Integration Of Fuzzy Logic And Deep Learning For Medical Image Analysis In Neuroimaging

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ABSTRACT

Input from magnetic resonance imaging (MRI) scans is used by contemporary deep learning algorithms to assess changes in brain structure. Over the past several years, a variety of deep learning techniques have gained popularity for their application in the process of feature learning and the enhancement of the responsiveness of systems for learning. We are able to apply a deep learning classifier to identify structural changes in the brain and express the spatial information in this study. This is made possible by integrating the transfer learning model with a fuzzy convolutional neural network (CNN) that performed 3D convolutions at earlier levels. Through the utilisation of ResNet and 2D fuzzy convolutional layers, the model makes use of MCI, which is more often referred to as AD, in order to enhance class separability. To facilitate binary classification in the study, the suggested model is trained and evaluated over a collection of sagittal, coronal, or transverse MRI slices. This is done in order to facilitate the job. An approach known as 5-fold cross-valuation is utilised in this research project in order to investigate the accuracy that was achieved via the use of classification issues during testing and training. In terms of accuracy, the suggested technique achieves a rate of 99%, which is higher than both existing methods and methods that do not use ResNet and 2D Fuzzy convolutional layers. This is according to the data obtained from simulations.

1. Introduction

A condition that affects the nerve system and is gradual and irreversible. Alzheimer's disease (AD) is characterised by a number of symptoms, including dementia, decreased memory, cognitive decline, gradual loss of motor skills, and an inability to care for oneself on a daily basis [1]. The estimated 47–

152 million additional instances of Alzheimer's disease everywhere in the globe by the year 2030 will have significant repercussions for society, medicine, and the economy [2]. There has been no discovery of a medication that can halt the advancement of Alzheimer's disease, nor has there been a cure that has been identified. There is a correlation between screening for amnestic moderate cognitive impairment (MCI) and an increased risk of Alzheimer's disease (AD) when compared to screening for healthy cognition (HC) that is age identical [3]. Early detection of mild cognitive impairment (MCI) is essential for the development of novel medications and treatments that can slow down the evolution of Alzheimer's disease. Screening for MCI can assist detect the disorder at later stages.

By utilising neuroimaging techniques such as magnetic resonance imaging (MRI) of the brain, it is now possible to investigate changes associated with Alzheimer's disease (AD) without having to resort to invasive methodologies. The use of magnetic resonance imaging (MRI) in support vector machines and random forests, two of the most intriguing and promising applications of machine learning, has resulted in an improvement in the prediction of Alzheimer's disease [4, 5]. The present approaches to machine learning usually rely on human interaction to manually identify regions of interest (ROIs) in the brain that are related with recognised MRI indications of Alzheimer's disease (AD). This is because of the fact that human intervention is necessary. This is because there is a dearth of knowledge on definitive MRI biomarkers for Alzheimer's disease. As a result, it is highly unlikely that pre-selected regions of interest will capture all of the information that could assist in comprehending the complexity of the disease. Manual selection is associated with a number of drawbacks, including the fact that it necessitates a significant time and cost investment, as well as the possibility of human error [6].

There is a possibility that the target space poses an integrated challenge because to the irregularity of the fit of the MRI pixels belonging to the different classes. By way of illustration, if you simply use 2D fuzzy-CNN [7] or 3D-CNN [8], you will end up losing layer information, which will significantly increase the complexity of the approach. This is clearly proved by study that was done in the past. In addition to this, it prohibits the procedures that were previously stated from obtaining exceptionally high levels of accuracy. The fact that spectral MRI data is intrinsically volumetric is the fundamental reason for this, and it is the fact that this is the primary reason. When just the 2D Fuzzy-CNN is subjected to spectrographic analysis, the production of feature maps that are of any utility will be impossible. A deep three-dimensional convolutional neural network, on the other hand, calls for a considerable amount of processing power. When used on its own, it performs poorly for classes that have numerous spectral channels that contain features that are distributed and comparable to one another. Additionally, the processing time for spectral-spatial data analysis and interpretation utilising these methods is longer than usual.

For this reason, we make use of a deep learning classifier in our investigation in order to identify the abnormalities in the brain. The following are the primary areas that this work contributes to:

- The authors combine transfer learning with a 3D-2D Fuzzy CNN that makes use of ResNet and 2D Fuzzy convolutional layers in order to increase the ability to differentiate between the two groups (resistance-induced cognitive impairment and Alzheimer's disease).
- The authors train and test the proposed model over a set of multiple MRI slices, such as sagittal, coronal, or transverse slices, in order to enable binary classification. This is done in order to enable binary classification.

Related works

For the purpose of classification, [9] made use of support vector machines in conjunction with a rankwise-selected MMSE score and variables that had an impact on categorisation. However, not every possible combination of elements was taken into consideration, and as a result, it is possible that a combination that has the potential to be successful was overlooked for consideration.

Additionally, [10] looked into the possibility of using a wavelet transform in conjunction with the Naive Bayes classifier. According to our findings, this one is not only simpler to comprehend but also more accurate than the others. The challenging interpretation of the wavelet transform, on the other hand, combined a number of situations into a single aberration, which rendered this method unsuitable for the classification of diseases.

The method of classification that was utilised by [11] was a binary support vector machine that was integrated with voxel morphometry. Despite the fact that the exact proportion varied depending on the availability of MRI datasets, the accuracy that was achieved was one hundred percent.

The utilisation of TANNN, which was proposed by [12], is another method that can be utilised to uncover the micro-level classification patterns that have been noticed. If this method had been able to mine all of the other image components, such as form and texture, it would have been extremely effective [13]. Combining top-down and bottom-up methods is an extra approach that may be utilised for the purpose of detecting patterns inside datasets. The hybrid approach is the name given to this particular strategy. Due to the limited scope of this strategy, it tragically failed to expose the complex web of relationships that exists between the numerous villages that are located in close proximity to one another.

On the other hand, [14] research stated that fractal analysis has the potential to detect structural changes in a timely and accurate manner. The computation of fractal Brownian motion was made possible by making use of the difference in pixel intensity that exists between every row and every column pairing. The accuracy of this particular method of fractal analysis was shown to be higher than that of fractal analysis itself.

Particle swarm optimisation was employed by [15] in order to determine the eigen-brain of a particular slice of three-dimensional data. This was done in order to achieve better outcomes. The method that was presented by [16] is an example of a statistical feature ranking selection strategy that has the potential to assist in lowering the number of inaccurate outcomes. Every one of these methods for recognising patterns in the brain comes with its own separate and distinct set of challenges. Consequently, the utilisation of software for the purpose of doing such studies became more generally advocated.

The multivariate tool was developed by [17], who were responsible for the development of the concepts. It was possible for the model described to acquire the spatial biomarkers for partial least squares analysis, despite the fact that the method only required 259 variables to do this task. A significant improvement in the accuracy of the results was achieved by comparing the measures of regional thickness with the measurements of cortical and subcortical volume.

2. Methodology

Through the utilisation of a deep learning classifier in conjunction with a transfer learning model, this research endeavours to identify anatomical changes inside the brain. The neural network is a 3D-2D fuzzy convolutional neural network, and the early layers of the network make use of 3D convolutions to model spatial information. In a similar manner, three-dimensional convolutions are utilised in the early layers of the network in order to replicate spatial information. In order to improve its ability to discern between additional categories, such as MCI and AD, the model makes use of ResNet and 2D fuzzy convolutional layers. A number of different types of magnetic resonance imaging (MRI) slices were utilised in the research project. These included sagittal, coronal, and transverse slices. Both training and evaluation are carried out with the help of these slices, and Figure 1 illustrates both the proposed model and the full processes involved.

Preprocessing

As can be seen in Figure 2, publications that describe brain MRI segmentation pipelines frequently adopt a top-down presentation. Pre-processing, data preparation, segmentation, and post-processing are the four primary process phases that are broken down into their respective categories in this section. Before the pictures can be used to segment the various types of brain tissue, there are a number of preprocessing processes that need to be undertaken once an MRI has been obtained. These steps are necessary before the images can be used. It is necessary to complete the preprocessing step before beginning an MRI scan. This preprocessing includes a number of different steps, including the registration of pictures, the extraction of brain areas, and the correction of bias fields.

- Magnetic resonance imaging (MRI) of the brain reveals the presence of fat, cornea, and brain tissue in addition to the spinal cord. It is because of the absence of a brain that this region shows the anatomy of the skull and the eyes. Because it distinguishes brain tissue from other types of tissue, skull stripping is an essential step in the process of identifying voxels as either brain or non-brain. In addition to a new picture that is formed entirely of brain voxels, it is also feasible to create a binary number that is also built entirely of brain voxels. Components of the brain include the cerebrospinal fluid (CSF), the general mechanism (GM), and the white matter (WM) of the cerebral cortex and subcortical regions. Brain voxels are distinguished from non-brain voxels in a number of ways, one of which being that the cerebellum is not included in the former of the two.
- The restoration of a more uniform magnetic field is one of the ways that bias field correction helps to increase visual contrast. During the magnetic resonance imaging (MRI) test at a field strength of 0.5 T, the bias field is hardly evident. Magnetic resonance imaging (MRI) may produce skewed results if the strength of the magnetic field that is applied is greater than or equal to three times the normal.
- The purpose of noise reduction is to lessen the amount of locally changing Rician noise that is observed in magnetic resonance imaging (MRI) scans. For applications that make use of deep learning for categorisation, this is a comparatively less significant problem.
- Depending on the particular requirements of the patient, the process of aligning images in common anatomical regions is referred to as either inter-patient image registration or intra-patient image registration. With the help of this approach, we are able to achieve the objective that was outlined earlier. Multichannel characterisation is supplied for every site inside the brain by aligning MRI sequences (such as T1- and T2-W images) using image registration of both within and between patients. This allows for the provision of multichannel characterisation. The process of image registration is helpful in achieving this goal. A data augmentation approach, also known as a patch-based method, is utilised to finish the data preparation process after the initial data processing has been done. In the following step, the research's intended use of the input modalities and patch dimensions serves as the driving force behind the segmentation and categorisation of the data. The process of modifying the results might be as straightforward as selecting the largest groupings or as complex as smoothing out the areas that are produced by the findings.

Dimensionality Reduction

Through the process of extracting orthogonal features from a dataset, principle component analysis (PCA), which is a type of unsupervised feature extraction, can reduce the dimensionality of the feature space. Additionally, spectral redundancy and dataset imbalance were reduced as a result of the reduction in dimensionality at initial I by the utilisation of principal component analysis (PCA). In the spectral-spatial MRI data, there is a significant amount of information that is duplicated for each pixel. This is due to the fact that each pixel displays numerous combinations of land cover classes. With the help of principle component analysis (PCA), it is possible to ascertain the initial class class of an object. In this research, the height H and width W are kept in their precise spatial dimensions. This is done in order to reduce the widths of the layers (that is, from N to S).

$$P \in R^{W \times H \times N}$$

Where *P* defines the transformed input after PCA.

Immediately after the data was collected, we separated it into a number of small 3D patches that overlapped each other: $Q \in R^{S \times S \times N}$. The size of the covering window was represented by these dots in both the horizontal and vertical directions, as can be seen in the figure. When it comes to determining the truth labels, the pixel that is situated at the associated coordinates (α,β) in the middle of the class label is the final option. S 3D patches (n) can have their shapes determined in three dimensions, and this is something that can be done.

$(W\text{-}S+1)\times(H\text{-}S+1)$

In order to position the three-dimensional patch at the coordinates (α, β), the principal component analysis (PCA) decomposed data P and all N spectral layers were utilised. The widths of the patch ranged from (α-0.5(S-1) to (α+0.5(S-1)).

Before making an effort to re-enter the data volume at the location where it was initially stored, it is important to move the data volume. For the purpose of getting ready for the research, we first calculate the average spectrum value for each layer, and then we subtract that value. The third step involves transposing the data matrix that has been preprocessed before utilising it to build the covariance matrix for the data volume. The fourth step is to make use of the covariance matrix in order to obtain the eigenvectors that are pertinent. It is possible to reduce the number of eigenvectors in stages 5 and 6 of the techniques in order to obtain an image with fewer dimensions.

The initial high-dimensional dataset can be reduced to a more manageable size with the help of these strategies, which allow us to minimise its size. Initially and most importantly, the explained variance ratio that is produced by a principal component analysis (PCA) locates a happy medium between the total variance and the main component. The percentage of variation that could be explained was extremely close to 75% across all five groups of samples that were included in the dataset.

Feature extraction

By employing a technique known as feature extraction, all of the unnecessary information that is contained within the dataset is extracted. However, in order to train the learning algorithm, just a small portion of the features contained in the dataset were utilised. The objective of this method, which required determining the suitable subset of features for the learning approach, was to achieve the highest possible level of efficiency while simultaneously lowering the cost of measurement. The study made use of a number of different statistical measures, including the mean, entropy, correlation, homogeneity, and skewness. Additionally, it employed the black area, gradient mean, and symmetry. Some of the extra features that were investigated were the total dark area as well as the gradient mean.

3D-2D Fuzzy CNN Classification

Using image recognition and classification, it is now possible to differentiate between a large number of aberrant brain images based on the feature set. In this section, you can find information regarding the appearance of anomalies identified during brain imaging training and evaluation.

In spite of the fact that the implementations of the two models are significantly different from one another, the 3D-2D Fuzzy-CNNTL model and the recommended model have certain shared similarities in their fundamental architecture. One is able to retrieve the spectral properties that are stored in a multi-layer structure that additionally incorporates spatial information by combining layers of fuzzy convolutional neural networks that are both 3D and 2D.

With the 2D Fuzzy-CNN network, geographical features are learnt, whereas the 3D-CNN network learns the abstract spatial-spectral representation. Both networks are used to learn geographical data. Prior to flattening the layers, it is important to make use of the convolutional blocks that are incorporated into the ResNet model. The split-transform-merge approach is responsible for the production of ResNet blocks, which are distinguished by their high cardinality and deep residual networks during the process. Through the utilisation of the branching paths of the cells, it is possible to alter the remaining building components. When the skip connection path and ResNet block output were utilised, there was an increase in the residual network depth that occurred in an orthogonal sequence.

$$y = x + \sum_{i=1}^{C} \tau_i(x)$$

where

x - Preceding network layer input,

C - Cardinality

y - Output,

τ_i - arbitrary function

Fitness function

Due to the fact that the ResNet model is regarded as being satisfactory, the fine-tuning step did not include any significant weight adjustments. In the study, the Adam optimiser was utilised, and the parameters that were utilised included a learning rate of 0.001 and a weight decay of 1e-06.

When it comes to optimisation, the Adam optimiser is typically more effective than the SGD optimiser. The likelihood of overfitting increases when there is a deficiency in the amount of necessary training data. Early halting with dropout regularisation procedures were utilised by us in order to decrease the amount of model overfitting and increase the amount of generalisation error. We were able to put a stop to the model at an early stage by utilising these strategies.

We did, however, decide to set the dropout rate at 0.55 because the sample size of the dataset that was being evaluated was significantly bigger. We investigated the possibility of utilising an early stopping criterion in order to swiftly terminate training, which involves reducing validation performance in order to guarantee that convergence has taken place. As a consequence of this, this pattern is taken into consideration continuously during the training process in order to simplify calculation without compromising classification accuracy. After reducing the number of components to 75 by computation, we carried out each experiment for a total of one hundred epochs. The most realistic comparison to the output of the HybridSN model would be possible, according to our reasoning, if we used a spatial window that was 25 by 25. The model that we have proposed for the dataset contains a certain number of parameters, which are described in greater detail in Table 1.

We make use of the activation function of ResNets when we are dealing with the process of convergence. When compared to other types of saturating activation functions, this particular type of function often results in a faster convergence rate during the training experience. As a result of this, the expenses associated with testing and training are reduced, the model is able to more precisely reflect complex functional relationships, and its optimisation skills are improved.

$$f(x) = \max(0,x).$$

Pseudocode

1. Load Dataset
- Load MRI images and their corresponding labels
- Perform any necessary preprocessing (e.g., normalization, resizing)

2. Dimensionality Reduction using PCA
- Apply PCA to the dataset
- Compute the mean of each spectral layer
- Subtract the mean from each data sample
- Compute the covariance matrix of the preprocessed data
- Calculate eigenvectors and eigenvalues from the covariance matrix
- Select the top principal components to reduce dimensionality
- Transform the data using these components

3. Data Preparation
- Divide the data into overlapping 3D patches (Q ∈ RS×S×N)
- Determine the truth labels based on the central pixel of each patch
- Compute the dimensions of the patches (e.g., (W-S+1) × (H-S+1))

4. Feature Learning with 3D-CNN
- Initialize a 3D-CNN model
- For each layer (i), apply 3D convolutions with kernel size (2γ+1, 2η+1, 2δ+1)
- Use ReLU or another activation function for non-linearity
- Apply weight and bias constraints during training
- Use gradient descent for optimization

5. Feature Learning with 2D Fuzzy-CNN
- Initialize a 2D Fuzzy-CNN model
- Apply 2D convolutions to the output of the 3D-CNN layers
- Use ReLU or another activation function for non-linearity
- Use weight and bias constraints during training

6. ResNet Model Integration
- Initialize a ResNet-50 model
- Construct ResNet blocks with bottleneck architecture
- Apply the split-transform-merge method to build residual networks
- Use convolutional blocks before flattening layers
- Configure the model with a dropout rate of 0.55 and early stopping

7. Model Training
- Define the loss function (Softmax loss)
- Use the Adam optimizer with learning rate of 0.001 and weight decay of 1e-06
- Train the model for 100 epochs
- Monitor validation performance and apply early stopping if needed
- Flatten the output before feeding it into the fully connected (FC) layers
- Output the class probabilities

8. Evaluation
- Assess the model's performance on the test set
- Compare results with the HybridSN model and other benchmarks

9. Post-processing
- Analyze the results

3. Results and discussion

One set of data samples is used for testing, and the other set is used for training. This is accomplished by the utilisation of a random number generator. Using the sample data that was received from the training set, the suggested DL classifier is trained, as can be seen in the image. Therefore, by applying the concepts of learning and training, it is possible to construct a classification model and to carry out research on samples taken from test sets. Utilising test set samples, the trained model is able to make predictions regarding future classifications and assess the accuracy of classifications that have been made in the past.

During the process of training and validating the model, a number of volumes of subcortical and cortical structures, as well as surface area and cortical thickness, were employed in a sequential manner.

Dataset

CSF, GM, and WM are the three distinct datasets that are utilised in the classification of patients who have been diagnosed with Alzheimer's disease (AD). In order to evaluate a three-dimensional magnetic resonance imaging (MRI), these datasets are employed. A few examples of publicly available datasets are the following: the Internet Brain Segmentation Repository (IBSR), the Open Access Series of Imaging Studies (OASIS), the Medical Image Computing and Computer-assisted Intervention (MICCAI) project, and the Alzheimer Disease Neuroimaging Project (ADNI).

OASIS

The Alzheimer Disease Research Centre at Washington University in St. Louis is the organisation that is in charge of the OASIS dataset. This dataset contains a substantial amount of longitudinal and cross-sectional brain MRI data from patients with dementia as well as healthy individuals. The cross-sectional dataset includes information from 424 people ranging in age from 18 to 96 years old, whereas the longitudinal dataset includes scans from all of the participants at different intervals in time. For the purpose of identifying whether or whether an individual is at risk for Alzheimer's disease, the clinical dementia rating (CDR) and the mini-mental state examination (MMSE) are utilised as useful instruments.

ADNI

Magnetic resonance imaging (MRI) of the brain is performed on 843 individuals in the Alzheimer's Disease National Initiative (ADNI). The strength of the fields used in the MRI ranges from 1.5T to 3T, which allows for the diagnosis of Alzheimer's disease (AD). Mild cognitive impairment, also referred to as MCI, is a condition that is diagnosed in people who have a lower cognitive capacity. This means that they have difficulty remembering information and thinking coherently. Because of this, we classify them as a distinct group from those who suffer from Alzheimer's disease.

IBSR

Through the use of the IBSR dataset, a wide variety of algorithms for brain image segmentation can be evaluated and developed. In addition to the results of the MRI scan, this dataset also contains the outcomes of expert segmentation performed with hand direction and subjected to human guidance. For the purpose of this inquiry, the ground truth consists of twenty actual T1-weighted (T1-W) magnetic resonance imaging (MRI) pictures, each of which has expert segmentation findings shown and led by hand.

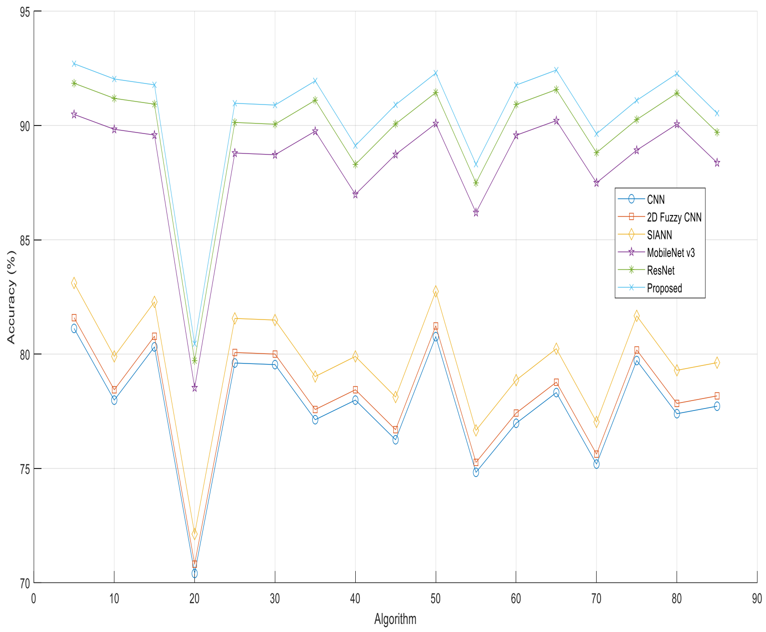

Figure 2: Accuracy of OASIS

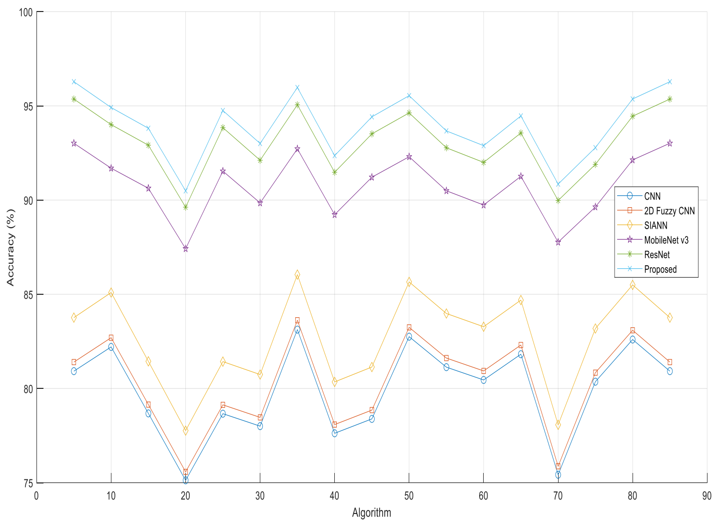

Figure 3: Accuracy of ADNI

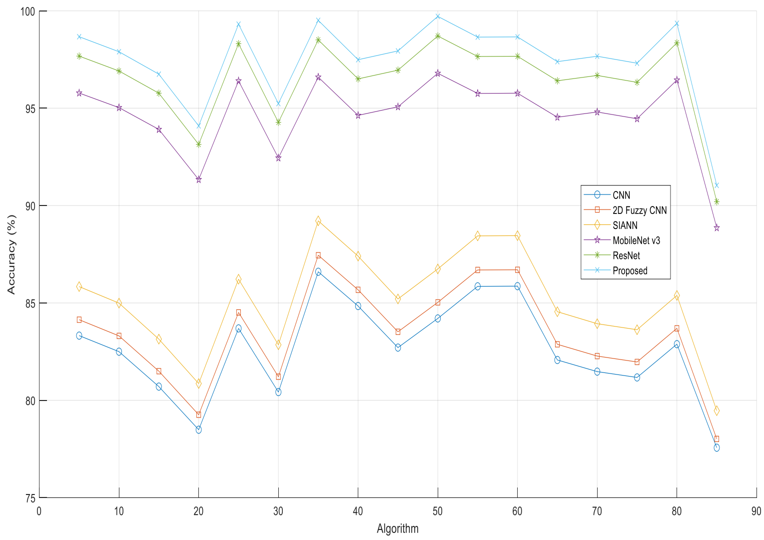

Figure 4: Accuracy of IBSR and MICCAI

Given the results presented in figure 2-4, it can be concluded that the proposed method is superior to the others in terms of classification accuracy. We have integrated the IBSR and MICCAI datasets because there is a limited availability of samples; nonetheless, even after combining, the data availability is still rather limited. This is because of the limited availability of samples. The utilisation of a data augmentation technique has resulted in the development of 553 training examples and 85 test samples. According to the average accuracy values (Figures 4–6), the proposed technique performs better than the alternatives in terms of classification rate for AD type identification. Therefore, the proposed method is superior.

4. Conclusion and future scope

In order to model spatial information utilising a transfer learning paradigm, this deep learning classifier employs a 3D-2D fuzzy convolutional neural network (CNN) in its early layers. The next thing that needs to be done is to identify the particular brain areas that are impacted by the deep learning classifier. A better ability to discern between various sorts of disorders, such as mild cognitive impairment and Alzheimer's disease, can be achieved by utilising ResNet in conjunction with 2D fuzzy-clustering. A number of different types of magnetic resonance imaging (MRI) slices were utilised in the research project. These included sagittal, coronal, and transverse slices. In order to train and validate the proposed model, these slices are now being utilised. The purpose of this study is to establish the degree of correctness by analysing the results of running categorisation activities at different phases of training and assessment using five-fold cross-valuation. The proposed solution exceeds the existing methods by a significant margin; it achieves an average accuracy of 94% (97.4% for Dataset 1, 94% of dataset 2, and 91% for datasets 3 and 4 combined). This is accomplished by combining it with 2D Fuzzy CL-ResNet..

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