RESEARCH ARTICLE

Improved Alzheimer's Detection with a Modified Multi-Focus Attention Mechanism using Computational Techniques

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Abstract: Alzheimer disease is a common type of dementia which shrinks the brain cells and eventually causes death. It disturbs the life quality of patients with progressive symptoms such as memory loss, conversation, etc. It is vital to identify the disease earlier to get precise treatment. Besides, it is significant to locate the forms of Alzheimer's such as AD (Alzheimer Disease), CN (Cognitive Normal), and MCI (Mild Cognitive Impairment). Traditionally, manual screening of Alzheimer's is carried out by qualified physicians, which is a time-consuming mechanism, expensive, and prone to human error. To resolve the issue, several conventional researches attempted to attain better efficiency in the Alzheimer classification but were limited through accuracy, speed, and inefficacy. To address the challenge of classifying Alzheimer's in its various forms (AD, CN, and MCI), the proposed system utilizes the Modified Multi-Focus Attention and Hierarchical Scalerated Convolutional Neural Network (HSCN) mechanisms within the ResNet-101 model. The system undergoes testing with custom datasets such as OASIS, AIBL, and ADNI, and the classification performance is assessed using efficiency factors to gauge the effectiveness of the research.

***Background*:** Alzheimer is a century-old disease, still there is no concrete method to diagnose the disease. Many time diagnosis takes large time and the patient has been referred to many doctors.

***Objective*:** The objective of the study is to create a prediction model using deep learning which will be able to classify the patient into three different classes, CN, MCI,, and AD. The model is trained on hetero dataset, ADNI, AIBL,, and OASIS.

***Method*:** For the deep learning model, we have used Resnet 101 in which the convolution layer is changed to Hierarchical Scalerated CNN and the bottleneck layer is changed to modified multi-focus attention. The preprocessing of the image is also done as the initial step of process.

***Results*:** Our model accuracy is more than 99% for all three datasets used for the research.

***Conclusion*:** The model is trained for MRI from different datasets, the same model should be used for PET scans for Alzheimer's diagnosis, and the same model can be used to diagnose other disease patients which will be very useful for mankind.

Keywords: Alzheimer Disease, Resnet-101, Attention Mechanism, Deep Learning, Cognitive Normal, Mild Cognitive Impairment.

1. INTRODUCTION

Globally, Alzheimer's is a hazardous disease caused by the abnormal accumulation of proteins in and around the brain cells [1, 2]. It disrupts the social life of patients by affecting their conversational capability [3, 4]. Moreover, it can cause symptoms such as memory loss and ultimately lead to death [5, 6]. Mild Cognitive Impairment (MCI) is a health condition that affects the thinking ability of patients. It is crucial to predict the disease early to provide precise treatment and avoid future consequences [7]. The traditional Alzheimer's screening is performed by doctors analyzing MRI (Magnetic Resonance Imaging) data, which is a time--consuming and invasive procedure with potentially inaccu-

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rate and expensive results [8]. To address this issue, a technology-based classification system is needed to enhance the screening process. Artificial Intelligence (AI) is one such technology used in Alzheimer's classification. It leverages machine learning (ML) and deep learning (DL) algorithms and has various applications in the medical field. Correspondingly, the enormous conventional model has thrived to accomplish better classification of Alzheimer disease. For instance, in the existing research, DCNN (Deep Convolutional Neural Network) has been used for Alzheimer disease classification. Here, three stages of Alzheimer are deliberated such as AD, CN, and MCI. The outcome of the experiment signifies better efficiency with the accuracy of 79.12% [9]. Similarly, multi-class classification has been constructed in the classical system with the CNN mechanism. Here, the analysis has been performed on several ML-based algorithms like KNN (K-nearest Neighbor), RF (Random Forest), etc. Besides, the classification has been processed on the FMRI (Functional Magnetic Resonance Imaging) data. The classification result represent better classification performance with an accuracy value of 98.1% [10]. Likewise, enormous classical systems attempted the classification of Alzheimer but lack in accuracy, speed, noise handling task, etc.

To resolve the issue, the proposed system utilized a particular set of techniques for enhancing classification accuracy. Here, three diverse datasets are used to improve the efficiency of the presented system such as ADNI, AIBL,, and OASIS. Primarily, the dataset is loaded in the system which is followed by the preprocessing activities such as image resizing and image data normalization.

"In the preparation of the dataset for classification, an 80:20 data split is employed, with eighty percent used for training and the remaining twenty percent for evaluation. The classification model is built using the Modified Multi--Focus Attention Scale for Enhanced ResNet101. The efficiency of the classification is then assessed using performance metrics.

The key contributions of the proposed system are as follows:

(1) Implementation of the Modified Multi-Focus Attention Scale for Enhanced ResNet101 for classifying Alzheimer's disease into three forms: AD, CN, and MCI.
(2) Utilization of three diverse datasets, including ADNI, AIBL, and OASIS, to enhance the efficacy of the proposed system.
(3) Application of performance metrics to determine classification efficiency.

The paper is structured to explore the methodologies employed in the classification of Alzheimer's disease, as discussed in Section II. Section III outlines the proposed methodology, while Section IV presents the outcomes. Finally, Section V covers the conclusion and future work related to the model."

2. REVIEW OF LITERATURE

The analysis of the existing researches is represented in this section.

In the conventional model, RF (Random Forest) based system has been used in the classification of Alzheimer's disease. Here, brain MRI data has been utilized where three stages of the disease has considered such as CN, MCI, and ADNI. Besides, three sets of features are deliberated in the classical approach. The experimental result signify the better efficacy of the classification with better accuracy [11]. Correspondingly, CNN based framework has been used for Alzheimer's classification [12] on the MRI data. Moreover, the ADNI (Alzhemer's Disease NeuroImaging) dataset has been utilized for the classification of CN and AD. The outcome of the classification represents better efficiency with an accuracy of 97.8% [13]. Similarly, the classification of Alzheimer's disease has been carried out using the CNN technique [13]. In addition, ResNet50 has been utilized in the classical system. The dataset has been extracted from the kaggle website which comprises of MRI data with four classes such as very mild demented, mild demented, moderate demented,, and non-demented. The classification result signify better efficacy with a better accuracy of 90% [14]. Likewise, ResNet-18 aided CNN mechanism has been utilized in the classification of Alzheimer's disease [15]. Here, ImageNet and Transfer Learning Systems has been used in the classical method to enhance the efficacy of the traditional research. The accuracy of the model illustrates better performance with the accuracy of 69.1% has acquired by baseline system and 88.3% has processed with the transfer learning method [16].

Correspondingly, CNN aided system has been used for multiclass and binary class Alzheimer's classification [17]. Here, 4463 slides had been used by the two groups for training and testing. In addition, it has been tested with 10 fold cross-validation method. The result of the classification represents a better accuracy of 96.2% [18]. In the same way, Mp-CNN (multi-plane Convolutional Neural Network))-based architecture has been designed in the traditional model. It has comprise of three stages with three slices like three greatest 3-planes to signify the entire 3D-MRI data as multi-2DCNN technique inputs. The experimental result represent better efficiency with an accuracy value of 95% with NC, 91% with MCI,, and 93% with AD [19]. Likewise, FMRI (Functional Magnetic Resonance Imaging) has been used for the classification of Alzheimer's disease. To attain this, 3D-CNN mechanism has been used in the conventional model. The experimental outcome signifies better efficacy in the Alzheimer's classification [20]. Similarly, pre--trained CNN with AlexNet and ResNet50 has been used in the traditional system for the classification of Alzheimer's. Besides, data for the classification has been acquired from the Kaggle website which comprises MRI data. Here, the classification outcome signifies that the AlexNet attained better performance with an accuracy of 94.53% [21].

In the same way, CNN-based architecture has been constructed for classification of Alzheimer's [22, 23] with three sets of stages such as MCI, AD, and CN. The data extracted from the images of the hippocampus region in the MRI brain data. Accordingly, the dataset has been acquired from the ADNI database. Here, the segmentation has been processed with the matching of ICBM (International Consortium for Brain Mapping Template) with 3D slicer software. The classification outcome signifies better efficiency with an accuracy value of 92.3% [24]. Correspondingly, four forms of Alzheimer's disease [25] have been designed with CNN CNN-aided method. Furthermore, the classical model has been trained using Python with tensor flow library. Here, the dataset has been extracted from the kaggle website with 10432 image data. The classification outcome of the traditional model signify better performance with better accuracy [26]. DCNN mechanism has been deployed for the classification of hippocampus classification and segmentation. Here, structural MRI data has been used for the classification mechanism. Accordingly, the traditional model attained better efficiency with the accuracy of 92.5% [27].

CNN-based model has been used for the classification of Alzheimer's but limited through computational complexity, and noise handling mechanism [20].

Accuracy is the essential factor which determines the whole performance of the classification. Conversely, enormous existing researches lacked in accuracy value [13, 14, 16, 18, 21, 24, 27].

Several traditional systems focused on a single dataset for the Alzheimer disease classification. However, classification of multiple diverse datasets shows the greater efficiency of the classification performance, which is inadequate in the classical systems [13, 24].

3. PROPOSED METHODOLOGY

Alzheimer is a common kind of dementia which is a hazardous illness that disturbs the quality of life of patients. Primarily, it disturbs with the symptoms like mild memory loss to affect the capability of conversation of the patients. It is necessary to predict the disease earlier to give precise treatment for the patients to avoid future consequences. Traditional Alzheimer's screening is carried out by qualified physicians which is the time invasive mechanism as it takes specific time duration to process the results. Moreover, manual screening can be error prone, expensive, and inaccurate. To tackle the limitations, enormous conventional models attempted to attain better classification of Alzheimer but limited by accuracy, speed, and handling larger and diverse datasets. To address the problem, the proposed system utilized a specified set of techniques for the classification of Alzheimer. Fig. (**1**) represents the design of the methodology used in the presented model.

Fig. (**1**) signifies the design flow of the proposed research. It depicts that the respective model in the Alzheimer classification comprises of data collection, preprocessing, data splitting,, and classification. The following subsection presents a detailed description of the presented system.

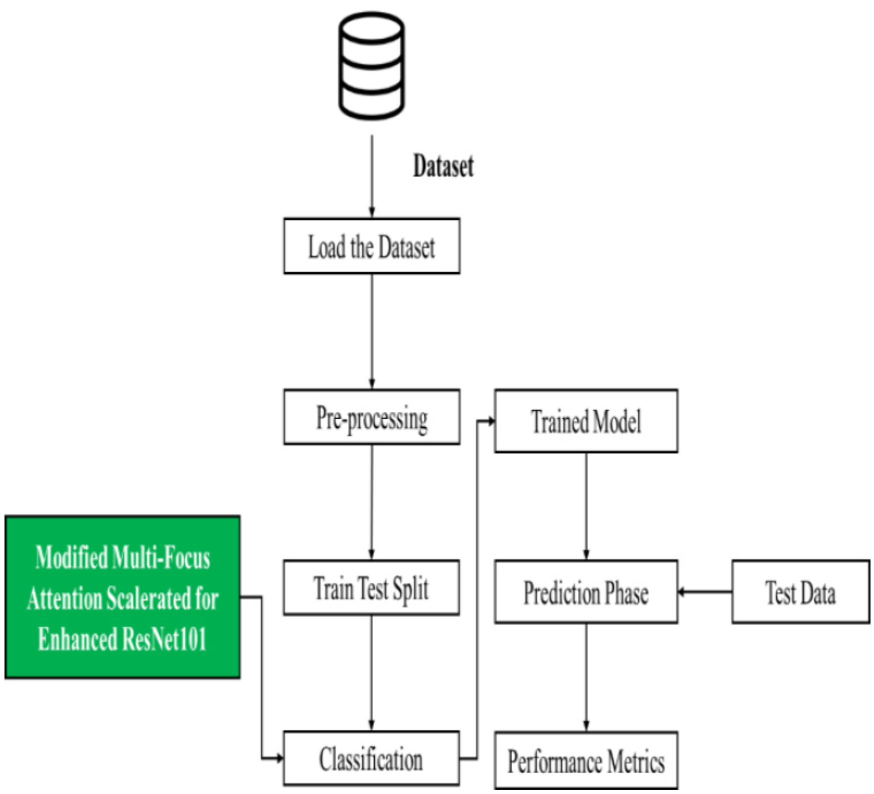

Fig. (1). Technique Design of the Projected System. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

3.1. Data Collection

The proposed research utilized a three diverse sets of custom datasets for enhancing the efficiency of Alzheimer classification. Besides, it is used to evaluate the performance of the projected model on three different datasets. Accordingly, the datasets applied in the respective approach are signified in the following:

- ADNI Database
- AIBL Database
- OASIS Database

Correspondingly, these databases comprise of the MRI data of Alzheimer patients. Here, three classes of Alzheimer's are considered for the proposed classification such as AD, MCI,, and NC.

3.1.1. Alzheimer Disease NeuroImaging Initiative Database

It is a clinical dataset that includes clinical data about every subject which includes extensive patient measurements like MRI data, RNA expression, etc. It comprises of data collected from North American female and male individuals. Besides, it contains 502 attributes taken from 1737 participants. Here, male data was taken from 1453 patients and female data was taken from 1074 patients.

3.1.2. Australian Imaging, Biomarker, and Lifestyle

It is a dataset that is collected through a longitudinal study in the region of Australia. Accordingly, data in the AIBL database comprise of genetic, cognitive, imaging, etc. Besides, it is intended to recognize the risk factors and bio makers related to Alzheimer disease. Here, male data was taken from 1327 patients, and female data taken from 1175 patients.

3.1.3. Open Access Series of Imaging Studies Database

It is a dataset that delivers neuroimaging and associated clinical data. It contains neuroimaging data transversely through the genetic spectrum, cognitive, and demographic for the usage of research related to Alzheimer disease. Here, male data were collected from 1317 patients and female data collected from 1911 patients.

3.2. Pre-processing

The preprocessing is the technique utilized to prepare the dataset for classification. Here, image resizing and image data normalization technique are used for preprocessing the data. The following explains the precise depiction of the preprocessing model.

3.2.1. Image Resizing

It is a significant preprocessing method that alters the image dimensions while retaining the aspect ratio and original content. The image resizing model is utilized to ensure the data encompass of similar dimensions. It is a significant mechanism in the presented approach for extracting the data from a neural network because it requires the data to be in a similar dimension. Besides, it supports in minimizing memory necessity and computational load in the system.

3.2.2. Image Data Normalization

It is a common model in image preprocessing to ensure the pixel value of the data is in the similar scale. The data normalization is utilized to enhance the performance and convergence of the system. It includes scaling the value of pixels to the common scale from 0 and 1 or -1 and 1. Subsequently, it can minimize the influence of varying pixel range in diverse image, which supports enhancing the efficiency of the classification.

3.3. Data Splitting

The preprocessed data were further divided into training and testing on the basis of ratio 80: 20. Eighty percent of the data is used for training and twenty percent of the data is utilized for testing the model. Accordingly, the projected system uses training data for training the classification model, and testing data is utilized to evaluate the efficacy of the proposed classification.

3.4. Classification: Modified Multi-Focus Attention Scalerated by Enhanced ResNet101

The respective research used Modified Multi-Focus Attention Scalerated by Enhanced ResNet101 for the classification of Alzheimer's. The ResNet-101 is the DNN with 101 layers that have the probability to learn more difficult features and capture complicated patterns in the data. However, it may have a certain limitations such as computational complexity and memory requirements, which need to be considered to improve the efficacy of the proposed model. Fig. (**2**) signifies the classification model of the proposed mechanism.

Fig. (**2**) indicates the classification model of the suggested method. Correspondingly, to tackle the problem of the existing ResNet101 and to improve the performance of the classification, Modified Multi-Focus Attention Scalerated by Enhanced ResNet101 is employed in the respective research. The following subsection represents the classical ResNet101 method and Enhanced ResNet101 mechanism in the classification of Alzheimer.

3.4.1. Classical ResNet101 Technique

“The traditional ResNet101 consists of convolutional layers, residual blocks, shortcut connections, pooling layers, and fully connected layers. Initially, a single convolutional layer is processed with a max pooling layer. The residual block consists of multiple residual blocks, each containing multiple convolutional layers. The shortcut connection, or skip connection, allows the network to learn the residual mapping and solve the residual mapping problem. The pooling layers use occasional max pooling for downsampling the spatial dimension in the feature maps. Lastly, the fully connected layers function as the classification mechanism.

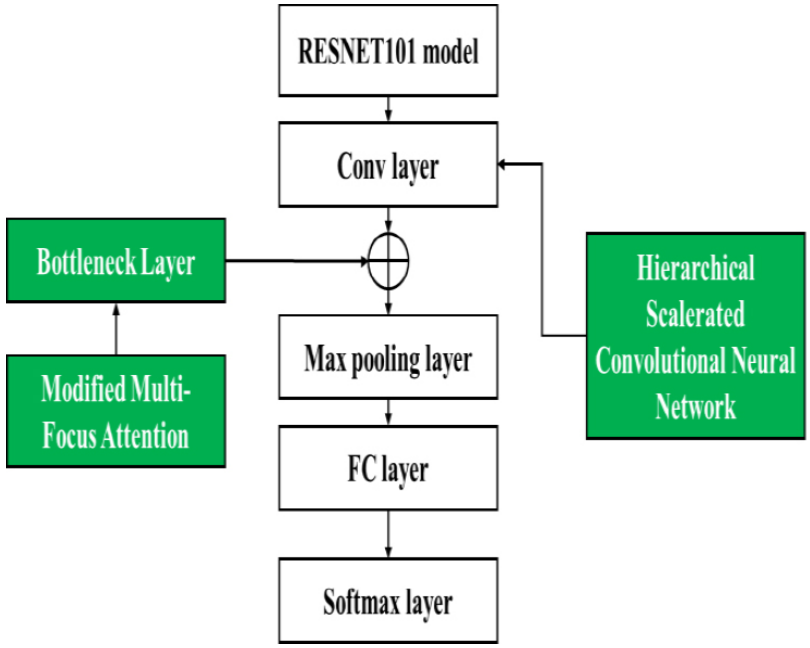

Fig. (2). Classification Model of the Projected System. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

The advantages of ResNet101 include:

- Ability to handle complex patterns

- Capability of managing the vanishing gradient problem

- Enhanced gradient flow

- Better capacity to learn high-dimensional features"

Conversely, it comprises of certain drawbacks, memory requirements,, and computational complexity which will affect the efficiency of the research. To resolve the issue in the conventional ResNet101, the respective research utilized Modified Multi-Focus Attention Scalerated by Enhanced ResNet101. The detailed description of the proposed method is signified in the following section.

3.4.2. Modified Multi-Focus Attention Scalerated by Enhanced ResNet101

The ResNet101 is utilized in the proposed method as it is an effective technique for the prediction of MRI images. The advantages of ResNet101 such as strong generalization capability, exceptional depth, and greater efficacy make it suitable for the proposed classification. To address the limitations of the classical ResNet101 such as computational complexity and memory requirements, the presented system incorporated an enhanced function for improving the classification performance. Fig. (**3**) signifies the enhanced ResNet101 for the classification of Alzheimer.

Fig. (**3**) indicates the proposed ResNet101 system. Here, the respective models integrated the HSCN mechanism and MMFA for Alzheimer's classification. The comprehensive representation is projected in the following.

The proposed system used HSCN as an alternative to the convolutional layer of the ResNet101 with three diverse scales. This technique utilizes concatenation and sampling to retain the essential features. Besides, bottleneck residual blocks for decreasing the computational time of the system. Correspondingly, a 3 x 3 convolution is employed for the last bottleneck of ResNet is substituted with the HSCN blocks in ResNet. This modification is used to improve the capability of feature extraction and enhance the computational efficacy of the classification. Accordingly, an attention mechanism is embedded in the system, which is the self-attention function that highlights the important features in the data. It is signified in equation **1**.

$$m = \text{softmax}\,(pa^{K}+pc^{K})v \quad (1)$$

Correspondingly, MMFA is used in the last bottleneck block in the ResNet-101. It enables the extraction of significant features from the input feature map. Moreover, this modification intends to improve the capability of the feature extraction and computation efficacy of the proposed research in the classification of Alzheimer's.

Lastly, the proposed system is evaluated with the performance metrics to evaluate the efficacy of the system.

4. RESULTS AND DISCUSSIONS

The section represents the results acquired by the proposed system.

4.1. EDA (Exploratory Data Analysis)

The EDA is utilized to view and analyze the data in the dataset. Fig. (**4**) represents the MRI data from the dataset.

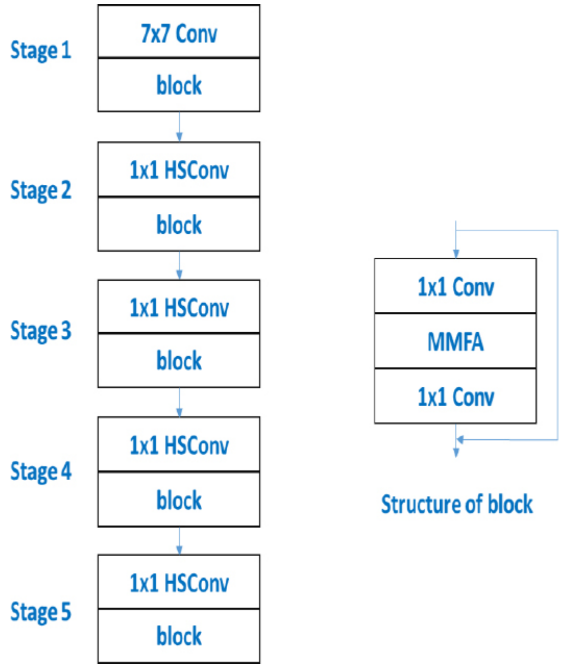

Fig. (3). Proposed ResNet-101 Structure. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

Fig. (**4**) signifies the MRI data from the dataset.

4.2. Experimental Setup

The section represents the tools and requirements for the function of the presented method to process Alzheimer's classification. Table **1** has the experimental setup details.

4.3. Performance Metrics

The effectiveness of the proposed Modified Multi-Focus Attention Scalerated by Enhanced ResNet101 is evaluated with performance metrics. The performance metric are signified in this section.

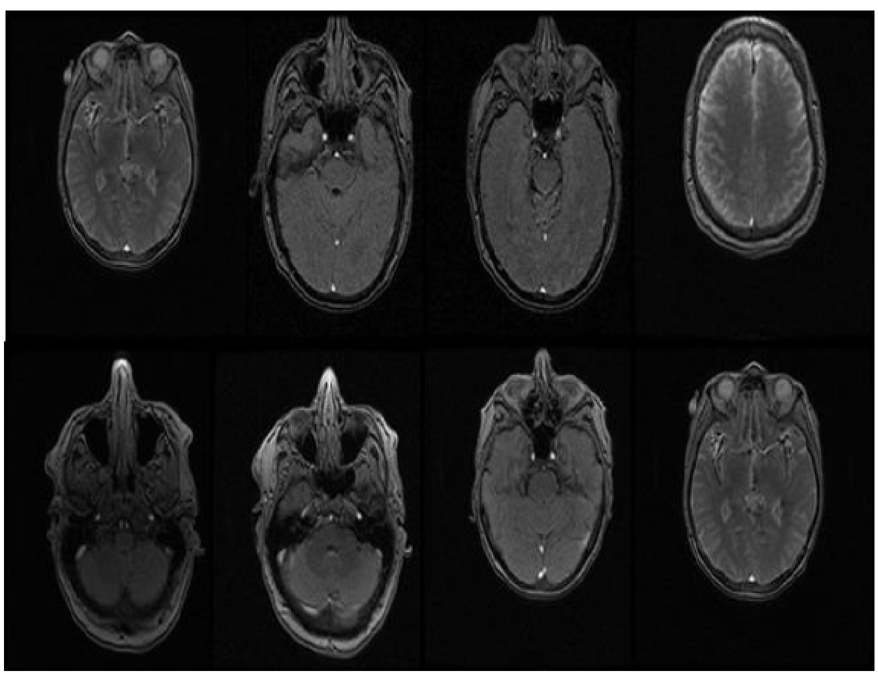

Fig. (4). MRI Data. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

1. F1-score: It is calculated through the values of recall and precision by processing the mean values. The formula is depicted in equation (2),

$$\text{F1} - \text{Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} \tag{2}$$

2. Accuracy: It is stated as a function of taking the ratio of correct identification in the system to complete Alzheimer classification. It is illustrated in equation (3),

$$\text{Accuracy} = \frac{\text{Tp+Tn}}{\text{Tp+Fp+Tn+Fn}} \tag{3}$$

Where Tn is True Negative, Tp is True Positive, Fn is False Negative, Fp is False Positive

3. Recall: The ratio of correctly recognized results to overall classified outcomes. The recall is also called sensitivity or specificity and is represented by equation (4),

$$\text{Recall} = \frac{\text{Tp}}{\text{Tp+Fn}} \tag{4}$$

Where Fn Tp are False Negative and True Positive.

4. Precision: It is the value of the classified positive figure and is stated by the fraction of true positives to the average of true positives and false positives and given in equation (5),

$$\text{Precision} = \frac{\text{Tp}}{\text{Tp+Fp}} \tag{5}$$

Where Fp is False Positive, Tp is True Positive.

4.4. Experimental Results

The outcome attained by the presented model is represented in this section. Table **2** and Fig. (**5**) illustrate the classification outcome of the proposed method for three datasets.

Table **2** and Fig. (**5**) demonstrates the classification outcome of the respective research for the three datasets. It is identified that the proposed system attained greater results in ADNI dataset with an accuracy value of 0.9921. Besides, OASIS attained the classification accuracy of 0.9912 and AIBL accomplished lesser accuracy when compared with the other datasets by attaining 0.99. Moreover, for the metric f1-score, recall, and precision, proposed method accomplished similar results by scoring 0.99 values. Therefore, the experimental results illustrating ADNI dataset accomplished higher results than AIBL and OASIS dataset.

4.5. Performance Analysis

The section analyzes performance of the proposed system on three diverse datasets. Fig. (**6**) depicts the accuracy and loss curve of the respective research on the ADNI dataset.

Fig. (**6**) illustrates the accuracy and loss curve of the presented model on ADNI dataset. It is recognized that the accuracy enhanced at 600 epoch and the loss curve decreased at 500 epoch. Fig. (**7**) depicts the accuracy and loss curve of the respective research on AIBL dataset.

Fig. (**7**) illustrates the accuracy and loss curve of the presented model on AIBL dataset. It is identified that the accuracy enhanced at 800 epoch and the loss curve decreased at 800 epoch. Fig. (**8**) depicts the accuracy and loss curve of the respective research on the OASIS dataset.

Table 1. Experimental Setup.

S.No	Techniques	Tools And Requirements
1.	MRI Image Data,	• MRI datasets(brain)
2.	Hardware Requirements	• Adequate computational properties: CPU and RAMGPU.
3.	Software Requirements	• Python or other programming languages • Image processing libraries and frameworks such as OpenCV (Open Source Computer Vision Library) and TensorFlow.
4.	Visualization Tools	• Matplotlib visualization of volumetric medical images.
5.	Data Pre-processing Tools	• DICOM (Digital Imaging and Communications in Medicine) format conversion python code.

Table 2. Outcome of the Presented System.

MRI image	Accuracy	Precision	Recall	F1-Score
ADNI	0.9921	0.99	0.99	0.99
AIBL	0.99	0.99	0.99	0.99
OASIS	0.9912	0.99	0.99	0.99

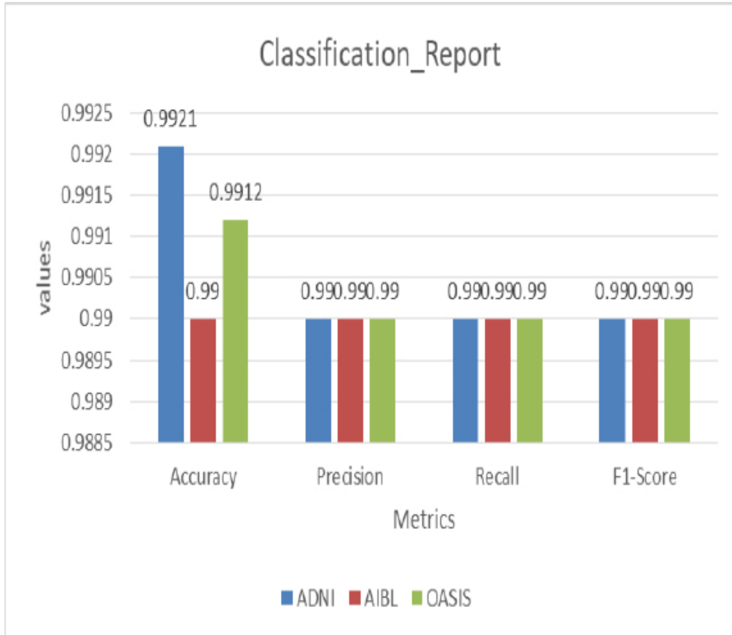

Fig. (5). Results Attained By Projected System. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

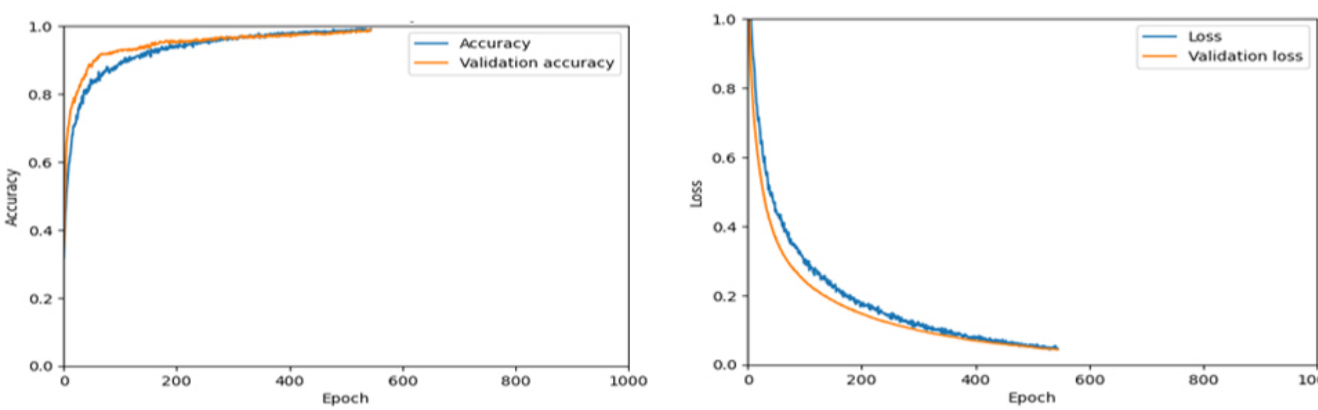

Fig. (6). Accuracy and Loss Curve of ADNI Dataset. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

Fig. (**8**) illustrates the accuracy and loss curve of the presented model on OASIS dataset. It is recognized that the accuracy enhanced at 700 epoch and the loss curve decreased at the 700 epoch. The Fig. (**9**) illustrates the confusion matrix of the proposed approach on the ADNI dataset.

Fig. (**9**) depicts the confusion matrix of the proposed model on the ADNI dataset. Here, it is represented by three forms of Alzheimer such as AD, CN, and MCI. It is identified that the AD form comprises higher correct prediction as 176, CN as 165,, and MCI as 160. Correspondingly, The Fig. (**10**) shows the confusion matrix of the proposed approach on the AIBL dataset.

Fig. (**10**) depicts the confusion matrix of the proposed model on the AIBL dataset. Here, it is represented by three forms of Alzheimer such as AD, CN, and MCI. It is identified that the AD form comprises of higher correct predictions as 175, CN as 161, and MCI as 160. Congruently, The Fig. (**11**) shows the confusion matrix of the proposed approach on OASIS dataset.

Fig. (**11**) depicts the confusion matrix of the proposed model on the AIBL dataset. Here, it is represented by three forms of Alzheimer such as AD, CN, and MCI. It is identified that the CN form comprises of higher correct predictions as 269, AD as 206,, and MCI as 203.

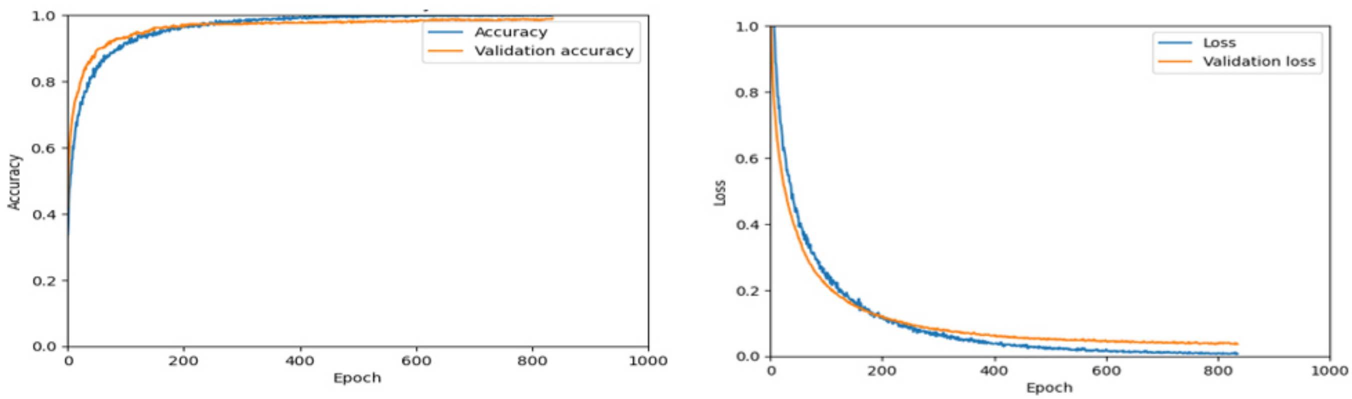

Fig. (7). Accuracy and Loss Curve of AIBL Dataset. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

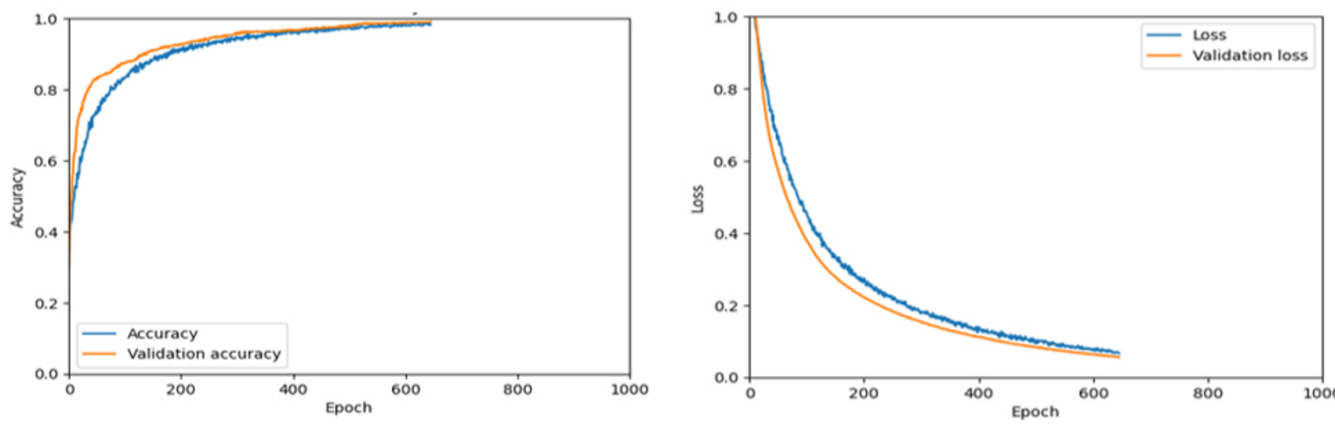

Fig. (8). Accuracy and Loss Curve of OASIS Dataset. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

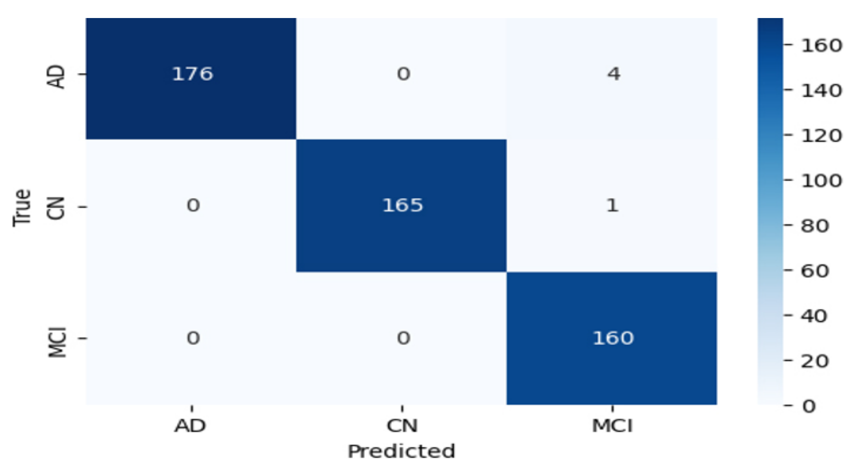

Fig. (9). Confusion Matrix of ADNI Dataset. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

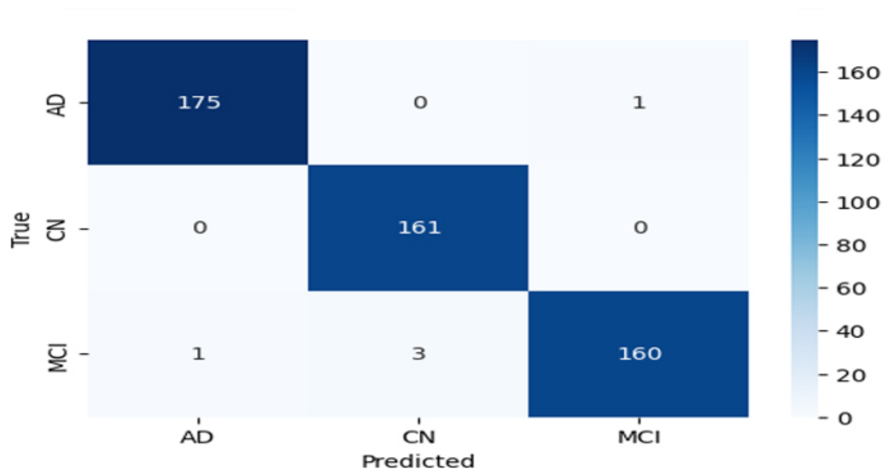

Fig. (10). Confusion Matrix of AIBL Dataset. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

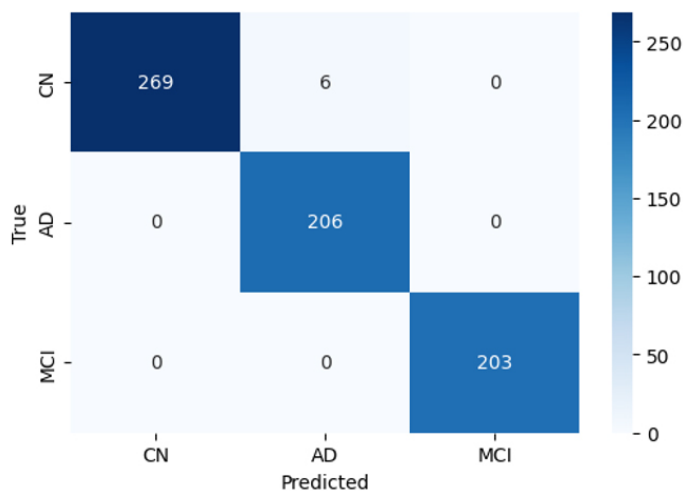

Fig. (11). Confusion Matrix of OASIS Dataset. (*A higher resolution/colour version of this figure is available in the electronic copy of the article*).

5. DISCUSSION

Numerous traditional research studies have previously focused solely on using specific datasets for classification, neglecting the utilization of diverse datasets within a single model. The proposed system seeks to bridge this gap by working with three distinct datasets: OASIS, AIBL, and ADNI. In evaluating performance, accuracy serves as the determining factor for classification efficiency. In contrast, existing models have limitations in accuracy value. The proposed system achieved a notably higher accuracy of 0.9921 with the ADNI dataset. The respective research leveraged the advantages of HSCN mechanism and MMFA for Alzheimer's classification in the ResNet-101 model, incorporating Modified Multi-Focus Attention for Enhanced ResNet101 in the classification of Alzheimer’s across three different forms: AD, CN, and MCI. These techniques were deployed across three diverse datasets.OASIS, AIBL, and ADNI. Besides, the experimental result represent better efficiency of the ADNI with the accuracy value of 0.9921. Moreover, OASIS and AIBL represent better performance with the accuracy value of 0.9912 and 0.99, which reveals the better efficiency of the presented model with the advantages of greater accuracy, speed, and handling of larger and diverse datasets.

CONCLUSION

Alzheimer's disease is the most prevalent type of dementia globally, characterized by progressive symptoms such as memory loss and impaired communication. Accurate disease staging is essential for appropriate treatment and to prevent potential complications. Conventional screening methods are time-consuming, expensive, and often inaccurate, necessitating the use of automated screening mechanisms. To address these challenges, the proposed system utilized Modified Multi-Focus Attention Scalerated by Enhanced ResNet101 for classifying Alzheimer's disease into three distinct forms: AD, CN, and MCI. This research utilized three diverse datasets: OASIS, AIBL, and ADNI, and performance measurement metrics were employed to assess classification accuracy. The experimental results indicate that the ADNI dataset achieved a superior accuracy value of 0.9921 compared to the other datasets. Additionally, both the OASIS and AIBL datasets demonstrated commendable performance, with accuracy values of 0.9912 and 0.99, respectively. Furthermore, the proposed system could potentially be applied to enhance the efficiency of diagnosing other types of diseases in the future.

AUTHORS' CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: study conception and design: J. Pruthi, D. Saraee; analysis and interpretation of results: S.B. Khan, N.A. Alkhaldi; draft manuscript: P.K. Pandey. All authors reviewed the results and approved the final version of the manuscript.

LIST OF ABBREVIATIONS

AD	=	Alzheimer Disease
CN	=	Cognitive Normal
MCI	=	Mild Cognitive Impairment
HSCN	=	Hierarchical Scalerated Convolutional Neural Network

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

Not applicable.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

FUNDING

None

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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Declared none.

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