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CSCOOT: Competitive Swarm Coot Optimization-Based CNN Transfer Learning for Alzheimer's Disease Classification.

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ABSTRACT:
A person with Alzheimer's disease (AD) experiences a gradual decline in brain function and a total loss of cognitive capacity. Currently, it is said that differentiating between AD stages is a difficult task because many of these stages overlap. Hence, a recently suggested strategy for Alzheimer's disease classification using Competitive Swarm Coot Optimization in a the CSCOOT_CNN Convolutional Neural Network does well when trained via transfer learning. Input photographs are sourced from the ADNI collection before moving on to the pre-processing stage. One of the pre-processing modules uses a median filter to get rid of noise. After that, feature extraction is performed on the pre-processed image, specifically for convolutional neural network (CNN) feature extraction. The next step is to feed the collected features into the classification level, where the disease is labelled using convolutional neural networks (CNNs) with transfer learning. In this case, the CNNs are trained using hyper parameters from the visual geometry group 19 (VGG19) model. Furthermore, the suggested CSCOOT algorithm is used to fine-tune CNNs that incorporate transfer learning. In addition, a new method called CSCOOT, which combines the COOT optimizer with Competitive Swarm Optimizer (CSO), has been introduced. Therefore, with values of 0.926 for accuracy, 0.979 for specificity, and 0.909 for sensitivity, the suggested CSCOOT_CNN achieved better results.

KEYWORDS: Convolutional Neural Network (CNN), Deep Neuro Fuzzy Network (DNFN), Competitive Swarm Optimizer (CSO), COOT optimizer.

1. INTRODUCTION:

AD is very rapidly developing some disorders in old peoples, which commonly begins gradually and it affects human brain ensuring death of cells in brain. A single person affected by this AD slowly loses the capability of thinking and thus forgets their regular activities. Occasionally, they are frequently not able to do daily actions and takes much time for recalling their neighborhood names also. AD is very general type of dementia, which causes memory, behavior and thinking problems.

Anyone having advanced AD might be not able to live their own life and have nervousness, feels insecurity and was unable to interact with other peoples in a society. The chance of patient recovering from severe AD is lesser and thus, it must be treated and predicted in its earlier stages [1].

The most of AD patients suffering from sporadic AD for which various risk factors additionally to age had been developed and is presently explored. Even though, the AD etiology is not still entirely obvious, the higher information about few significant path mechanisms in AD permits for initial time in developing drugs, which intended in modification of specific characteristic of AD processing [2].

It not only affects the older people but also the elder generations. In mild conditions, its outcomes in lack of memory and as disease increases, it affects long and short-term memory. It has important effect on life quality. Presently, the treatments available can adjust the course of disease and modernizes few symptoms, though there are no proven effectual therapeutic cures for Alzheimer disease had been developed till now [3].

In order to diagnose Alzheimer's disease, magnetic resonance imaging (MRI) is often used. For Alzheimer's disease patients, a visual assessment can signify the shape of brain and alteration of cerebral ventricle becomes very rounded when compared with non-AD individuals. If MRI sensitivity for AD detection is high than volume alteration and if the shape alters could be consistently estimated, then the method could be applicable for earlier detection of AD [4].

Magnetic resonance imaging (MRI) has many advantages over other imaging modalities, including its adaptability, low radiation exposure, high contrast ratios, and capacity to shed light on the brain's structure. It is regarded as significant for developing a best computer-aided diagnosis system, which can understand MRI and determines whether the patients are healthier or has Alzheimer’s disease. The convolutional deep learning methods utilize the cortical surface for CNN input to execute AD classification on MRI images [5].

MRI is regarded as non-invasive diagnosis imaging method, which creates cross section images of human body with no utilization of ionizing radiation. A remarkable reflection of MRI's diagnostic relevance is the ever-increasing number of MRI scanner installations [6].

Several image segmentation techniques are generally grouped as edge-enabled approaches, boundary-enabled approaches, hybrid-enabled approaches and region-enabled approaches. It is depended on two fundamental pixel properties such as discontinuity and similarity. The clustering view point of these techniques is classified as supervised and unsupervised texture segmentation. Thus, the mentioned segmentation techniques are integrated and could be overlapped [7].

In Alzheimer's disease, there are three distinct phases: dementia with moderate symptoms, CN, and AD itself. Mild cognitive impairment can progress through two distinct stages: early and late. The former is called early mild cognitive impairment (EMCI), while the latter is known as late moderate cognitive impairment (LMCI). Memory loss is one symptom of mild cognitive impairment, which occurs prior to AD dementia or else other dementias [8].

Several classification methods are utilized in categorizing AD in MRI. The symmetry, intensity, statistical and texture features and so on that utilize Alzheimer gray value are employed for classification of AD [9].

Presently, deep learning techniques are utilized neuro-imaging area for automatic extraction of feature and assessing human brain data making use of GPUs and increased computing power. The automatic feature extraction in deep learning methods is the key to their superior performance [10].

The utilization of deep learning is observed as offering promising as well as precise outputs for medicinal data. The deep learning technique is capable of classification, extraction of high-level features and also assists in precise diagnosis of AD patients in lesser time [11].

In deep learning, CNN is extensively known for its capability for performing higher accuracy by means of medicinal image classification. Moreover, the major benefit of CNNs, when comparing to traditional machine learning approaches is that CNNs does not need manual extraction of feature because CNNs are able to extract the efficient features in automatic manner and thereafter, classifying the phases of AD [12].

One major objective of this study is to introduce a novel approach to AD categorization by means of CSCOOT_CNN and transfer learning. The first step is to get the input images from a certain dataset. The next step is to apply a median filter during the pre-processing of the photos. In the feature extraction module, CNN features are recovered from a pre-processed image. Classification level uses CNN with transfer learning to categories diseases based on the retrieved features [13].

Hyperparameters from the trained model VGG19 are utilized in this case by means of a CNN [14].

Furthermore, the suggested CSCOOT method is used to fine-tune CNNs that incorporate transfer learning. Combining the CSO with the COOT optimizer, a newly-developed algorithm is the CSCOOT algorithm [15].
Below, we outline a crucial contribution of this study.
Proposed CSCOOT_CNN with transfer learning for classification of Alzheimer's disease: A recently developed method for first-level Alzheimer's disease classification, CSCOOT_CNN with transfer learning, trains CNNs with transfer learning using CSCOOT. On the other hand, CSCOOT is a new optimizer that combines CSO and COOT.

A residual segment of this work is set as mentioned: Section 2 interprets a literature view of present approaches in accordance to AD classification. Section 3 reveals proposed approaches for classification of Alzheimer's disease. Section 4 elucidates outcomes of newly devised techniques. Section 5 expounds conclusion.

This section discusses the pros and cons of utilizing a literature review to compile research articles, as well as its methodology. These constraints should encourage researchers to develop novel methods for AD classification in the future.

2. LITERATURE SURVEY:

This part describes the reviews that were conducted using the papers that were classified according to AD.

The Deep Siamese CNN was created to forecast the stages of Alzheimer's disease categorization. Still, the approach allowed for a more thorough evaluation of the usefulness of the MRI slices for information extraction. However, the model's application to computer-aided diagnostic issues was not investigated [1].

While the CNN architecture proposed for the classification task was able to extract useful features for the classification work, fine-tuning was unable to increase the algorithm's overall performance [2].

To classify the six stages of Alzheimer's illness, set out to create residual neural networks. This method proved useful for deciding on an early AD diagnosis, but it was only when combined with clinical imaging and deep learning algorithms that it was able to reveal patterns of functional brain changes associated with the onset of Alzheimer's disease [3].

The optimizer's resilience in terms of both energy efficiency and cost was demonstrated by Sakeena, who presented DNFN for effective load and cost optimization. This approach was ineffective since it used the same set of rules for all of the parameters [4].

Dementia Network (DEMNET) was created to identify the phases of dementia using magnetic resonance imaging (MRI). Although the created model could identify Alzheimer's disease-related brain regions, it was unable to handle computational challenges due to insufficient data [5].

For medical picture classification and Alzheimer's disease detection, The E2AD2C approach allows for the early diagnosis and classification of AD from beginning to end. Computing complexity, memory requirements, over-fitting, and overall processing time were all decreased using this method [6].

In this method, MRI segmentation was not used before classification. C to highlight Alzheimer's characteristics. For AD classification from MRI scans, constructed convolutional neural network (CNN) algorithms that were influenced by VGG-16; nevertheless, they failed to account for axial & coronal perspectives [7].

The purpose of the deep 2D convolutional neural networks (2D-CNNs) designed for Alzheimer's disease classification to enhance performance bias categorization. New network frameworks, especially three-dimensional designs, were not investigated by this created method [8].

3. METHODOLOGY:

The following are some of the issues that have been raised in relation to the examined methods for AD classification.

- suggested a strategy for AD classification stage prediction, however it neglected to examine clever splitting of training data classification and dealt inaccurately with parameter counts.

- The convolutional neural network (CNN) described in reference 2 was used to correctly categories brain structural MRI slices, despite the fact that the data used was insufficient and added processing complexity.
- The (AUC) for all phases of Alzheimer's disease was larger in the model that was provided in [3] for AD classification. Additionally, the data that is accessible for model evaluation and training has a significant impact on the clinical analysis applications of such systems.
- The DNFN in [4] was implemented to optimize costs and loads effectively, but it did not change the number of epochs or error tolerance to enhance system performance.
- Despite the significant impact of Alzheimer's disease on public health, researchers have yet to discover effective treatments to alleviate its symptoms or prevent further progression of the disease.
- Proposed CSCOOT_CNN with Transfer Learning AD Classification
- The progressive brain condition known as Alzheimer's disease (AD) has a gradual onset but a steady decline over time with time, killing off nerve cells and causing tissue loss all across the brain. The initial step is to examine input photographs from a certain dataset. The next step is to do the photographs undergo pre-processing, which entails enhancing their quality by reducing noise using it is a median filter. The feature extraction module is tasked with extracting CNN features from the pre-processed image. In the first stage of disease classification, the acquired features were passed to the first level using convolutional neural networks (CNNs) with transfer learning—more precisely, CNNs with hyper parameters from the training model VGG19. EMCI, LMCI, MCI, AD, and CN. Using the suggested CSCOOT method, the CNN is fine-tuned via transfer learning. Furthermore, by combining CSO and COOT optimizer, the CSCOOT algorithm is presented. Figure 1 shows a visual representation of the new method for AD categorization.

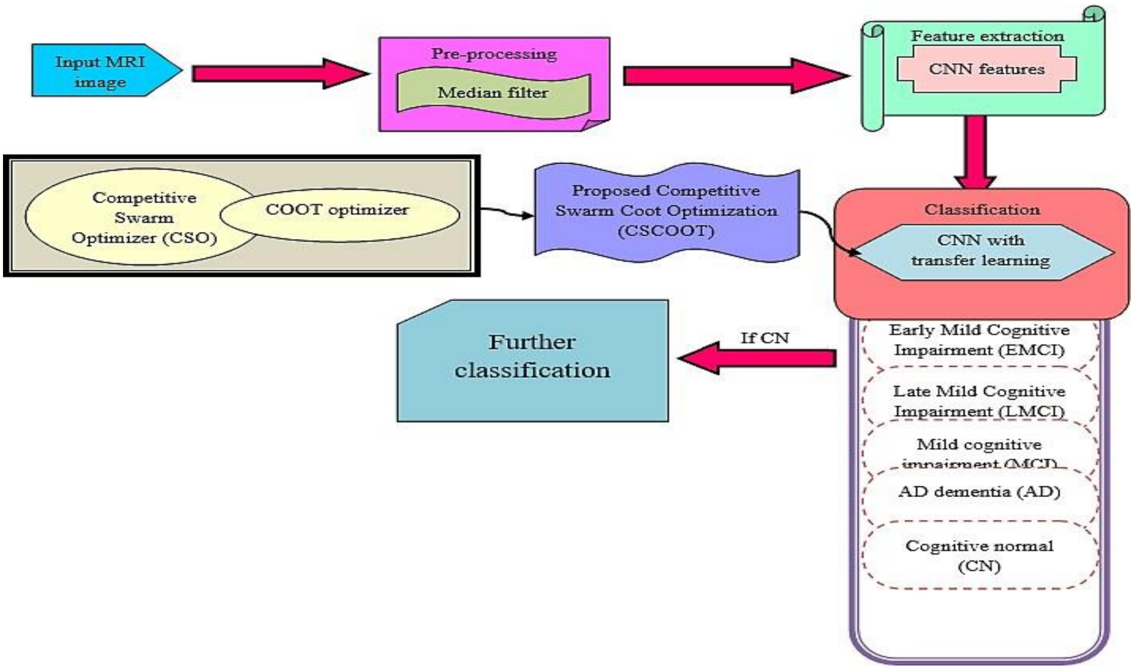

Figure 1. Visual representation of recently developed methods for AD categorization Input image acquisition

Consider MRI image for AD classification that is obtained from ADNI website. It is illustrated by,

$$A = \{D_1, D_2, \ldots\ldots, D_z, \ldots\ldots\ldots. D_m\} \qquad (1)$$

Where, total training images in training dataset D is indicated by m and Z^{th} input image is implied by D_z.

The sample input images are shown in figure below:

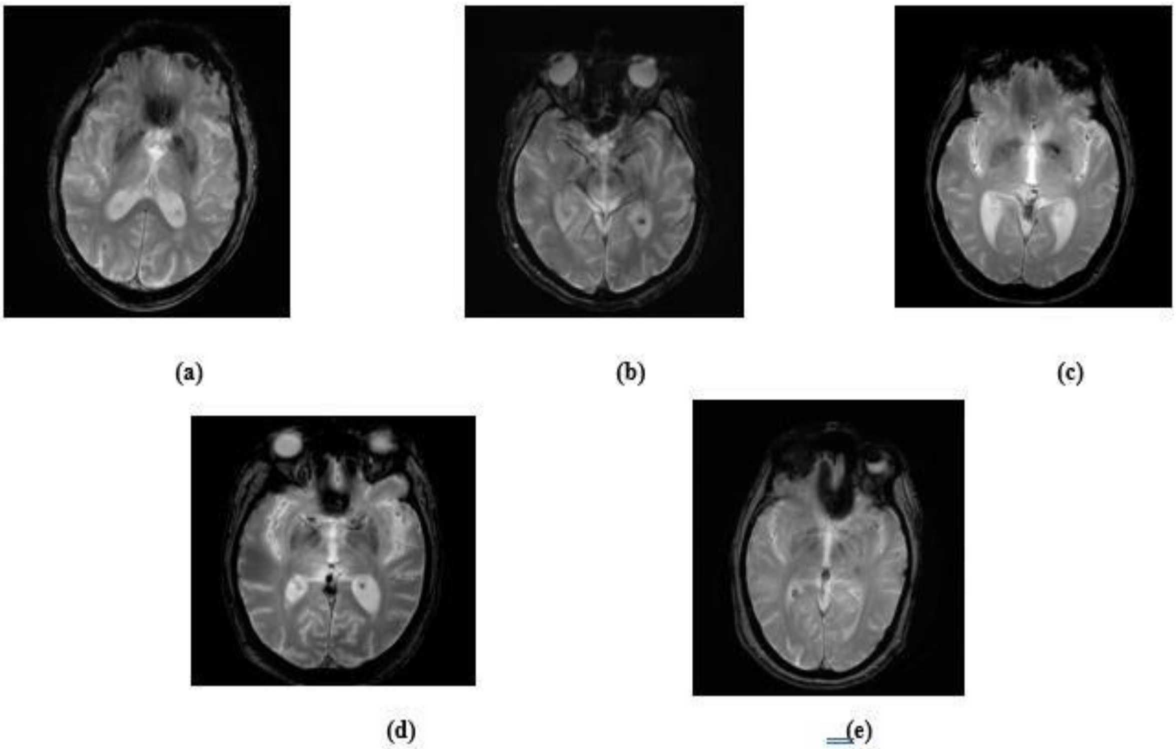

Fig 2. Sample Input Data (a) EMCI (b) LMCI (c) MCI (d) AD (e) CN

Utilizing the median filter for pre-processing the picture:

As the images are transmitted over digital media, there is a chance of bit errors in transmission. Also, outliers may be included during signal acquisition. This sound is categorized as pepper & salt noise. The term "nonlinear spatial filter" [18] refers to the median filter, which is an effective method of eliminating noise caused by salt and pepper and is following the principles of order statistics. It substitutes the median of the nearby grey levels for a pixel's value, effectively reducing contrast. The median filter with two dimensions will be,

$$F(r, s) = median_{(u,v)\in U_{rs}}\{G(u, v)\} \qquad (2)$$

Here, U_{rs} indicates the $b \times c$ sub-image of an input noisy image G. It is centred at the coordinates (r, s). F_{rs} signifies that coordinates' filter's answer. What the pre-processing module produces as an output is Z_a.

Feature extraction: Following pre-processing, a picture is fed as input into the feature extraction Z_a stage. For feature extraction VGG19 is used. In feature extraction phase, 113 CNN features are extracted. CNN is comprised of five layers namely input, fully connected, pooling, convolutional and output. Various CNNs composed of diverse configurations of layers.

Convolutional layer: The convolutional layer function is extraction of features from data, which comprises numerous layers of convolutional kernels whereas individual layer corresponds to weight as well as deviation coefficient. While convolution kernel k is in functioning, the coefficient of weight is assumed as W_k deviation quantity is denoted by d_k and an input of convolutional layer k is I_{k-1}. The process of convolution is formulated by,

$$I_k = f(W_k \otimes I_{k-1} + d_k) \tag{3}$$

Here, I_k indicates an output outcome of convolution kernel k, convolution operation is signified by $\otimes$ and activation function is symbolized by $f(i)$.

A convolution kernel frequently cleans an input data for extracting attribute information. Moreover, $ReLU$ is considered as an activation function of convolutional layer. When comparing with $sigmoid$, tanh and some other kind of activation operations, $ReLU$ activation operation derivation is easy that can speed the training model and efficiently avoids the disappearance of gradient. $ReLU$ is illustrated by,

$$ReLU(I_k) = \begin{cases} I_k & (I_k > 0) \\ 0 & (I_k \leq 0) \end{cases} \tag{4}$$

Pooling layer: The major operation of pooling layer is realization of in-variance and decreases a complication of CNN by elimination of unnecessary information through down sampling. It has two significant paths for entire pooling such as average as well as max-pooling. An average pooling refers to an average value in assessment region, which is considered as pooling outcome of region whereas max-pooling refers to maximal value present in the region, which is selected as a pooling outcome. While comparing with the average pooling, max-pooling could maintain most significant information. Therefore, max-pooling is represented by,

$$P_p = Max(K_p^0, K_p^1, K_p^2, K_p^3, \ldots\ldots\ldots\ldots\ldots.. K_p^z) \tag{5}$$

Here, P_p indicates the output outcome of pooling area p, Max represents a max-pooling function and K_p^z implies an element τ of pooling area p.

Fully connected layer: A fully connected layer acts as classifiers in whole CNN. The vital functioning of fully connected layer is to take weight of features in convolutional layer as well as pooling layer that are mapped to space of hidden layer and re-map then to space of sample marker. In fully connected layer, relating dropout operation is fixed to remove neurons randomly for preventing the over-fitting occurrence. Thus, the CNN features have number of features, which are combined to form a feature vector and are signified by E_a .

Proposed CSCOOT_CNN with transfer learning for classification of Alzheimer's disease:
After that, the extracted features are used for the first level classification of AD, which uses CNN with transfer learning to classify the diseases EMCI, LMCI, MCI, AD, and CN. CNN is used using hyperparameters from a trained model, VGG19. The suggested CSCOOT approach fine-tunes the CNN incorporating transfer learning. However, the merger of CSO and COOT optimizer results in the creation of the suggested CSCOOT algorithm.

CNN with transfer learning for classification of Alzheimer's disease:
The CNN is most popular owing to its enhanced performance in classification of image. It comprises of three types of layers namely convolutional layer for learning the features, max-pooling layers for image down sampling as well as decreasing dimensionality and fully connected layer for equipping a network with classification abilities. CNN generally performs better in large database than smaller database. Transfer learning is helpful in CNN applications, where datasets are not larger. In recent times, transfer learning is utilized in applications of several fields like screening of baggage, manufacturing and medical. It eliminates the necessary of having larger database and decreases the longer training time.

The VGG network (VGGNet) is a kind of deep neural network having multi-layered functioning. It is based upon CNN architecture and VGG-19 is very valuable owing to its straightforward nature, such as convolutional layers installed at the top to add depth. In the VGG-19, the max-pooling layers are used as a handler to reduce a size of volume. With 4096 neurons, two completely connected layers are used. Convolutional layers are used to extract features during the training phase, and a limited number of max-pooling layers are coupled to of convolutional layers for reducing dimensionality of features. In an initial convolutional layer, 64 kernels having 3×3filter dimension are used to extract characteristics from input pictures. Completely linked layers are used to prepare the feature vector.

Here, the feature vector E_a is given to VGG-19 for training, where, the hyper parameters are fetched. A pre-trained CNN (VGG19) automatically extracts 4096 features. 1186 of the top features were chosen. Then, the feature vector is trained along with CNN and thus, the classified output is achieved. The CNN with transfer learning is tuned by CSCOOT algorithm. T_a illustrates an output achieved from the CNN with transfer learning. Figure 2 illustrates a CNN procedure that uses the learned VGG19's hyperparameters.

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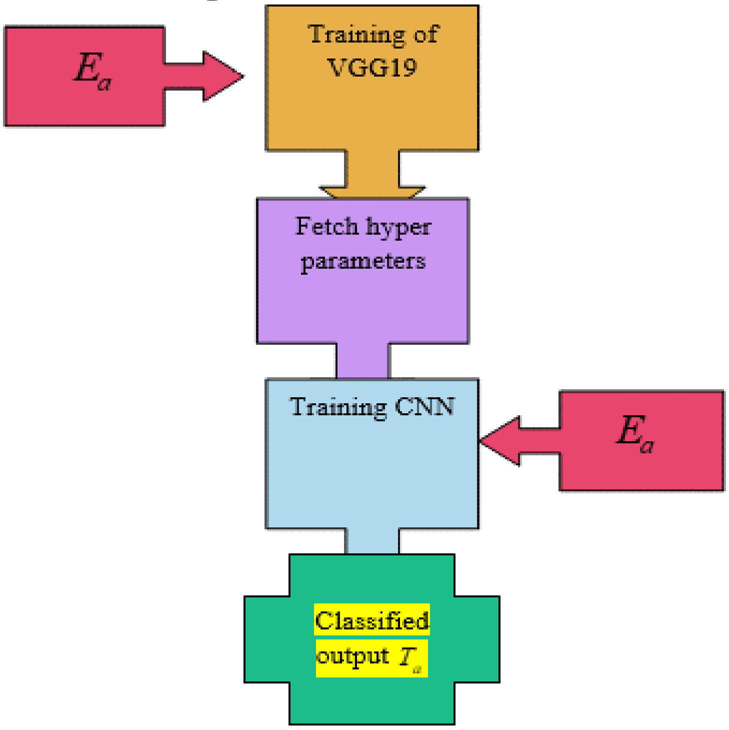


Fig 3. Process of CNN utilized with hyper parameters of trained VGG19

Training of CNN using proposed CSCOOT:

Although it differs conceptually from particle swarm optimisation (PSO), the CSO is designed for larger-scale optimisation. Particle update in CSO involves the participation of either the global or personal best location for each individual particle. As an alternative, a pair-wise competition processing is shown, in which the losing particles update their location by gaining knowledge from the victor. The COOT algorithm draws inspiration from the coot behaviour of birds. It imitates two different ways that birds move on water. The migration of birds is irregular in the first phase and regular in the secondary phase. In this case, the two approaches are combined and referred to as CSCOOT in order to train CNN via transfer learning. As a result, this recently developed method performs better while tackling optimisation challenges.

Competitive Swarm position encoding:

By adjusting the learning parameterβ , the expression is obtained to obtain the best result in the search space.

$$\mu = [1 \times \beta] \qquad (6)$$

Fitness function:

In convolutional neural network (CNN) training via transfer learning, the fitness function is the difference between the desired and actual outputs. This is achieved by the use of,

$$\eta = \frac{1}{m} \sum_{a=1}^{m} [\, J_a - T_a\,]^2 \qquad (7)$$

In this case, the total samples are represented by y whereas J_a and T_a ,the intended and actual outputs of the deep neural network (DNN) developed by the process of transfer learning.

Here we will go over the steps that the algorithm takes to train a CNN with the recently created CSCOOT and transfer learning.

Step 1: Solution initialization

The optimization issues are initially initialized by obtaining an initialized population using the following equation.

$$C = \{C_1, C_2, \dots \dots C_i, \dots ., C_j\} \quad (8)$$

Where, C_i represents the i^{th} candidate solution whereas j implies, where v is the number of variables & s is the current solution.

Step 2: Evaluation of objective function

For attaining finest solution, in this case, we use an objective function that is determined by subtracting the goal output from the observed output using CNN as well as transfer learning. Equation is used to formulate the expression. (7).

Step 3: Random selection of two particles

The position and velocity vectors of each particle has μ are in three has μ dimensions. $Q(g) = Q_1(g), Q_2(g), \dots\dots Q_\mu(g)$. In every generation, the particles in $R(g)$ are divided into $t/2$ pairs at random; a swarm t with an even number of particles is called a couple. Then, two particles from each pair compete with each other. In the end, every kind of competition If a particle has the highest fitness as ω, it is directly fed into the next generation swarm $R(g+1)$; if it has the lowest fitness, it updates its location and speed by gaining insight from the victor through λ.

After then, the unsuccessful particle undergoes a swarm learning process. $R(g+1)$. The particles compete with one another simultaneously. In relation to the swarm's size, $t/2$ competitions happen and consequently, the position & speed of each particle are both factors in a single competition of $t/2$ particles are updated.

4. Results and Discussion

Here we show the outcomes and talk about the newly introduced CSCOOT_CNN with transfer learning in terms of the performance metrics (namely, accuracy, sensitivity) that are in use. Subsections following include elaborate on experimental settings, dataset descriptions, evaluation measures, experiment results, and comparisons to existing approaches.

4.1 Experimentation setup

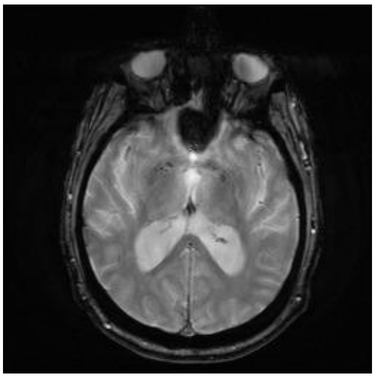
The system requirements include an 8 GB RAM, Windows 10, and an Intel Core i3 CPU is used to execute the AD categorization procedures that have been devised using the Jupiter Python tool.

4.2 Description of dataset

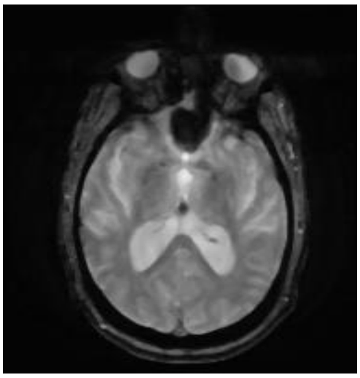
The dataset utilized in this research was sourced from the ADNI website. The Alzheimer's-ADNI dataset contains 145 pictures for AD, 493 for CN, 204 for EMCI, 61 for LMCI, and 198 for MCI.

4. RESULTS:

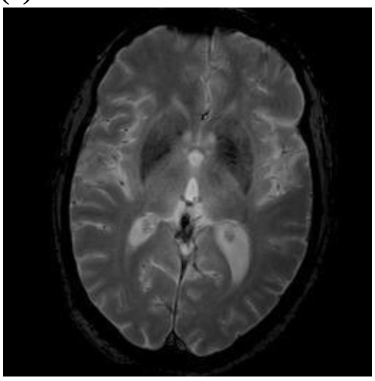
The outcomes of the trials that were carried out to categorize AD utilizing the developed approaches are shown in Figure 4. Both the input image-1 and the pre-processed image-1 may be seen in Figure 4(a) and 4(b), respectively. The processed version of the same image is shown in Figure 4(d), whereas Figure 4(c) displays the original input image. In Figure 4(e) and 4(f), you can see the input image in its original and modified forms, respectively.



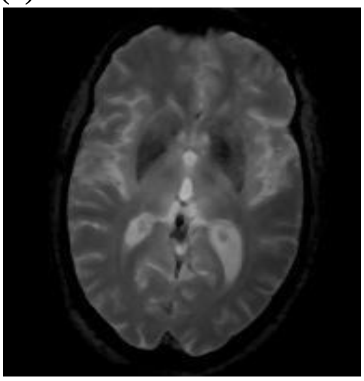
(a)



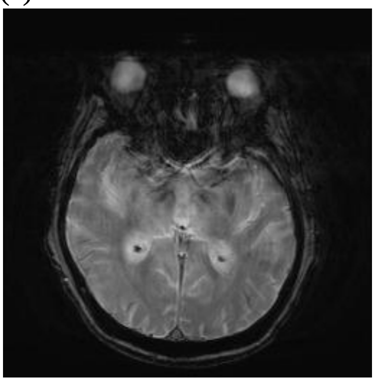
(b)



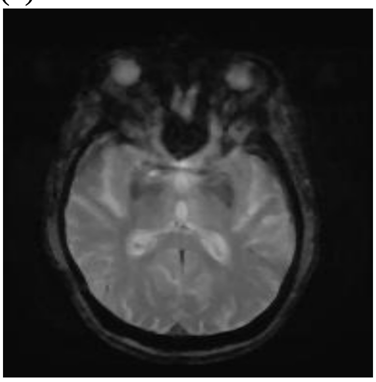
(c)



(d)



(e)



(f)

Fig 4(a). Experiment outcomes of input image-1, Fig 4(b) pre-processed image-1, Fig 4(c) input image-2, Fig 4(d) pre-processed image-2, Fig 4(e) input image-3, Fig 4(f)pre-processed image-3

Performance measures:
Below, we explain the performance measures that were used to conduct an examination into the proposed methods for AD classification.

Accuracy: The term "accuracy" refers to the ratio of right predictions to all input samples. It could be made by,

$$\delta = \frac{H + B}{(H + E + B + T)} \quad (9)$$

In this case, for every true negative, there is a corresponding true positive, and for every false negative, there is a corresponding false negative sign.

Sensitivity: The following is how to calculate sensitivity, which is defined as the ability to identify an individual with AD as positive,

$$\varepsilon = \frac{H}{H + T} \quad (10)$$

Specificity: A measure of specificity is the proportion of individuals in a sample who do not have Alzheimer's disease (AD) when tested for the condition. Here is the formula that is used to calculate it.

$$\partial = \frac{B}{B + E} \quad (11)$$

Comparative techniques: This section aims to demonstrate the effectiveness of newly developed techniques by comparing them to some traditional methods, such as Competitive Swarm Multi-Verse Optimizer (CSMVO)+DNFN, CNN, Deep Siamese CNN, Residual neural network, and CNN all figure prominently. This aptly describes the methods that have been suggested.

Comparative analysis: The next sections elaborate on a comparison of the introduced technique to classical procedures in terms of performance measures.

Analysis based on classification: When it comes to classification, we test out the suggested CNN and CSCOOT_CNN with transfer learning using different k-fold values and training data percentages as performance indicators.

Analysis based upon k-fold value Figure 5(a),5(b),5(c) shows an analogous CSCOOT_CNN estimate according to performance metrics utilizing transfer learning by altering k-fold from 6 to 10.

Figure 5(a) shows the accuracy evaluation of CSCOOT_CNN with transfer learning. Current methods, such as Deep Siamese CNN, CNN, Residual neural network, DNFN, and CSMVO+DNFN, accomplished 0.593, 0.624, 0.647, 0.670, and 0.696 with a k-fold value of 6, respectively, in comparison to CNN with transfer learning's 0.926 accuracy.

The specificity of CSCOOT_CNN with transfer learning is seen in Figure 5(b). With a k-fold value of 6, other classic approaches such as Deep Siamese CNN, CNN, Residual neural network, DNFN, and CSMVO+DNFN produced specificities of 0.673, 0.695, 0.716, 0.765, and 0.782, respectively. In contrast, CNN with transfer learning and CSCOOT_CNN with transfer learning achieved specificities of 0.972 and 0.979, respectively.

Figure 5(c) defines an evaluation of CSCOOT_CNN with transfer learning through sensitivity. Existing approaches, including Siamese deep the sensitivity values for CNN, Residual neural network, DNFN, and CSMVO+DNFN were 0.620, 0.658, 0.680, and 0.712, respectively, with a k-fold value of 6. While CSCOOT_CNN with transfer learning attained a sensitivity of 0.909, CNN with transfer learning reached 0.881.

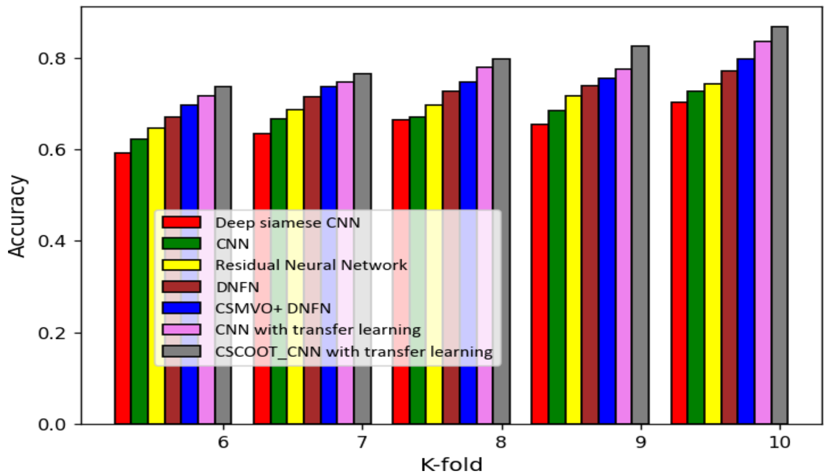


Fig.5(a). Evaluation based upon value of k-fold Accuracy

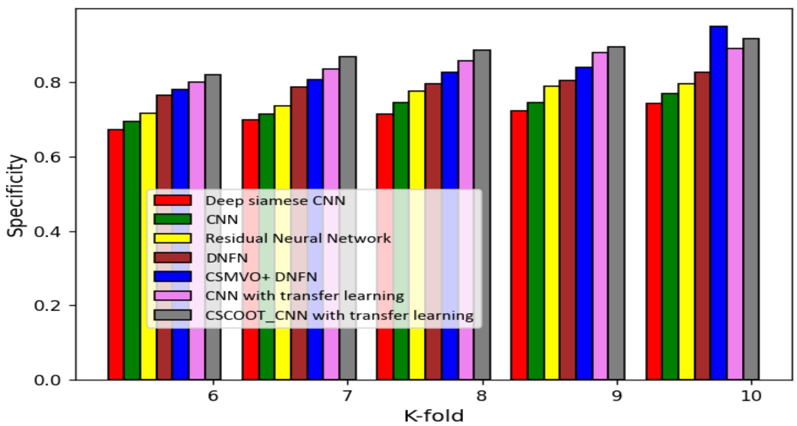


Fig.5(a). Evaluation based upon value of k-fold Specificity

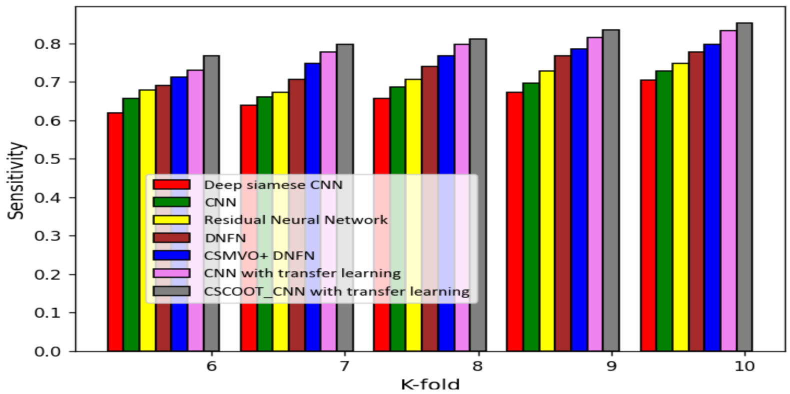


Fig.5(a). Evaluation based upon value of k-fold Sensitivity

Analysis based upon training data: Figure 6(a),6(b),6(c) shows that the proposed CSCOOT_CNN with transfer learning undergoes a comparable performance measure evaluation when the proportion of training data is increased from 60% to 90%. The accuracy of CSCOOT_CNN with transfer learning is shown in Figure 6 (a). Both the suggested CNN and With data=60%, CSCOOT_CNN with transfer learning achieved an accuracy of 0.869 and an accuracy of 0.827, respectively, while the other methods, such as Deep Siamese, confined neural network, convolutional neural network, residual neural network, DNFN, and CSMVO+DNFN, reached 0.702, 0.713, 0.746, 0.765, and 0.787. Expressed in figure 6 (b) is an assessment of the suggested CSCOOT_CNN using specificity-based transfer learning. At data=60%, CNN with transfer learning and CSCOOT_CNN with transfer learning got specificities of 0.780 and 0.799, respectively, whereas more conventional approaches like A specificity of 0.651 was achieved by Deep Siamese CNN, 0.674 by CNN, 0.709 by Residual neural network, 0.728 by DNFN, and 0.750 by CSMVO+DNFN. An evaluation of CSCOOT_CNN with transfer learning is shown in Figure 6(c) with respect to sensitivity. In a 60% data set, for instance, CSCOOT_CNN achieved a sensitivity value of 0.909, while classical approaches like Deep Siamese CNN, CNN, Residual neural network, DNFN, and CSMVO+DNFN reached sensitivity values of 0.731, 0.768, 0.791, 0.814, and 0.839, respectively.

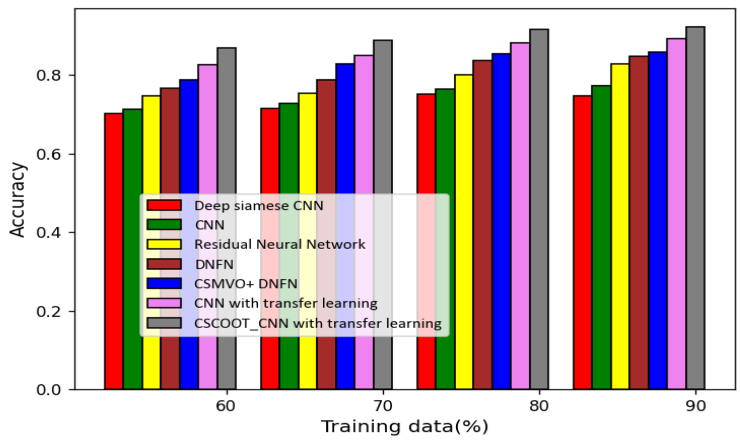


Fig.6(a). Evaluation based upon training data Accuracy

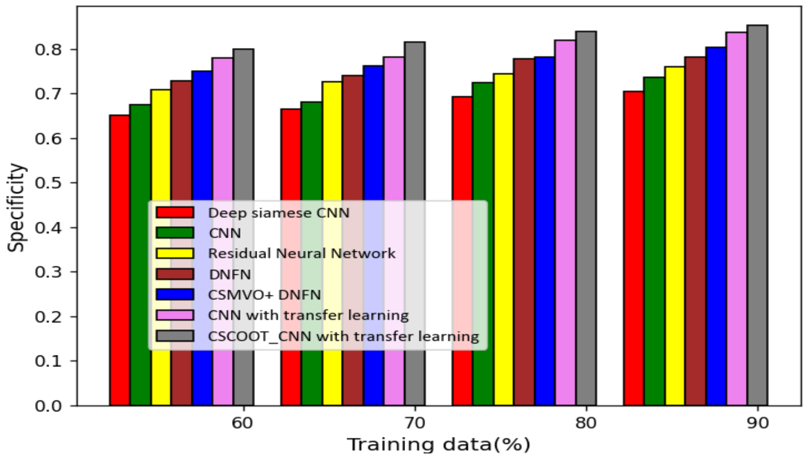


Fig.6(b). Evaluation based upon training data Specificity

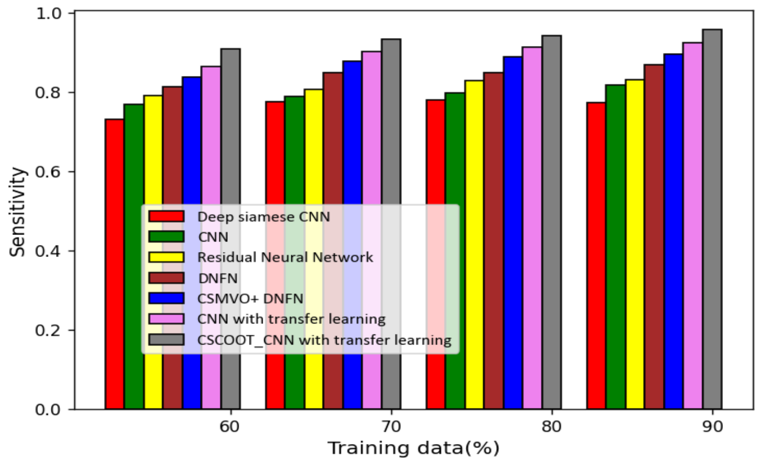


Fig.6(c). Evaluation based upon training data Sensitivity

Comparative discussion: The recently created CSCOOT_CNN is compared to transfer learning in Table 1. At 60% data, CSCOOT_CNN achieves an accuracy of 0.869, a specificity of 0.799, and a sensitivity of 0.909. These metrics are shown in the table.

Table 1. Comparative discussion of CSCOOT_CNN with transfer learning

Analysis based upon	K-fold value=6			Training data=60%		
Metrics/Methods	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity
Deep Siamese CNN	0.593	0.673	0.620	0.702	0.651	0.731
CNN	0.624	0.695	0.658	0.713	0.674	0.768

Residual neural network	0.647	0.716	0.680	0.746	0.709	0.791
DNFN	0.670	0.765	0.691	0.765	0.728	0.814
CSMVO + DNFN	0.696	0.782	0.712	0.787	0.750	0.839
CNN with transfer learning	0.91	0.972	0.881	0.827	0.780	0.866
Proposed CSCOOT_CNN with transfer learning	0.926	0.979	0.909	0.869	0.799	0.909

5. CONCLUSION:

An earlier recognition of AD acts a vital part in controlling and prevention of its progress. Hence, an effective technique is introduced namely CSCOOT_CNN with transfer learning for AD classification. Firstly, the input images are considered from ADNI dataset. The input images are next passed on to the pre-processing step, when the median filter is employed, in order to remove any noise. Then, CNN features are recovered from the pre-processed image by passing it via feature extraction. The initial stage of classification uses convolutional neural networks (CNNs) with transfer learning to classify diseases; in this case, the trained model VGG19's hyper parameters are applied to the CNNs. Feature extraction follows. In addition, the CSCOOT method is used to fine-tune CNNs that incorporate transfer learning. The CSCOOT technique is newly introduced by amalgamation of CSO and COOT optimizer. If the classified output is CN, then second level of classification can be performed. Moreover, proposed CSCOOT_CNN achieved maximal value of accuracy as 0.869, specificity as 0.799 and sensitivity as 0.909. As a future work, the proposed techniques will be intended to perform the segmentation of features before AD classification.

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