

An Enhanced Artificial Intelligence Model for Alzheimer Disease Diagnosis

Sabah Sayed ¹, Ashraf A. Mohamed ^{1,2,*}, and Fatma A. Omara ¹

¹ Faculty of Computing and Artificial Intelligence, Cairo University, Cairo, Egypt

² Faculty of Engineering Technology, ElSewedy University of Technology, Cairo, Egypt

Email: s.sayed@fci-cu.edu.eg (S.S.); ashraf.mohamed@sut.edu.eg (A.A.M.); f.omara@fci-cu.edu.eg (F.A.O.)

*Corresponding author

Abstract—Alzheimer's Disease (AD) has been widely investigated to improve diagnosis and prognosis. A lot of studies depended on structural and texture properties have already been conducted to help for identifying AD patients. The Artificial Intelligence (AI) approach, including Machine Learning (ML) and Deep Learning (DL) models, has shown promise of extracting and merging the diverse data to develop predictive models for diagnosing AD. In this paper, an AD Classifier (ADC) model has been proposed for classifying AD severity using image processing methodology to extract textural information from the Magnetic Resonance Imaging (MRI), and classify the patients into four groups; Non Demented, Moderate Demented, Mild Demented and Very Mild Demented using longitudinal cross-sectional data from Open Access Series of Imaging Studies-3 (OASIS-3) sourced from Kaggle database. As shown in the proposed ADC model, four ML and two DL algorithms have been applied for classifying AD severity. The used ML algorithms are Decision Tree (DT), K-Nearest Neighbors (K-NN), Support Vector Machines (SVM), and Random Forest (RF), while the used DL algorithms are Residual Network with 50 Layers (ResNet-50) and Visual Geometry Group 19-layer Network (VGG-19). The feature extraction of the AD using MRI is done using Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradient (HOG), and Local Binary Patterns (LBP) methods. A comparative study has been done among the used ML and DL algorithms to justify the proper algorithm for classifying AD severity. Looking at the results, it is found that the K-NN algorithm achieves the highest classification accuracy of 99.76% among the evaluated algorithms. Therefore, the K-NN algorithm could be favored for AD classifications because of its effective for early detection.

Keywords—Alzheimer disease, deep learning, texture analysis, machine learning

I. INTRODUCTION

According to current projections, the number of people with dementia globally will be risen to 75 million by 2030, up from 47 million in 2020. Alzheimer Disease (AD) is one of the dementias which causes gradual tissue loss throughout the brain [1]. Recently, AD has been extensively studied to improve diagnosis and prognosis.

AD has 3 stages: early, moderate cognitive and late. Patients in the moderate cognitive stage could be responding aggressively to treatment. On the other hand, the late stage of AD could cause heart failure and death respiratory system malfunction [2, 3]. These changes are diagnosed using clinical Magnetic Resonance Imaging (MRI). Previous research has shown that classification based on texture gives more accurate results rather than classification based on volume [4].

Neuroimaging methods, including the Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET), provide valuable information about the structural and functional brain changes associated with AD [5, 6].

Recently, Artificial Intelligence (AI) and computer vision approaches have been employed extensively combined with multimodality neuro images to explore further biomarkers and develop computer-aided system for early AD diagnosis [7]. The Machine Learning (ML) and Deep Learning (DL) approaches have shown a clear-cut advantage of diagnosing various diseases by analyzing medical data and helping for diagnosing and classifying AD. The most widely used ML algorithms as classifiers are Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), Decision Tree (DT) and Random Forest (RF) algorithms, which help in clinical diagnosis [8].

Recently, considerable research has focused on improving AD diagnosis and prognosis. Among the proposed approaches, structural and texture features have shown promising performance for AD detection. In this paper, an AD Classification model has been introduced, called AD Classifier (ADC) to classify the AD severity into four groups; Non-Demented, Moderate Demented, Mild Demented, and Very Mild Demented, based on image processing methodology combining with textural information.

The principal contributions of this study are summarized as follows:

- A framework that applies three texture descriptors feature Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradient (HOG), and Local

Binary Patterns (LBP) for AD diagnosis. The proposed approach providing useful representation than using one descriptor.

- A performance comparison is conducted among 4 ML classifiers (K-NN, SVM, RF, DT) and 2 DL models (Residual Network with 50 Layers (ResNet-50), Visual Geometry Group 19-layer Network (VGG-19)). This comparative providing an objective basis for algorithm selection in AD severity grading.
- 5-fold cross-validation is used to keep data independent. That giving fair results estimation on the dataset during classification process.

This paper is organized as: Section II shows related work. The proposed ADC model introduced in Section III. A comparative study among ML and DL introduced in Section IV. At end, the conclusions and future work are presented in Section V.

II. RELATED WORK

In recent years, doctors have started using computer systems to detect diseases at an early stage. This has helped both doctors and patients in many ways. ML has been used in many fields, such as data mining, image analysis, speech recognition, medical diagnosis, and robotics. Researchers have also applied it to clinical data to get accurate results. This is especially true in studies related to AD detection [9].

Nicholas *et al.* [10] have suggested a simple convolutional neural network for predicting AD. In their study, two experiments have been conducted using MRI scans that were given by AD Neuroimaging Initiative (ADNI) [11]. The authors prove that the SVM classifier is the most common ML algorithm to predict AD. Their decision is based on the idea that a successful method for finding AD can also be used to diagnose AD before it shows up. In the first test experiment, the SVM classifier gets accuracy of 84.41%, sensitivity of 95.3%, and specificity of 71.43%. For the second experiment, the authors used the Convolutional Neural Network (CNN) model. During the six evaluation processes, the authors used different datasets and different ways to divide up images to test the CNN model. They claim that the best way to divide an image is to use an extended ROI without looking for edges. This provides the best and most accurate results (i.e., accuracy 96%) with sensitivity of 96% and a specificity of 98 %.

Jallali *et al.* [12] proposed Modified Convolutional Neural Network (MCNN) with a Fine-Tuned VGGNet19 (FT-VGGNet19) system. The two models were tested on the AD Neuroimaging Initiative (ADNI) dataset. The FT-VGGNet19 model achieved the accuracy to 90% on the original dataset and 92%. The findings contribute to developing robust and scalable diagnostic systems, offering promising advancements in neurodegenerative disease management.

Çelebi and Emiroğlu [13] suggested of Tensor-Based Morphometry (TBM) with DL. the model related to early AD detection by brain MRI images. Their paper evaluated 3 models. This model based on many MRI. The best model result, that focused on hippocampus and temporal lobe

parts. It's achieved an accuracy of 93%. Their results showed the importance of anatomical region selection in improving AD classification.

Çelebi and Emiroğlu [14] improved a deep dense block-based model. The model related to AD staging by tensor-based morphometric analysis with CNN architectures. The model was developed using the Xception and combined with dense block layers. The goal of model to improve feature extraction. Their proposed model achieved an classification accuracy with 95.81%.

Chen *et al.* [15] presented Cognitive Assistive Technology Care (CAT). This is an intelligent assistive system for supporting people with mild dementia. The system integrates large language models: object detection, and indoor localization. Their study has been proven the potential of AI-driven for healthcare systems in improving patient independence.

A study has employed a variety of ML algorithms, including phase space reconstruction, extreme learning, eigenvector methods, multiclass SVM, time-frequency analysis, autoregressive modeling, and wavelet packet decomposition to classify Electroencephalogram (EEG) data for AD detection [16]. The Quantile Graph (QG) approach was utilized to differentiate AD patients from healthy individuals. The results showed that the QG method effectively distinguished AD from control groups, and the study suggests further exploration of QG and other preprocessing techniques for improving classification accuracy.

Gao [17] proposed system for AD by collecting features from EEG data and categorizing them into their respective classes using diverse ML algorithms. The aim of the purposed system was for automatically evaluate brain signals, and enhancing the efficiency and precision of the diagnostic process. Naïve Bayes, K-NN, RF algorithms and other ML algorithms were utilized to categorize EEG features taken from the datasets into their respective classes, which encompassed Control, mild AD, and moderate AD groups. The system demonstrated successful categorization of EEG data for providing potential for automatic AD diagnosis. The authors recommend continuing to optimize the algorithms and testing the system with larger, more diverse datasets to enhance diagnostic efficiency.

Rehman *et al.* [18] proposed an automated system for AD detection and staging using brain MRI data. The system utilized various pre-trained networks to extract deep features, followed by Canonical Correlation Analysis (CCA) for feature concatenation and binary-enhanced Whale Optimization Algorithm (WOA) for optimal feature selection. The used data consisted of deep features extracted from brain MRIs using EfficientNet-b0 and MobileNet-v2 models, generating 1280 features for each network. After CCA analysis, the feature set expanded to 2532 features. Binary-enhanced WOA further reduced the feature set to 953 optimal features. The proposed system achieved significant results with classification accuracies of 91.64% and 91.08% with EfficientNet-b0 and MobileNet-v2 features, respectively, 94.7% accuracy after feature concatenation with CCA, and an impressive

98.25% accuracy with the optimized feature set selected by binary-enhanced WOA. Comparative analyses showed that the WOA-based selection method was statistically significant ($p < 0.01$) compared to other techniques. The study recommends adopting this hybrid approach as a reliable and efficient tool for early detection and staging of AD, highlighting its potential to improve diagnostic accuracy and support timely intervention strategies.

Ali *et al.* [19] highlights a proposed system by utilizing DL algorithms, particularly CNNs, including 3D CNNs and recurrent neural networks, to analyze 3D imaging data for AD diagnosis. According to this study, a total of 87 articles published between 2020 and 2024 were reviewed, comprising 31 studies focused on theoretical approaches and 56 focused on practical implementations, using imaging modalities such as MRI, PET, and Computed Tomography (CT) scans. The results demonstrate that techniques like transfer learning, multimodal data integration, and attention mechanisms significantly enhance diagnostic accuracy, reliability, and efficiency by effectively capturing spatial and temporal features in volumetric data. The study recommends expanding multimodal approaches, improving model generalization across populations, developing explainable AI approach for clinical trust, addressing data limitations through data sharing, and conducting real-world evaluations through longitudinal studies and clinical trials.

According to the previous studies, it is shown that texture features, among other attributes, can provide excellent results in the analysis of medical images. However, existed researches have typically employed these features individually. In contrast, the work in this paper proposes a model that combines multiple texture feature extraction methods to achieve optimal accuracy. While various methods have been explored, the use of GLCM has consistently demonstrated superior performance, making it a key component in the proposed model alongside Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP).

III. THE PROPOSED AD CLASSIFICATION (ADC) MODEL

The proposed ADC model applies three texture features. These feature extractions are: GLCM, HOG, and LBP. The feature provides a comprehensive representation of MRI images. These methods can capture distinct feature of image texture. GLCM captures statistical gray-level relationships. HOG extracts edge and gradient orientations. LBP extracts local micro-structural patterns [20, 21]. The proposed ADC model consists of 3 steps as displays in Fig. 1. The principles of each phase are discussed below.

A. Preprocessing Phase

Image preprocessing done through the following stages:

Firstly, image normalization is employed [22]. For this process, the pixel values are rescaled to $[-1, 1]$ using a pixel-wise multiplication factor of $(0/255)$ as displays [23]:

$$\widehat{I}N = (1 - \hat{I}_{Min}^T) + \frac{\hat{I}_{Max}^T - \hat{I}_{Min}^T}{Max - Min} \hat{I}_{Min}^T \quad (1)$$

where I and $\widehat{I}N$ represent input and normalized brain image, respectively, $\hat{I}_{Max}^T, \hat{I}_{Min}^T$ are the normalized image's intensity range. $Min = 0$, and $Max = 255$ represent the input brain image's pixel intensity range.

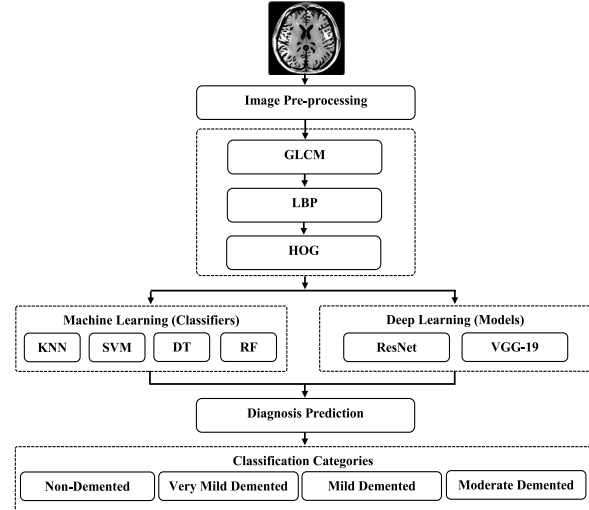


Fig. 1. The proposed framework.

Secondly, after normalization, the grayscale images are resized to 150×150 pixels before training [24]. Since the dataset is small and imbalanced, it leads to overfitting issues that negatively impact the efficiency and performance of the model. To address these challenges, data augmentation is commonly used as an effective approach to compensate data limitations and class imbalance.

According to the proposed model, data augmentation has been used to all MRI image. So, many augmentation methods have been used. These methods including: adjusting brightness, using zoom transformations, and rotating images at different angles. However, previous methods did not contribute positively to the proposed model. These methods resulted a decline in performance. This outcome is consistent with the nature of brain MRI images.

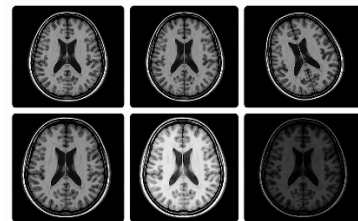


Fig. 2. Samples of augmentation images.

For example, horizontal flipping does not introduce new anatomical information. On another hand, geometric transformations as rotation may distort the spatial relationships among brain structures. But brightness adjustments can alter the relative signal intensities among gray, white matter, and cerebrospinal fluid features that are diagnostically significant in MRI. These findings are consistent with related papers that proven the important of

augmentation in medical imaging is highly task specific [25]. Fig. 2 shows samples of augmented images.

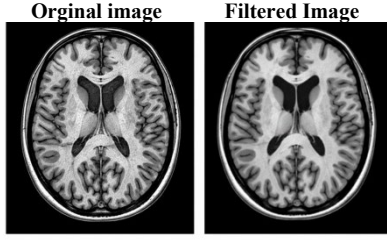


Fig. 3. Samples of images before and after horizontal flip.

Therefore, horizontal flipping method has been applied as a data augmentation technique to increase dataset diversity and potentially enhance model generalization. This method was selected for its simplicity and its ability to expand the dataset without altering the underlying anatomical features of the MRI images. Fig. 3 illustrates examples of augmented images before and after Horizontal Flip.

As a result, the dataset was expanded from 6400 to approximately 10,000 images. While the augmentation was intended to support improved model performance, its actual impact on classification results is further analyzed and discussed in the result section.

B. Feature Extraction Phase

The derivation of information and redundancy free data from different measures of texture, edge information, color, and boundary information are known as feature extraction [24]. These features provide useful information regarding an image for different computational tasks. On the other hand, feature extraction reduces the burden of computing resources such as memory and computational power by representing complex information in a simpler manner. Different methods, which are used to extract features in the proposed ADC model are discussed in the following sub-sections.

1) GLCM method

Texture is one of the significant parameters used for detecting the objects or Region of Interest (ROI) in an image [26]. The co-occurrences of the pixels with the values (m, n) are calculated by the co-occurrence matrix $G(m, n)$. In the proposed ADC model, fifty features are extracted to describe the characteristics [27]. These features and their equations are given in Table I.

2) HOG method

This method is a widely used feature extraction technique in image processing and computer vision [28]. It characterizes the local structure of brain MRI images by analyzing the distribution of gradient orientations [29]. The image is divided into small cells, and a histogram of gradient directions is computed for each cell to generate the final HOG feature vector [30]. The extraction of a HOG feature vector of an image is done according to the following steps [31].

Use gradient filter [1; 0; 1] to compute the horizontal $I_i(i, j)$ and vertical $I_j(i, j)$ gradient of an image.

$$|I(i, j)| = \sqrt{I_i(i, j)^2 + I_j(i, j)^2} \quad (2)$$

TABLE I. GLCM FEATURES [27]

Features	Mathematical Description	Description
Autocorrelation	$\sum_{m,n=0}^{N-1} (m, n) P_{m,n}$	Measure of linear dependency of a variable between two points in time.
Contrast	$\sum_{m,n=0}^{N-1} P_{m,n} (m - n)^2$	Measure the local intensity variation.
Correlation (corr)	$\sum_{m,n=0}^{N-1} P_{m,n} \left[\frac{(m - \mu_m)(n - \mu_n)}{\sqrt{(\sigma_1)^2(\sigma_2)^2}} \right]$	The linear dependencies of the gray level values are calculated based on neighboring pixels.
Correlation (corr)	$\sum_{m,n} \frac{(m, n) P(m, n) - \mu_x \mu_y}{\sigma_x \sigma_y}$	The linear dependencies of the gray level values are calculated based on neighboring pixels.
Cluster prominence	$\sum_{m,n=0}^{N-1} P_{m,n} (m + n - \mu_m - \mu_n)^4$	Measure the skewness.
Cluster shade	$\sum_{m,n=0}^{N-1} P_{m,n} (m + n - \mu_m - \mu_n)^3$	Measure the skewness and uniformity.
Dissimilarity	$\sum_{m,n=0}^{N-1} P_{m,n} m - n $	Measure comparisons between segmentations created by different algorithms.
Energy	$\sum_{m,n=0}^{N-1} P_{m,n}^2$	Sum of squared elements.
Entropy	$\sum_{m,n=0}^{N-1} P_{m,n} (-\ln P_{m,n})$	Measures the statistical randomness.
Homogeneity (homop)	$\sum_{m,n=0}^{N-1} \frac{P_{m,n}}{1 + (m - n)^2}$	Closeness of distribution in diagonal.
Homogeneity (homom)	$\sum_{m,n=0}^{N-1} \frac{P_{m,n}}{1 + m - n }$	Closeness of distribution in diagonal.
Maximum probability	$\max_{m,n} P_{m,n}$	Occurrences of the most predominant pair of neighboring intensity values.
Sum of squares: Variance	$\sum_{m,n=0}^{N-1} (m - \mu)^2 P_{m,n}$	Measure of variation from the gray level intensities.
Sum average	$\mu_m = \sum_{m,n=0}^{N-1} m(P_{m,n})$ $\mu_n = \sum_{m,n=0}^{N-1} n(P_{m,n})$	Average of a set of two/more values.
Sum variance	$\sigma_m^2 = \sum_{m,n=0}^{N-1} P_{m,n} (m - \mu_m)^2$ $\sigma_n^2 = \sum_{m,n=0}^{N-1} P_{m,n} (n - \mu_n)^2$	Measure of dispersion of a set of data calculated as the square root of variance by determining the difference between each pixel.

Compute the magnitude $I(i; j)$ and angle $\theta(i; j)$ of the gradient.

$$\theta(i, j) = \arctan\left(\frac{I_j(i, j)}{I_i(i, j)}\right) \quad (3)$$

Divide an image into cells of (8×8) pixels. After that, a histogram with nine orientation bins in $0^\circ - 180^\circ$ will be computed. Magnitude $|I(i, j)|$ whose angle $\theta(i, j)$ belongs to the same bin will be added up as the value of this bin. Adjacent cells are grouped into blocks. The histograms within each block are then normalized using the L2-Hys (Lowe-style clipped L2 norm) method. Finally, the normalized histograms from all blocks are combined to form the HOG feature vector.

3) LBP method

LBP Feature extraction method improves texture representation in image applications by dividing images into texture feature vectors, considering pixel neighbors and multi-scale models [32]. The LBP method includes $LBP_{P,R}$ operators which assign values to the pixels in an image based on whether they are greater than or equal to the center pixel. $LBP_{P,R}$ operators are described in detail in Fig. 4.

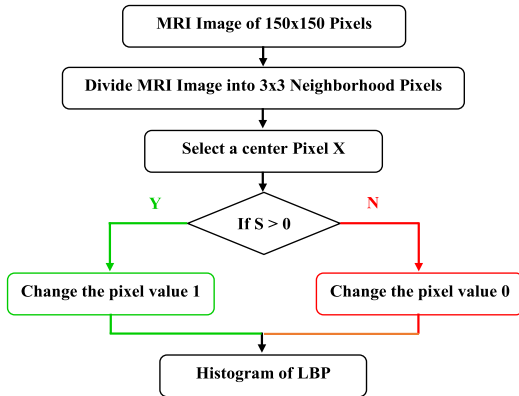


Fig. 4. The flow chart of the LBP method.

According to LBP method, Eq. (4) and Eq. (5) show that X as the location of the center pixel. As illustrated in Eq (4), X_i represents the location of the i th neighboring pixel, and Z represents the pixel intensity.

$$S = Z(X_i) - Z(X) \quad (4)$$

$$LBP_{P,R} = \sum_{i=0}^P F(S) 2^i, F(S) = \begin{cases} 1, & S \geq 0 \\ 0, & S < 0 \end{cases} \quad (5)$$

If S value is greater than or equal to the center pixel at the pixel position, the pixel is set to 1. Otherwise, it is set to 0. Subsequently, by using $P = 8$, $R = 1$, and LBP code for a neighborhood is created. The binary code's decimal value represents the local structural information surrounding a given pixel.

The LBP method creates 256 unique values; each value represents a unique pattern. The LBP pixel's histogram indicates the frequency of these patterns [33]. Each pattern

consists of 58 uniform binary patterns, with each one has an output label. Non-uniform patterns share a single label [34]. Fig. 4 display the Flow Chart of the LBP Method.

C. Classification Phase

Classification is a way to identify the category or class of a new observation based on a training set of data which contain the characteristics [35]. According to the proposed ADC model, four ML algorithms (DT, K-NN, RF, and SVM) and two DL algorithms (ResNet-50 and VGG-19) are used for AD classification. The principles of these algorithms are given below.

1) ML algorithms

The principles of the ML algorithms which are used in the classification phase are discussed in the following sections.

a) Decision Tree (DT) algorithm

DT algorithm divides data samples based on a determined parameter for solving both regression and classifications problems and maximizes the output by separating the data and sets output in a tree structure [36]. It is forms a binary tree, with the nodes called decision nodes and classification or leaf nodes to find the top categorical and numeric node for the feature split based on the conditions provided in the data. One of the significant challenges in DT algorithm is the identification of the attribute for the feature split [37]. According to DT algorithm, the attribute selection can achieve through Entropy or Gini Impurity methods. The Gini Impurity calculated by Eq. (6) [37]:

$$\text{Gini Impurity} = \sum_{i=1}^m f_i(1 - f_i) \quad (6)$$

where m represents the number of distinct class labels and f_i represents the proportion of samples belonging to class i at the given node. Entropy is calculated using Eq. (7).

$$\text{Entropy} = \sum_{i=1}^m -f_i \log(f_i) \quad (7)$$

b) K-Nearest Neighbor (K-NN) algorithm

K-NN algorithm represents a basic classification technique. As most supervised learning algorithms, it contains two phases; training and testing. It produces a good performance for optimal values of k [38]. K-NN classifier calculates the distance from the new data to every training data point, and it aims to detect the shortest distance as the best k neighbors [39]. k value is empirically determined using training samples classification error. In binary classification, k must be an odd integer, and must be different to class's number. Euclidean distance is the distance function exploited usually in K-NN [40].

For two feature vectors of n dimensions, $x = (x_1, x_2, \dots, x_n)^T$ and $y = (y_1, y_2, \dots, y_n)^T$, the Euclidean distance is calculated by Eq. (8):

$$\text{Euclidean distance}(\vec{x}, \vec{y}) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \dots + (x_n - y_n)^2} \quad (8)$$

c) Random Forest (RF) algorithm

RF is an ensemble classifier based on multiple decision trees [41]. Each tree makes its own prediction, and the final decision is made by combining the outputs of all trees. RF has been widely used by medical diagnosis, remote sensing, and image object detection [42]. While training, the algorithm uses the feature matrix extracted from the training dataset as input [42]. For each sample, a DT algorithm is created to make a classification decision and the significance of every feature in each tree is computed and the prediction in RF algorithm is taken as an average of the trees and the formula in RF is calculated by Eq. (9) [43]:

$$F(x) = \frac{1}{J} \sum_{j=1}^J C_{jfull} + \sum_{k=1}^K \left(\frac{1}{J} \sum_{j=1}^J \text{contribution}_j(x, j) \right) \quad (9)$$

where $F(x)$ is the prediction function, j is the number of trees in the RF algorithm, and k is the total number of features.

d) SVM algorithm

By SVM, the binary classification problem is two-dimensional objects that belong to two classes (+1, -1) that are simple to find out the line that can separate them perfectly in a higher dimension hyperplane according to structural risk minimization principle [44, 45].

The objective of SVM algorithm is to build a discriminating function that uses training data to classify new examples [44]:

$$f(m) = \pm(\sum a_i y_i K(s_i, x) + w_0) \quad (10)$$

where K is a kernel function and s_i is the support vectors and a_i is a weight constant that is derived from the support vector machine [46]. Fig. 5 display SVM classification scheme.

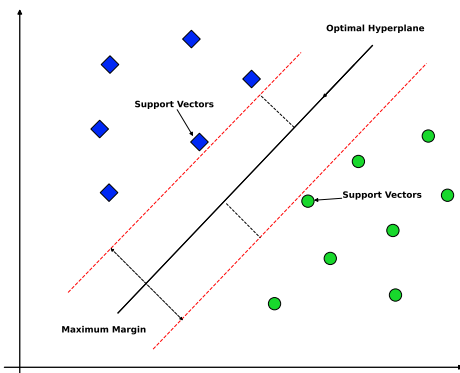


Fig. 5. SVM classification scheme.

2) DL algorithms

The principles of the DL algorithms which are used in the classification phase are discussed in the following sections.

a) ResNet-50 model

The ResNet-50 model is a form of deep ResNet architecture, consisting of 50 layers, and most ResNet models rely on skipping two or three layers using nonlinear

functions such as Rectified Linear Unit (ReLU) with batch normalization. Sometimes, the HighwayNet model is used, which uses an additional weight matrix to learn the weights of the skipped paths. The ResNet-50 architecture consists of a sequence of convolutional blocks followed by an average pooling layer, while the Softmax function is used in the last layer for classification purposes [47].

b) Visual Geometry Group (VGG-19) model

The VGG network is a tradename for the pre-trained CNN model proposed by Simonyan and Zisserman in early 2014 at the University of Oxford, UK [48]. VGG network was trained on ImageNet the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset of 1.3 million images consisting of 1000 classes for which 100,000 images were used for training and 50,000 for validation. VGG-19 model, a variant of VGG architectures, has 19 deeply connected layers which consistently achieved better performance as compared to other state-of-the-arts models. The VGG architecture consists of highly connected convolutional and fully-connected layers which enable better feature extraction, and the Maxpooling (in the place of average pooling) is used for down sampling prior classification using SoftMax activation function.

IV. THE IMPLEMENTATION OF THE PROPOSED ADC

One of the main objectives of this work is to evaluate the performance of the proposed ADC model for diagnosing Alzheimer disease. The proposed ADC model has been implemented using two frameworks. The first framework is based on ML approach using K-NN, RF, DT, and SVM classifiers. The second framework depends on DL approach using ResNet-50 and VGG-19 models.

A. Performance Metrics

The performance metrics which are used to evaluate the proposed ADC model are Accuracy, F1-score, Recall, Precision, and confusion matrix. The main parameters are used to calculate the performance metrics are as follows [49].

- True Positive. Transforms model prediction into true and positive values.
- False Positive. Predicts positive result, but actual value is false
- False Negative. Both model prediction and actual value are negative and false.
- True Negative. Indicates model prediction is incorrect and actual result is correct.
- Confusion matrix. It visualizes the performance of the proposed ADC model for each classifier in binary and multiclass. The Confusion matrix is based on positive and negative values as the following measurements [50]:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

$$\text{F1 - Score} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (12)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (13)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (14)$$

B. Dataset

In this study, the OASIS-3 dataset [51] was used. OASIS-3 dataset is a publicly available longitudinal neuroimaging repository maintained by the Washington University Knight Alzheimer Disease Research Center. It consists of T1_weighted MRI scans, clinical assessments, and cognitive test scores for participants spanning normal aging by AD. The dataset is accessible at: <https://www.oasis-brains.org/>.

Oasis-3 dataset consists of 6400 images classified into 4 classes:

- Non Demented (“CDR = 0, 3, 200 images”).
- Very Mild Demented (“CDR = 0.5, 2, 240 images”).
- Mild Demented (“CDR = 1, 896 images”).
- Moderate Demented (“CDR = 2, 64 images”).

C. Computing Environment

MATLAB 2021a is used to implement the classification phase of the proposed ADC model. Experiments have been done using Intel i5 processor and 8 GB of Random Access Memory (RAM). Three experiments have been implemented for classifying the AD.

- Experiment one: Done using ML algorithms (DT, K-NN, RF, and SVM).
- Experiment two: Done using DL models (ResNet-50 and VGG-19).
- Experiment three: is a comparison among ML and DL algorithms for proposed features extraction.

To evaluate the performance of the proposed ADC model using ML and DL approaches, K-fold cross-validation is used where epochs are randomly split into k groups.

Everyone has the comparatively the same number of features. Afterward, $(k-1)$ groups are used as training data to train the classifier and the remaining group is used as test classifier. This process is recurred (k) times, with each time different groups are used as test sets [52]. All groups would be used as train and test. To evaluate the performance of the classifier, 5-fold cross validation is performed and the accuracy result was calculated by average of 5-fold. Fig. 6 shows the distribution of training and testing across the 5 folds.

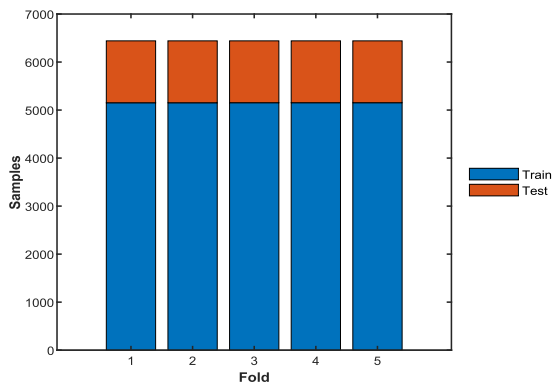


Fig. 6. Training and testing samples.

D. Experiment One: Using ML Algorithms

This section introduced the experimental results obtained after training 4 ML classifiers. The SVM classifier was trained using an RBF kernel function. Although Polynomial and Linear kernels were also evaluated, the Radial Basis Function (RBF) kernel produced the most favorable results. The K-NN classifier was trained using the Euclidean distance metric with (k) values ranging from 1 to 9. The optimal performance was achieved at $(k = 5)$, which provided a good balance among accuracy and noise sensitivity. Table II introduced the input parameters used for 4 ML classifier.

TABLE II. INPUT PARAMETERS FOR ML CLASSIFIERS

Classifier	Parameter
DT	Maximum depth = 8
	Criterion = GDI
	Min Leaf Size = 2
KNN	(Neighbors = 5)
RF	Estimators = 100
	InBagFraction = 0.8
	Min Leaf Size = 2
SVM	Num Predictors To Sample = 150
	Kernel = RBF

The Confusion Matrices (CM) of K-NN, RF, SVM, and DT classifiers using 5-fold cross-validation are introduced in following figures, and the corresponding performance metrics are detailed in following Tables.

1) K-NN

Table III presents the evaluation results of the K-NN classifier across all five folds. The KNN achieved high accuracy, with an average of 99.76%.

TABLE III. TEST RESULTS FOR KNN

Fold	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
1	99.90	99.96	99.92	99.99
2	99.90	99.96	99.92	99.99
3	99.61	99.57	99.69	99.44
4	99.80	99.38	99.84	98.92
5	99.60	99.80	99.61	99.99
Average	99.76	99.73	99.80	99.67

KNN Confusion Matrix

Predicted Class	MildDemented	269 100.0%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
	ModerateDemented	0 0.0%	19 100.0%	0 0.0%	0 0.0%	100.0% 0.0%
	NonDemented	0 0.0%	0 0.0%	959 99.9%	1 0.1%	99.9% 0.1%
	VeryMildDemented	0 0.0%	0 0.0%	1 0.1%	672 99.9%	99.9% 0.1%
		100.0% 0.0%	100.0% 0.0%	99.9% 0.1%	99.9% 0.1%	99.9% 0.1%
		MildDemented	ModerateDemented	NonDemented	VeryMildDemented	
		True Class				

Fig. 7. CM of K-NN classifier (Average over 5-fold cross-validation).

The KNN classifier achieved the highest evaluation results of 99.76% among all ML classifiers. It is a nonparametric method that needs no training phase. Classification is based on measuring distances among feature vectors. The GLCM, HOG, and LBP features capture detailed local patterns from MRI images, which suits distance-based approach for KNN. Additionally, the proposed dataset also helped for each test sample.

2) RF

Table IV display the evaluation results of the RF classifier. The RF introduced an average accuracy of 90.98%.

TABLE IV. TEST RESULTS FOR RF

Fold	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
1	(90.47)	(93.82)	(90.47)	(97.42)
2	91.64	95.26	91.64	99.17
3	90.63	94.46	90.63	98.63
4	90.39	93.65	90.39	97.16
5	91.80	94.78	91.80	97.96
Average	90.98	94.39	90.98	98.07

RF Confusion Matrix					
Predicted Class	MildDemented	ModerateDemented	NonDemented	VeryMildDemented	
	181 100.0%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
	0 0.0%	3 100.0%	0 0.0%	0 0.0%	100.0% 0.0%
	38 3.5%	6 0.6%	944 86.8%	99 9.1%	86.8% 13.2%
VeryMildDemented	44 7.0%	10 1.6%	14 2.2%	565 89.3%	89.3% 10.7%
	68.8% 31.2%	15.8% 84.2%	98.5% 1.5%	85.1% 14.9%	88.9% 11.1%
True Class					

Fig. 8. CM of RF classifier (Average over 5-fold cross-validation).

3) SVM

Table V display the evaluation results of the SVM with RBF kernel across all 5 folds. This method achieved an average accuracy of 99.36%.

The SVM with RBF kernel was selected for its effectiveness in handling nonlinear data and mapping features into a higher-dimensional space, enabling clear separation between AD severity classes.

TABLE V. TEST RESULTS FOR SVM

Fold	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
1	99.22	99.61	99.22	99.97
2	99.38	99.69	99.38	99.98
3	99.53	99.72	99.52	99.98
4	99.14	99.57	99.14	99.96
5	99.53	99.77	99.53	99.99
Average	99.36	99.68	99.36	99.98

SVM Confusion Matrix					
Predicted Class	MildDemented	ModerateDemented	NonDemented	VeryMildDemented	
	256 98.1%	0 0.0%	5 1.9%	0 0.0%	98.1% 1.9%
	0 0.0%	19 100.0%	0 0.0%	0 0.0%	100.0% 0.0%
	2 0.2%	0 0.0%	903 96.8%	28 3.0%	96.8% 3.2%
VeryMildDemented	11 1.6%	0 0.0%	52 7.4%	644 91.1%	91.1% 8.9%
	95.2% 4.8%	100.0% 0.0%	94.1% 5.9%	95.8% 4.2%	94.9% 5.1%
True Class					

Fig. 9. CM of SVM classifier (Average over 5-fold cross-validation).

4) DT

Table VI display the evaluation results of the DT method across all 5 folds. This result of DT is the lowest score of 63.39%. This reflecting the limitations of a single DT in capturing complex in MRI images during AD classification.

TABLE VI. TEST RESULTS FOR DT

Fold	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
1	64.77	54.40	64.73	46.96
2	62.73	55.28	62.73	49.41
3	62.19	53.37	62.19	46.74
4	64.21	52.77	64.22	44.79
5	63.05	52.61	63.05	45.14
Average	63.39	53.69	63.37	46.52

TABLE VII. AVERAGE PERFORMANCE COMPARISON OF ML CLASSIFIERS

Algorithm	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
K-NN	99.76	99.73	99.80	99.67
SVM	99.36	99.68	99.36	99.98
RF	90.98	94.39	90.98	98.07
DT	63.39	53.69	63.37	46.52

DT Confusion Matrix					
Predicted Class	MildDemented	ModerateDemented	NonDemented	VeryMildDemented	
	143 53.2%	4 1.5%	58 21.6%	64 23.8%	53.2% 46.8%
	1 10.0%	3 30.0%	4 40.0%	2 20.0%	30.0% 70.0%
	55 6.0%	4 0.4%	700 75.8%	164 17.8%	75.8% 24.2%
VeryMildDemented	69 10.1%	6 0.9%	175 25.5%	435 63.5%	63.5% 36.5%
	53.4% 46.6%	17.6% 82.4%	74.7% 25.3%	65.4% 34.6%	67.9% 32.1%
True Class					

Fig. 10. CM of DT classifier (Average over 5-fold cross-validation).

As shown in Table VII, the K-NN classifier achieves the highest accuracy followed by SVM at 99.36%, RF at 90.98%, and DT at 63.39%.

E. Experiment Two: Using DL Algorithms

This section presents the experimental results obtained after training two DL classifiers ResNet-50 and VGG-19 on the OASIS dataset. Both models were trained using the Adam optimizer with identical hyperparameter settings, as detailed in Table VIII.

TABLE VIII. INPUT PARAMETERS FOR DL CLASSIFIERS

Classifier	Parameter
ResNet-50 + VGG-19	Batch Size = 64; Learning Rate = 0.001; Optimizer = Adam; Epochs = 200; LR Decay Factor = 0.8

1) VGG-19

Table IX presents the performance metrics of the VGG-19 classifier across all five folds. VGG-19 achieved an average accuracy of 98.53%, demonstrating strong classification performance for AD severity staging. Fig. 11 displays the CM of the VGG-19 classifier averaged over 5-fold cross-validation.

TABLE IX. TEST RESULTS FOR VGG-19

Fold	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
1	98.03	98.39	98.10	98.85
2	98.83	99.14	98.83	99.47
3	98.67	99.04	98.67	99.40
4	98.83	99.41	99.83	99.46
5	98.24	98.86	98.28	99.44
Average	98.53	98.99	98.55	99.32

VGG-19 Confusion Matrix

Predicted Class \ True Class	MildDemented	ModerateDemented	NonDemented	VeryMildDemented
MildDemented	266 98.9%	0 0.0%	2 0.7%	1 0.4%
ModerateDemented	0 0.0%	19 100.0%	0 0.0%	0 0.0%
NonDemented	1 0.1%	0 0.0%	956 99.6%	3 0.3%
VeryMildDemented	2 0.3%	0 0.0%	1 0.1%	670 99.6%
	98.9% 1.1%	100.0% 0.0%	99.7% 0.3%	99.4% 0.6%

Fig. 11. CM of VGG-19 classifier (Average over 5-fold cross-validation).

2) ResNet-50

Table X displays the evaluation results of the (ResNet-50) by all 5 folds. This model scored an

average accuracy of 97.28%. Although this result is less than VGG-19 model, but still performs well for AD classification. Fig. 12 displays the CM of the ResNet-50 classifier averaged over 5-fold cross-validation

TABLE X. TEST RESULTS FOR RESNET-50

Fold	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
1	97.34	98.09	97.34	98.86
2	96.95	97.00	96.95	97.04
3	97.34	98.09	97.34	98.86
4	97.19	98.02	97.19	98.86
5	97.58	98.22	97.58	98.87
Average	97.28	97.88	97.28	98.50

ResNet-50 Confusion Matrix

Predicted Class \ True Class	MildDemented	ModerateDemented	NonDemented	VeryMildDemented
MildDemented	260 96.7%	0 0.0%	4 1.5%	5 1.9%
ModerateDemented	0 0.0%	18 100.0%	0 0.0%	0 0.0%
NonDemented	3 0.3%	0 0.0%	947 98.6%	10 1.0%
VeryMildDemented	5 0.7%	0 0.0%	7 1.0%	661 98.2%
	97.0% 3.0%	100.0% 0.0%	98.9% 1.1%	97.8% 2.2%

Fig. 12. CM of ResNet-50 classifier (Average over 5-fold cross-validation).

Based on the experimental results, VGG-19 outperforms ResNet-50 with an average accuracy of 98.53% versus 97.28%. Notably, both DL classifiers perform below the best ML classifier K-NN at 99.76% suggesting that the combination of handcrafted texture features (GLCM, HOG, LBP) with a proximity-based classifier is particularly well-suited for this classification task.

F. Experiment Three: Feature Contribution Analysis—Test Results of Feature Extraction Techniques

This experiment serves as an ablation study to evaluate the contribution of each feature extraction technique (GLCM, HOG, and LBP) individually and in combination (GLCM + HOG, GLCM + LBP, HOG + LBP) compared with the full proposed ADC model, as detailed in Table XI.

As shown in Table XI, integrating all three techniques (GLCM + HOG + LBP) in the proposed ADC model consistently achieves the superior performance across all classifiers, with K-NN reaching 99.76% accuracy, confirming that each technique contributes complementary information essential for optimal AD severity classification.

TABLE XI. TEST RESULTS OF ML AND DL CLASSIFIERS ACROSS FEATURE COMBINATIONS

Classifier	Feature Extraction	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
DT	GLCM	62.80	62.30	62.50	62.40
	HOG	61.25	60.80	61.00	60.90
	LBP	59.50	59.00	59.20	59.10
	(GLCM + HOG)	64.10	63.80	64.00	63.90
	(GLCM + LBP)	60.70	60.20	60.50	60.35
	(LBP + HOG)	61.75	61.30	61.50	61.40
	ADC Model	63.39	53.69	63.39	46.54
K-NN	GLCM	97.20	97.00	97.10	97.05
	HOG	95.80	95.50	95.60	95.55
	LBP	93.10	92.80	92.90	92.85
	(GLCM + HOG)	97.95	97.90	97.80	97.85
	(GLCM + LBP)	98.20	97.90	98.00	97.95
	(LBP + HOG)	98.75	98.50	98.60	98.55
	ADC Model	99.76	99.73	99.80	99.67
SVM	GLCM	94.85	94.50	94.70	94.60
	HOG	93.45	93.10	93.30	93.20
	LBP	91.50	91.00	91.20	91.10
	(GLCM + HOG)	96.12	95.90	96.00	95.95
	(GLCM + LBP)	94.50	94.20	94.40	94.30
	(LBP + HOG)	95.05	94.70	94.90	94.80
	ADC Model	99.36	99.68	99.36	99.98
RF	GLCM	90.80	90.50	90.70	90.60
	HOG	90.30	90.00	90.10	90.05
	LBP	80.10	79.80	79.90	79.85
	GLCM + HOG	91.76	91.50	91.80	91.65
	GLCM + LBP	90.80	90.50	90.60	90.55
	LBP + HOG	89.45	89.10	89.30	89.20
	ADC Model	90.98	94.39	90.98	98.07
ResNet-50	GLCM	97.80	97.50	97.60	97.55
	HOG	96.50	96.20	96.30	96.25
	LBP	94.30	94.00	94.10	94.05
	GLCM + HOG	98.95	98.70	98.80	98.75
	GLCM + LBP	96.70	96.40	96.50	96.45
	LBP + HOG	97.25	97.00	97.10	97.05
	ADC Model	97.28	97.88	97.28	98.50
VGG-19	GLCM	96.80	96.50	96.60	96.55
	HOG	95.40	95.10	95.20	95.15
	LBP	93.50	93.20	93.30	93.25
	(GLCM + HOG)	97.85	97.50	97.60	97.55
	(GLCM + LBP)	95.80	95.50	95.60	95.55
	(LBP + HOG)	96.35	96.10	96.20	96.15
	ADC Model	98.53	98.99	98.55	99.32

G. Summary

AD is a major neurodegenerative disease which continues to receive significant attention in computational medical research. One of the main objectives of the work in this paper is to classify the Alzheimer Disease based on extracted features of MRI images by implementing texture analysis methods. The experiments have been conducted using MRI images from OASIS 3 database. Three experiments have been conducted. In the first experiment, four ML algorithms; SVM, DT, RF, and K-NN algorithms are concerned, while the second experiment concerns two DL models; VGG-19 and ResNet-50. In the third experiment, a comparison has been done for the ML and DL algorithms using permutations and combinations of GLCM, HOG, LBP methods for texture features extraction.

According to the results of experiment one, it is found that K-NN classifier achieves high performance with an average performance of 99.76% for accuracy, 99.73% for

F1-score, 99.67% for recall and 99.80% for precision comparing to other ML classifiers.

According to the results of experiment two, it is found that VGG-19 model achieves high performance with 98.53% accuracy, 98.99% F1-score, 98.5% precision, and 99.32% Recall comparing to ResNet-50 model. Despite applying data augmentation techniques to improve model performance, no significant improvement in results was observed. This is because of using 5-Fold Cross Validation, which ensures that the model was trained and tested on all parts of the original dataset, leading to good generalization. Moreover, recent studies indicate that the effectiveness of data augmentation techniques in medical imaging heavily depends on selecting appropriate methods, as some techniques may be ineffective or even harmful if not applied correctly.

By comparing the results of experiments one and two, it is found that using ML approach outperforms DL approach, where K-NN classifier achieved higher results than VGG-19 model.

TABLE XII. COMPARISON ACCURACY WITH PREVIOUS STUDIES

Authors	Dataset	Methods	Accuracy (%)
Oommen <i>et al.</i> [9]	ADNI	Scattering Wavelet Transforms (SWT) feature + SVM + KNN + DT + NB	SVM = 98.10
			KNN = 96.30
			DT = 89.00
			NB = 88.70
Nicholas <i>et al.</i> [10]	OASIS	LBP + HOG + LBDP + LWP Feature + KNN	LBP + KNN = 91.2
			HOG + KNN = 86.7
			LBDP + KNN = 83.5
			LWP + KNN = 81.0
Cui <i>et al.</i> [11]	ADNI	ROI +DTFL + SVM	SVM= 75.13
Celebi <i>et al.</i> [13]	ADNI	SVM + KNN + wrapper method	SVM = 92.3
			KNN = 91.7
Gao [17]	OASIS	GLCM Feature + Extreme Learning Machine (ELM)	ELM = 92.30
Francis <i>et al.</i> [53]	ADNI	Hessian Detector + LBP + PCA + CNN	CNN = 88.99
		ADC (GLCM + LBP + HOG) + K-NN	KNN = 99.67
The Proposed ADC Model	OASIS 3	ADC (GLCM + LBP + HOG) + VGG-19	VGG-19 = 98.50

Based on the results, it is evident that using ML approach, especially K-NN classifier, achieves high efficient for diagnosis, detection, and classification of AD. According to the results of experiment three, it is also observed that by using a combination of texture features extraction techniques plays a pivotal role for early diagnosis of AD.

By comparing the performance results of the propose ADC model and the previous studies with respect to the accuracy, it is found that the accuracy of the proposed ADC model based on the combination of texture features extraction methods for early AD diagnosis plays a pivotal role using Oasis 3 dataset (see Table XII).

V. CONCLUSIONS AND FUTURE WORK

This paper presented the ADC model for four-class AD severity classification using GLCM, HOG, and LBP feature extraction methods with six classifiers on the OASIS-3 dataset. The K-NN classifier achieved the highest ML performance with 99.76% accuracy, 99.73% F1-score, 99.80% precision, and 99.67% recall. Among DL models, VGG-19 outperformed ResNet-50 with 98.53% accuracy and 98.99% F1-score.

The results demonstrate that handcrafted texture features combined with ML classifiers provide competitive performance for AD classification from T1-weighted MRI. The K-NN classifier proved particularly suitable for the proposed feature space, while the comparative evaluation between ML and DL approaches provides a useful reference for future studies.

This study has several limitations. The 5-fold cross-validation was applied at the image level rather than the patient level, which may introduce potential data leakage. In addition, the Moderate Demented class contains only 64 original images, which may affect performance estimation for this minority class. Finally, external validation on an independent dataset such as ADNI was not performed, and future work will aim to address these limitations. Future work will explore volumetric 3D MRI analysis, multimodal data integration including PET imaging and cognitive scores, and longitudinal modeling to predict disease progression rate between severity stages.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Sabah Sayed: Conceptualization, formal analysis, methodology, supervision, validation, writing-review and editing. Ashraf A. Mohammed: Conceptualization, analyzed the data, software, resources, formal analysis, methodology, validation, writing original draft. Fatma A. Omara: Formal analysis, investigation, super vision, validation, writing review and editing. All authors had approved the final version.

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