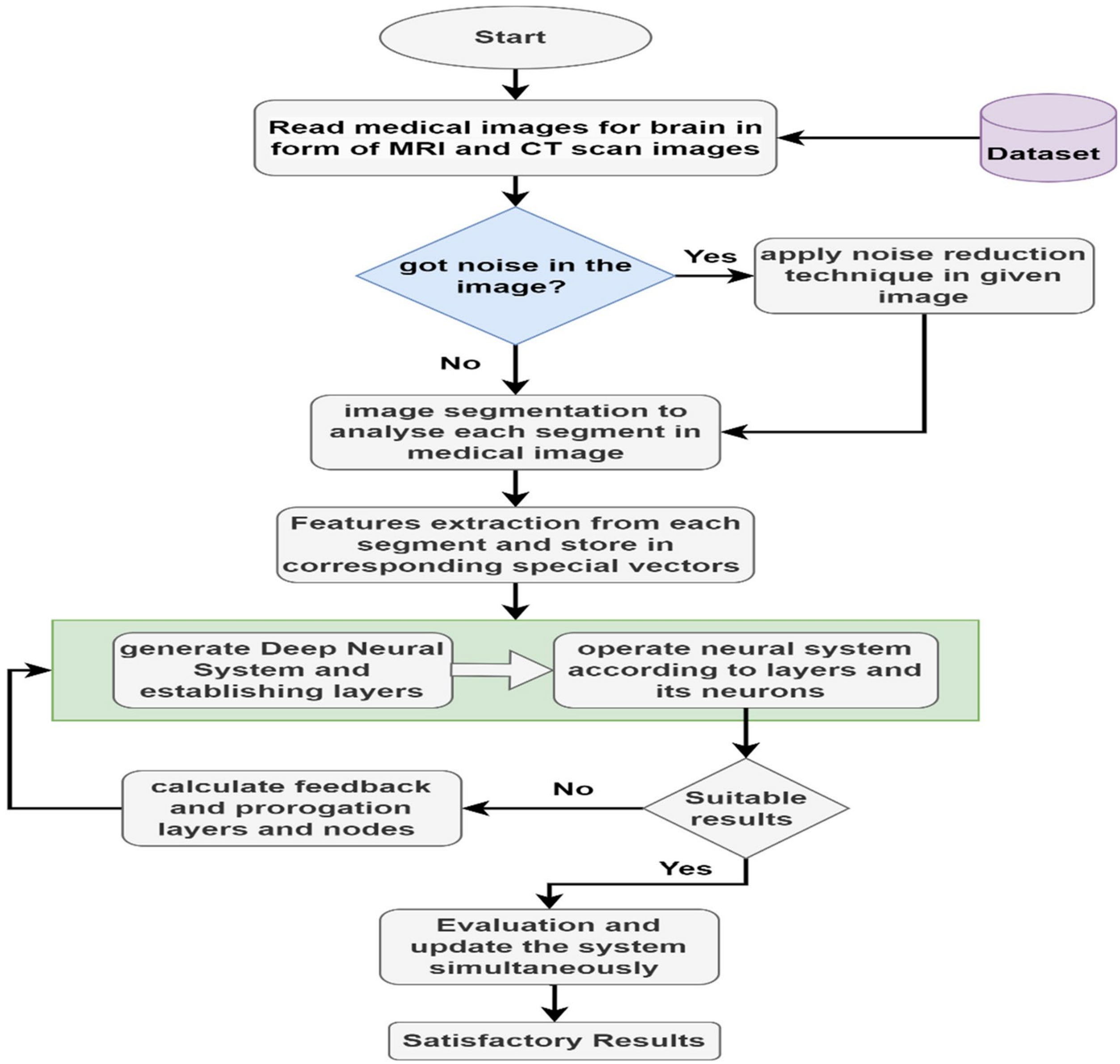

Fig. 2 General framework of proposed system including entire stages effected in the system

details during discussing design neural network. Figure 7 shows the adaptive design of deep neural network.

w consider the weight of neural network derived from each hidden layer such as hidden layer got variable length (number of nodes) from certain layer into next layer can get by:

$$y_m = w_{nm}.x_m \tag{1}$$

These function called transection function from layer to another layer (except recursive flow), and source node given by $x_m = x_{m-1} mod x_m$ and destination node given by $y_m = y_m + y_{m+1}$. Most important thing is how to control the recursive function that will discuss in the next paragraph.

Output layer consider the final results that reflect the complexity with desired results. Hyperbolic equation that reflect the result after many iterations in neural stage to achieve good prediction, neural machine can give many encryption and we need to choose automatically the best one that help proposed system so deep learning in term of machine learning proposed and next section will illustrate the detail contribution in this issue.

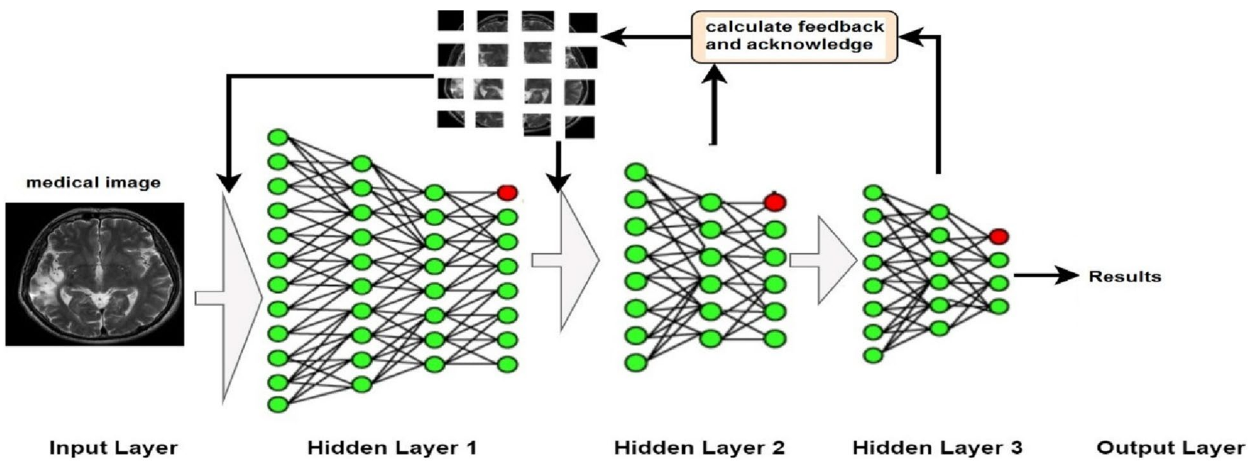

Fig. 3 Deep neural network established in the proposed system

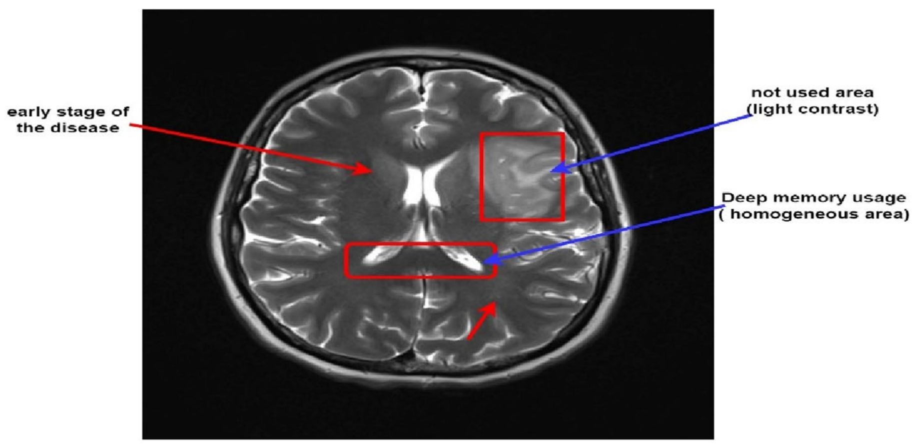

Fig. 4 Extracting features within segmented medical image

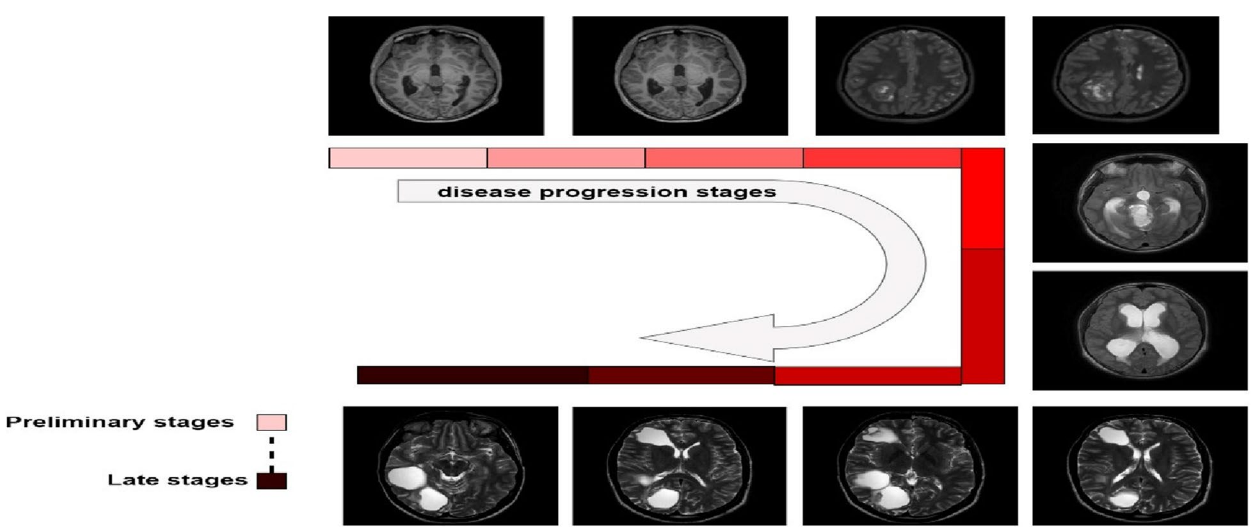

Fig. 5 The development of the pathological condition during the time period and its impact on the image of the brain

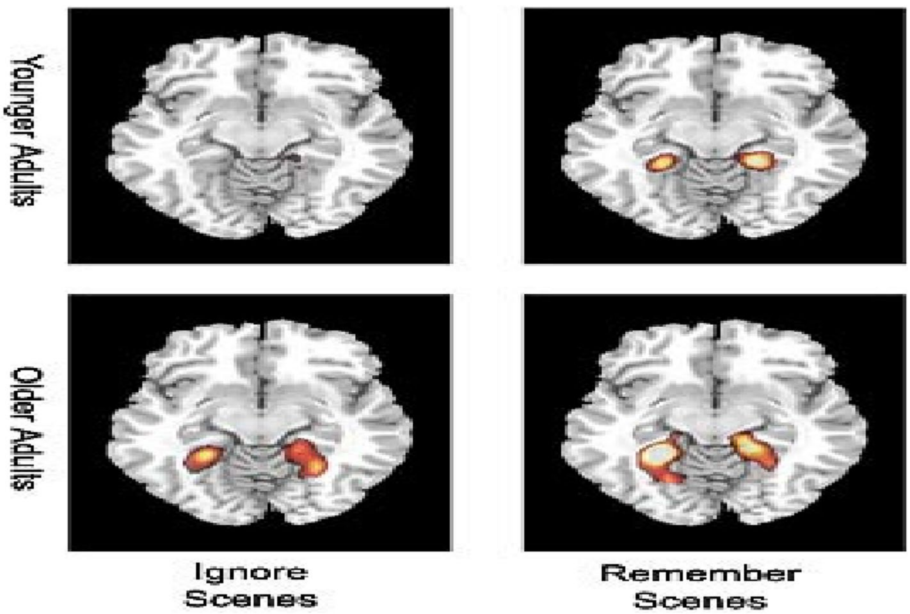

Fig. 6 The difference between two age groups and the amount of brain memory

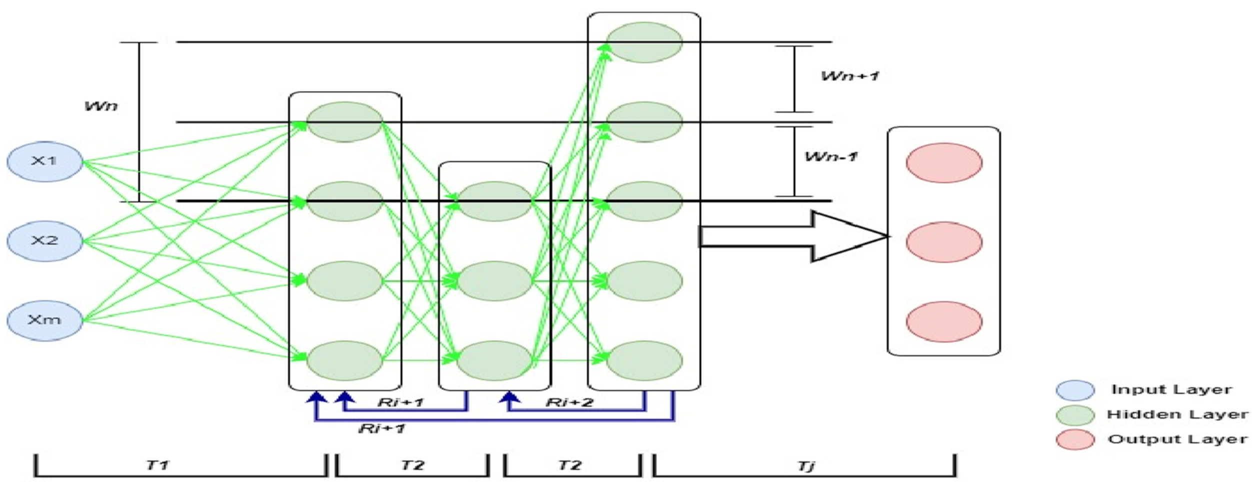

Fig. 7 proposed structure of neural network

Many variables control the neural network and by training the network with these variables, the best possible prediction result can be controlled. The main interest of parameters is weight, transection, recursive number and flow, number of iteration ratio with feedback and finally acknowledge from each neuron and layer. To find the high impact parameter must integrate the structure of neural network and make the network fully connected to achieve result of each stage with flow of information through these stages.

– The standard enclosure of neural system represents by infinite weighted summation with two samples present and past for input signal $(x_j(n))$ and delayed one is $(x_j(n\text{-}1))$ represent delay by *1* time and the output signal $y_j(n)$ can give by Eq. 2:

$$y_k(n) = \sum_{i=0}^{\infty} w^{i+1} x_j(n-1) \tag{2}$$

where w is the weight that control the flow of data within network, i is number of ` for training network. The structure will be as Fig. 8.

In this regard weight derived from structure achieve three cases distinguished as: first, $|w| < 1$ represents by the output signal of $y_k(n)$ as exponentially which mean the system is stable; second, $|w| = 1$ represent the linear behavior while the third case when$|w| > 1$, represent as negative exponential.

Now, for power N, the factor $|w|$ will be small enough to achieve neglecting case as w^N, for practical purpose the situation produce the finite sum of y_k.

$$y_k(n) \approx \sum_{l=0}^{N-1} w^{l+1} x_j(n-1) \tag{3}$$

That's mean the suggested weight will be:

$$y_k(n) = wx_j(n) + w^2 x_j(n-1) + w^3 x_j(n-2) + \cdots + w^N x_j(n-N+1) \tag{4}$$

Then derived *weight (w)* will store in vector for next classification. Thus in deep neural network the weight will changed according the behavior of the system will increase or decrease for each iteration, our contribution is to classify this weight parameter in additional to other parameters to get the best prediction in the deep learning system.

– The flow of the system is the second parameter that considered in proposed system due to effects directly to the result of next stage. There are many cases in the data flow such as when one input to the node produce one input, or two inputs from different nodes then produce one output of the node, and many cases for different iteration in the system. If input will classify into Boolean number such accepted or not in certain stage, and weight w consider the bias or control to the system in one stage and in one node.

This step will estimate the neurons in the next step based on output function and bias that control the weight at each stage.

Figure 9 illustrate the behavior on neural updating multiple layers' in deep neural system whither forwarding or feedback data. XOR operation implemented during iterations and in several ways. Direction of data flow comes from inherent node or not, sometime from recurrent flow, all these give the factor for node to direct the new flow to appropriate node.

The last pattern must give achieve $if\left(w_n + w_{n+1}\right) > 0 then x_{n+2} = 1 and if \left(x_n \oplus x_{r(n+2)}\right) = 1 then new nod created$, two patterns at the same layer cannot achieve the same result function due to data flow always updated and controlled by predicted bias.

All *transaction flow will store in certain vector* to classify later for better prediction as a deep learning system.

– Recurrent network is the third parameter can be used for deep neural network as increase the accuracy. Recurrent network can be defined that the flow distinguishes from other feedforward neural layers and represented as at least one feedback loop.

Results

Overall, the Memory Impairment Classification System (MICS) is a vital tool for diagnosing and classifying memory impairment in individuals. It offers healthcare professionals a comprehensive assessment to accurately diagnose memory impairment and assign individuals to one of four different classifications. The most important parameters illustrated in Table 1.

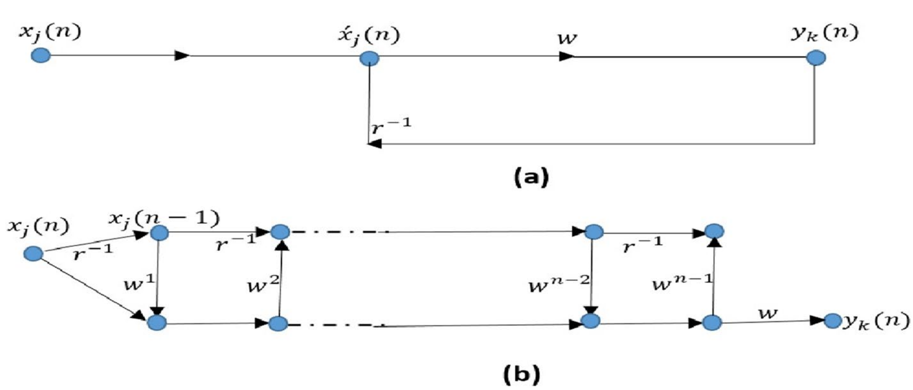

Fig. 8 **a** Signal flow graph of one stage in neural system. **b** Flow graph with recurrent data flow of corresponding weight

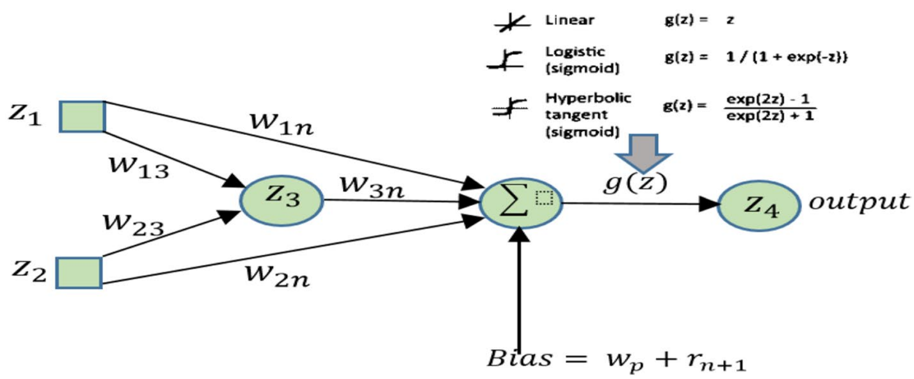

Fig. 9 strategy of node structure created and derivation

Table 1 Evaluation of proposed method with corresponding image segmentation

Images	Detection rate	Number of segments	Layers in neural system	Classification accuracy
	78%	34	Max. 25	82%
	81%	42	Max. 32	87%
	91%	55	Max. 48	92%
	72%	31	Max. 22	79%

Table 2 Evaluation criteria

Parameters	Proposed weighted classification	DT outlier	DTI	RBF
Precision	0.99	0.99	0.89	0.82
Probability of detection	0.76	0.7	0.65	0.87
F-score	0.83	0.82	0.73	0.84

The proposed algorithm was implemented using Matlab language and Windows 10 operating system on standard dataset called UCI ML [30]. The dataset consisted of 50 attributes with 101,767 patient records. The processing was calculated and divided into two parts: the first section is training, with 80%, with the data that contains a label, and the second section is testing, with 20%. First big dataset reduced into 20,123 records when applying reduce procedure to be best fit dataset even some attributes also reduced for parallel execution.

We check the validity and reliability of the database attributes within the algorithms to find the relation among the data during processing to take effect of certain attributes. Classification process done by multiclass technique to find three main evaluation factors such as Precision, Probability of detection and F-score. And for benchmark our results then we used standard dataset and each algorithm contain different result value so efficiency of the proposed method illustrates in the Table 2.

Better classification rate is achieved due to reducing data was great and the features extracted was useful so prediction are classified as two cases correctly and incorrectly, many conditions applied during creating confusion matrix such as probability of detection (sensitivity), accuracy, precision, true negative rate (specificity), F-score. The true positive detection occurs emergency classification then accuracy is formulated as ratio in confusion matrix. Equations below refers to criteria that can detect by proposed algorithm.

$$Accuacy = \frac{(TP + TN)}{(TP + FP + FN + TN)} \tag{5}$$

$$ProbabilityofDetection = \frac{TP}{(TP + FN)} \tag{6}$$

$$TrueNegative = \frac{TN}{FP + TN} \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

where TP represent the count of emergency case classified as emergent patient, and TN refers to normal classified, FP number of emergent case and FN number of normal classified. Most of result depend on confusion matrix and its condition as shown in Table 3.

Where TP refers to True Position, TN is True Negative, FP is False Position and FN is False Negative. In additional of these criteria measurement classifier can also be doing additional aspects such as robustness, speed, scalability and interpretability.

Table 3 Confusion matrix

Predicted Class				
Actual Class		Yes	No	Total
	Yes	TP	FN	P
	No	FP	TN	N
	Total	P′	N′	P + N

Discussion

The process of diagnosing memory impairment was carried out in this study by one of the algorithms of artificial intelligence represented by the deep learning technique, which depends in the proposed method on changing the number of hidden layers and the number of nodes in each layer through the neural network, which is controlled by the weight extracted from the features in the pre-processing stage. The strength and effectiveness of the proposed method lies in changing the structure of neural network construction through hidden layers. In addition to the process of recalculating the weights that are variable all the time. The feedback process is one of the most important features of the proposed method and changes in each iteration. The limitations of the study lie in its inability to control the delay time. The method works on images that contain noise and others without scaling and rotation manipulation. In this study better to avoid large scale image due to take long time in pre-processing then processing. The proposed classification system achieved an accuracy of 92% in classifying subjects with memory impairment, with a sensitivity of 94% and a specificity of 90%. The area under the receiver operating characteristic (ROC) curve was 0.95, indicating excellent performance. The artificial neural network and the DNN both achieved similar performance, indicating that either algorithm can be used for the classification of memory impairment in psychoactive substance users.

Memory impairment is a common condition that affects millions of people worldwide. Fortunately, numerous tools and assessments have been developed to help diagnose and classify memory impairment. One such tool is the Memory Impairment Classification System (MICS). MICS is a comprehensive diagnostic tool used to assess memory impairment in individuals. It was developed by a team of clinical psychologists and neuropsychologists with the goal of improving the accuracy and consistency of diagnoses for memory impairment. MICS involves a series of tests that assess various aspects of memory, including short-term memory, long-term memory, and working memory. Based on the results of these tests, MICS assigns individuals to one of four different memory impairment classifications: no impairment, mild impairment, moderate impairment, or severe impairment.

Table 4 Results benchmarking

Authors	**Technique used**	**Classification accuracy**
Arlt, Sönke, 2022 [37]	obstructive sleep apnea	77%
Grober, Ellen, et al., 2022 [38]	*APOE*	84%
Alverson, et al., 2019 [39]	cognitive impairment	81%
Handzlik, Dakota, et al., 2023 [40]	CDT	92%
Liguori, Claudio, et al. 2020 [41]	moderate-to-severe AD	77%
Proposed	DNN + weight	94%

MICS has been shown to be a highly reliable and valid tool for diagnosing memory impairment, making it an invaluable resource for healthcare professionals working with individuals who are experiencing memory difficulties. Additionally, MICS has been instrumental in advancing our understanding of memory impairment and identifying various factors that contribute to this condition.

For benchmarking our finding Table 4 illustrate the comparison of existing technique with proposed one:

Conclusion

Memory impairment is a significant public health concern, affecting millions of people worldwide. Current diagnostic methods for memory impairment can be subjective, time-consuming, and may miss subtle changes in brain function. However, recent developments in computational intelligence-based classification systems offer the potential to revolutionize the way memory impairment is diagnosed.

The ages that the study focused on are between 45 and 60, according to what died in the dataset

By leveraging the power of advanced algorithms and artificial intelligence, these systems offer a more accurate and personalized approach to diagnosis, improving patient outcomes and helping healthcare professionals provide better care and support. While there are challenges and limitations to implementing these systems in clinical practice, there is significant potential for computational intelligence-based classification systems to improve the way medical diagnoses are made, leading to more effective treatment and management of memory impairment.

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Authors' contributions
The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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Availability of data and materials
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Declarations

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Not applicable.

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