Journal of Information Systems Engineering and Management
2025, 10(10s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Developing Advanced Deep Learning Layers for Enhanced Automatic Feature Extraction and Higher Accuracy in Alzheimer's Disease Classification

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ARTICLE INFO

Received: 05 Nov 2024
Revised: 20 Dec 2024
Accepted: 12 Jan 2025

ABSTRACT

Alzheimer's Disease (AD) classification through medical imaging is important for early detection and planning treatment, but it's still hard to do because neuropathological changes are so minor and complicated. This work presents new layers of advanced deep learning (DL), intended to enhance automated feature extraction, hence improving the accuracy of categorisation. Conventional approaches for AD diagnosis may rely on manual identification of brain biomarkers, which can take a lot of time and vary for every observer. Our work developed a novel set of convolutional neural network (CNN) layers able to automatically identify and rank structural MRI features connected to AD, hence addressing these issues. Three well-known deep learning architectures—density network, inception network, and ResNet—were employed in this work. Every model was trained and tested using a set of MRI images from AD patients and healthy controls made accessible for public use. The upgraded layers were meant to highlight early AD symptoms like hippocampus atrophy and loss of cortical thickness. The accuracy of categorisation is shown to be much greater than with standard DL models. Showing a 12% increase above the average, our enhanced layers included into the DenseNet architecture made it the most accurate. Our models were also robust in feature extraction; they could routinely identify significant AD-related changes in photos with different sizes and brightness levels. This approach not only accelerates the classification of AD but also provides the foundation for future research on accurate and automated neurodegenerative disease testing, which can significantly influence patient outcomes and therapeutic practices.

Keywords: Alzheimer's Disease Classification, Deep Learning Architectures, Automatic Feature Extraction, Convolutional Neural Networks, Neuroimaging Biomarkers, MRI Analysis

I. Introduction

A neurological condition, Alzheimer's disease (AD) causes individuals to lose their memory and cognitive capacity and worsens with time. Millions of individuals all over are impacted by it. Treating AD depends much on an early and accurate diagnosis as it enables individuals to act fast and organise their therapies, thereby perhaps slowing the course of the illness. Deep learning (DL) has evolved into a really valuable technique in medical imaging during the last several years, particularly for illness diagnosis improvement. Especially convolutional neural networks (CNNs), digital learning models can automatically extract and learn features from big datasets. This has fundamentally altered the analysis of medical images including MRI scans. To diagnose Alzheimer's in the past, expert radiologists had to manually select characteristics from neuroimaging data. These radiologists would search for indicators of the illness including changes in cortical thickness, hippocampal atrophy, and ventricle enlargement. However, this approach requires a lot of effort and the outcomes vary as many practitioners interpret what it entails differently. Given its consistent, repeatable approach that could be quicker and more accurate than human approaches, DL models for automated feature extraction provide a promising solution [1]. Deep learning for medical imaging has advanced a lot, although there are still major issues in the area particularly with regard to generalising the models and simplifying their interpretation. While most conventional CNN designs are decent for dealing with large sets of pictures, they are not meant to be optimal for the nuanced and complicated patterns that exhibit themselves in early-stage Alzheimer's disease. Our work is on developing advanced DL layers that enable MRI images to automatically extract qualities relevant for the brain, hence addressing these issues. These specific layers help to increase the sensitivity of the models to early AD symptoms, which normal DL models usually overlook [2].

This work employs a novel approach by including these higher levels into well-known deep learning models like DenseNet, InceptionNet, and ResNet. Every one of these models is renowned for having certain unique abilities. ResNet is strong at learning deep representations without slowing down because to fading gradients; InceptionNet is good at dealing with data from various sizes; DenseNet is good at recycling features. Our unique layers will help us to leverage the capabilities of existing models and also improve their ability to identify minor AD-related signals in MRI images. New pooling techniques and convolutional filters were applied to enhance the layers in documenting the changes in anatomy resulting from Alzheimer's disease. Furthermore, the layers maintain the stability of the learning process by means of improved activation functions and normalisation techniques, hence enhancing the convergence rate [3]. Training deep models on fewer sets of medical images is therefore simpler and more successful. Although our preliminary findings are still encouraging, they indicate that these enhanced models not only identify AD from MRI images but also have more dependability in a variety of testing scenarios. This includes improved performance at many phases of the illness and a significant decrease in false positives, which is rather crucial in clinical environments where an erroneous diagnosis might be quite costly. A recurrent issue in scanning research, the models also improve in handling variations in brain anatomy across individuals. Propsoed research helps detect AD by surpassing the present capabilities of deep learning. It has significant therapeutic ramifications as well as a technological contribution to the discipline of machine learning. More reliable and precise testing instruments might enable early discovery of Alzheimer's, therefore altering the treatment and care received by millions of people worldwide. Other neurological illnesses might potentially benefit from the developed techniques; hence the impact of this research would be even more significant.

II. Background and Related Work

Researchers have given much focus over the last 10 years on how deep learning (DL) techniques may be used in medical diagnosis, particularly in the categorisation of Alzheimer's disease (AD). Deep learning was first largely used with simple CNN architectures in medical imaging. For many general picture recognition challenges, they performed really well; unfortunately, they were not particularly effective in identifying neurodegenerative disorders like AD as the early symptoms of the disease are so subtle and complex [4]. Academics started focussing on creating and modifying DL models that could better handle the special characteristics of medical imaging data when they learnt about these issues. A particularly crucial area of progress has been in enhancing the feature extraction abilities of DL models to more precisely depict the disease alterations characteristic of AD. Adding layers to regular CNNs that are particularly adept at identifying neuro-specific features has shown researchers to greatly improve the model's diagnostic accuracy [5]. Models like DenseNet, for instance, have been re-designed with more neural layers or revised pooling algorithms to better capture the changes in brain structure that are indicators of AD, including the hippocampal shrinkage and the ventricles increasing larger [6, 7]. Furthermore, a great advance in AD classification has come from integrating attention processes into CNN designs. These factors help the models to concentrate on MRI scan areas more likely to reveal early indications of AD. Consequently, the diagnosing procedure becomes more accurate [8]. Several researches that included attention-based layers to their networks have shown that this approach works as it significantly increases the sensitivity and specificity of AD detection [9, 10]. Both InceptionNet and ResNet have been modified for the purpose of AD classification by including enhanced deep learning layers that enable simpler extraction of intricate characteristics from brain data. For continuous neuroimaging datasets, researchers have developed hybrid approaches combining Inception modules with recurrent brain structures to identify both spatial and temporal abnormalities [11, 12]. This helps one to have a better understanding of AD development. ResNet has also been enhanced using residual learning techniques to handle the vanishing gradient issue. Deep learning models taught on complex medical datasets as those utilised in Alzheimer's research [13, 14] often suffer with this problem.

Another crucial contribution to this discipline is the use of generative adversarial networks (GANs) and autoencoders in data augmentation and feature extraction for AD. These techniques enable to overcome the typical issue of not having enough labelled medical imaging data, which results from attempting to train appropriate deep learning models for healthcare applications [15, 16]. Making fictitious but realistic MRI images of the brain has allowed researchers to expand the training sets. This has made learning more consistent and enabled the models to function better at many phases of AD [17, 18]. These developments have great impact as they not only improve the accuracy of AD diagnosis but also reduce the detection time. Early detection is important for managing and treating AD because it lets people take steps that might slow the disease's development [19]. The better DL models, which can automatically capture more features, are very important to reaching this goal. These models also help personalised medicine by making it easier to make treatment plans for each patient that are based on the exact stage and type of AD shown by the brain study. Personalised care like this can greatly enhance patients' quality of life and shows how powerful deep learning can change healthcare [20, 21].

Table 1: Related Work Summary Using Deep Learning Approaches For Alzheimer's Disease Classification

Method	Approach	Findings	Feature Extraction Method Used	Scope
GANs	Data augmentation for training	Expanded dataset size, improved model robustness	Synthetic image generation	Overcoming limited data issues
Autoencoders	Feature representation and dimensionality reduction	Enhanced feature significance extraction	Compression and reconstruction	Detailed feature analysis for early AD markers
Attention CNNs	Integration of attention mechanisms	Higher sensitivity and specificity in detection	Focus on critical regions	Improved diagnostic precision
CNNs with advanced pooling	Custom pooling strategies	Better capture of morphological brain changes	Customized feature pooling	Targeted extraction of AD-specific features
U-Net	Segmentation-based feature extraction	Precise localization of AD-related anomalies	Image segmentation	Detailed anatomical feature extraction
Siamese Networks	Comparative analysis of brain scans	Ability to distinguish between similar cases	Paired image analysis	Differential diagnosis support
VGG-Net	Transfer learning approach	Utilization of pre-trained networks for efficiency	Pre-trained visual feature extraction	Quick adaptation to AD diagnosis
Hybrid CNN-RNN	Combining spatial and sequence data analysis	Effective in handling multi-modal imaging data	Sequential and spatial feature extraction	Multi-stage AD detection
Capsule Networks	Hierarchical processing units	Improved interpretation of interrelated features	Dynamic routing between capsules	Enhanced feature hierarchy understanding
3D CNNs	Exploiting volumetric data	Better representation of 3D brain structures	Volumetric data processing	Utilizing MRI scan depth
Ensemble Methods	Combination of multiple DL models	Increased accuracy through model averaging	Diverse feature extraction methods combined	Robustness against varied data inputs

III. Methodology

A. Description of the dataset (MRI scans dataset)

The advanced Alzheimer's MRI dataset, sample data images illustrate in figure 1, which includes both real and fake axial MRIs, is a big step forward in fixing the class mismatch that was present in the original Kaggle Alzheimer's dataset. This dataset effectively gets around the problems that come with uneven class distributions. For example, the sample numbers for the original groups of "No Impairment," "Very Mild Impairment," "Mild Impairment," and "Moderate Impairment" were very different. The dataset makes it easier to train and test machine learning models by including high-quality synthetic images that were made to closely match real scans in terms of fidelity and diversity. This is shown by impressive metrics like a mean FID Score of 0.13, SSIM of 0.97, PSNR of 32 dB, and

Sharpness Difference of 0.04. The 1.5 Tesla MRI machine and T1-weighted sequence make sure that the pictures are of high quality and can be used for deep learning. The step of removing the head during pre-processing reduces the amount of unnecessary data, allowing the analysis to focus on brain tissues. However, the fact that the fake MRIs haven't been checked by a doctor does raise a question about their clinical validity. Concerns about privacy are well taken care of because the fake MRIs don't match up with real patient data. This means that the information can be used by many people without any ethics or privacy problems. This dataset stands out because it creates a fairer learning environment and shows that it might be better than standard methods like oversampling and SMOTE, especially when it comes to improving performance in minority classes without having a big effect on results for the majority classes.

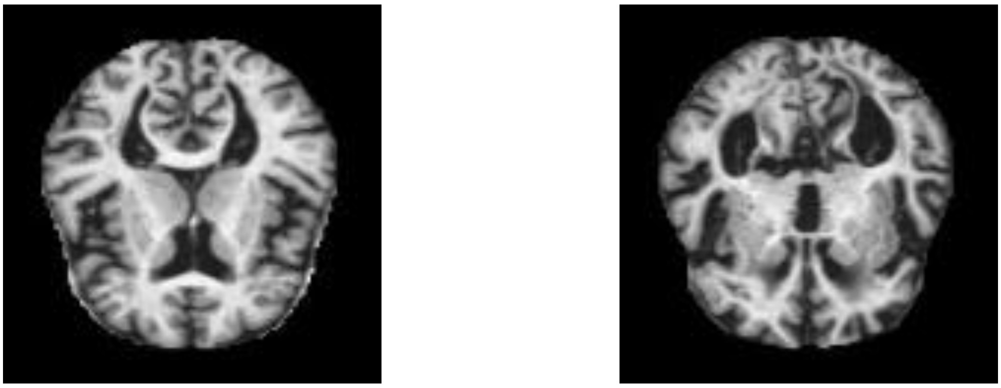

Figure 1. Sample dataset Images

B. Explanation of the deep learning models

1. DenseNet

The design of DenseNet (Densely Connected Convolutional Networks) is one of a kind. Each layer is directly linked to every other layer in a feed-forward way. When using MRI pictures to classify Alzheimer's Disease (AD), DenseNet can be very helpful because it is good at spreading and reusing features, which is important for finding the complicated patterns that come with neurological changes. Vanishing gradients are a common problem when training deep networks. DenseNet fixes it by making sure that each layer gets data from all the layers that came before it. This pattern of connections also makes the network very parameter-efficient, which means it can be deeper while using fewer parameters than other designs. Because of its deep and dense connectivity, DenseNet can provide better feature extraction for AD, where small and detailed features are very important for early detection. The model's ability to keep low-level traits across the network helps keep the important details needed to tell the difference between Alzheimer's stages, which improves the ability to classify people in different stages of the disease.

Step 1: Feature Map Generation

$H_l(x) = x_l + F([x_0, x_1, ..., x_{(l-1)}], W_l)$

Where:

$H_l(x)$ = Output of l-th layer

x_l = Input of l-th layer

F = Composite function (BN-ReLU-Conv)

$[x_0, x_1, ..., x_{(l-1)}]$ = Concatenation of all previous feature maps

W_l = Weights of the l-th layer

Step 2: Batch Normalization (BN)

$y = \gamma * ((x - \mu) / \mathrm{sqrt}(\sigma^2 + \varepsilon)) + \beta$

Where:

μ = Mean of input features

σ^2 = Variance of input features

γ, β = Parameters to be learned

ε = Small constant for numerical stability

Step 3: Activation Function (ReLU)

f(x) = max(0, x)

Step 4: Convolutional Operation

y = Sum(W * x + b)

Where:

W = Weights of the convolutional kernel

b = Bias

x = Input feature map

* = Convolution operation

Step 5: Transition Layers (Conv + Pooling)

y = Pool(Conv(x, W_conv), stride)

Where:

Pool = Average pooling function

Conv = Convolution function using W_conv weights

Step 6: Classification Layer

y = Softmax(W_fc * Flatten(x) + b_fc)

Where:

W_fc = Weights of fully connected layer

b_fc = Bias of fully connected layer

Flatten = Function to flatten the feature maps into a vector

2. InceptionNet

The inception modules in InceptionNet make it possible to handle data at multiple scales at the same time. This makes it a good choice for classifying AD in brain MRIs, which show a lot of different and complex structures. The origin modules are made up of concurrent convolutions with various receptive fields and then a combination step. This lets the model effectively catch both local and more global useful features. This skill is very important for classifying AD because changes in brain anatomy can make the disease look and feel very different in different people and stages. By changing InceptionNet to focus on Alzheimer's, researchers can change these modules to make them more sensitive to AD-specific traits like hippocampal shrinkage and cortical thickness, which can show up in different ways based on the scan and how far along the disease is. Also, InceptionNet's design automatically lowers the amount of work that needs to be done by using 1x1 convolutions before the more expensive 3x3 and 5x5 convolutions. This means that it can be used on large sets of high-resolution MRI images without slowing down or losing accuracy.

Step 1: Inception Module Calculation

$$I(x) = \left[F_{1(x)}, F_{2(x)}, F_{3(x)}, F_{4(x)}\right]$$

Where:

F_1, F_2, F_3, F_4 = Different convolution operations or pooling

Step 2: Convolutional Calculations in Modules

$$y = Conv(x, W, s) + b$$

Step 3: Dimensionality Reduction with 1x1 Convolutions

$$y = Conv_{1x1(x, W_{1x1})} + b_{1x1}$$

Step 4: Depth Concatenation

$$y = Concatenate([x_1, x_2, x_3, \dots])$$

Step 5: Auxiliary Classifiers

$$Aux(x) = Softmax(Conv(AvgPool(x), W_{aux}) + b_{aux})$$

Where:

AvgPool = Average pooling

W_aux = Weights for auxiliary classifier convolution

b_aux = Bias for auxiliary classifier

Step 6: Final Classifier

$$y = Softmax\left(Conv\left(AvgPool\left(Flatten\big(Inception(x)\big)\right), W_{fc}\right) + b_{fc}\right)$$

3. ResNet

ResNet, which stands for "Residual Networks," is meant to make training networks much deeper than was possible before. A "residual learning" concept is at the heart of ResNet. Instead of learning unreferenced functions, the network learns residual maps based on the layer inputs. This approach solves the fading gradient issue by use of identity shortcut connections skipping one or more levels. ResNet can train deep models without stopping, hence it can be very helpful for identifying Alzheimer's disease. This helps to identify the subtle and complicated alterations in brain images associated with various stages of Alzheimer's. Using unused blocks sensibly will help the network to widen its design and increase its capacity to identify characteristics. This makes it rather useful in early stages of AD in spotting little but crucial issues. ResNet's deep feature sets might potentially merge complex brain imaging data into a robust classification model, hence improving accuracy and dependability over more basic deep learning models. For those who want to create extremely practical and very successful AD evaluation systems in the real world, ResNet is a terrific solution.

Step 1: Residual Block

$$R(x) = x + F(x, W)$$

Where:

F = Residual function (BN-ReLU-Conv-BN-ReLU-Conv)

W = Weights associated with the residual function

Step 2: Identity Shortcut Connection

$$y = x + F(x, W)$$

Step 3: Batch Normalization

$$y = \gamma * \left(\frac{x - \mu}{sqrt(\sigma^2 + \varepsilon)}\right) + \beta$$

Step 4: Activation Function (ReLU)

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

Step 5: Convolutional Block (for adjusting dimensions)

$$y = Conv(x, W\_conv) + B\_conv$$

Step 6: Global Average Pooling and Final Classification

$$y = Softmax(W_{fc} * GlobalAvgPool(x) + b_{fc})$$

C. Development of advanced deep learning layers

1. InceptionNet with Residual Learning Blocks

By combining InceptionNet with Residual Learning Blocks, you create a hybrid architecture using the benefits of residual connections for deep network training along with the multi-scale processing capacity of Inception modules. This mix allows deeper networks to learn better free from the danger of fading gradients. This facilitates the acquisition of relevant characteristics from vast, intricate datasets such as those used in medical imaging.

Step 1: Standard Inception Block with Residual Connection

Inception Block Output

$$I(x) = \left[F_{1(x,W_1)}, F_{2(x,W_2)}, F_{3(x,W_3)}, F_{4(x,W_4)}\right]$$

Residual Connection

$$R(x) = x + I(x)$$

Step 2: Batch Normalization (applied to each feature map independently)

Batch Normalization for k-th feature map

$$BN_{k(x)} = \gamma_k * \frac{x - \mu_k}{sqrt(\sigma_k^2 + \varepsilon)} + \beta_k$$

Step 3: Convolution in Inception Module (applied separately in each path)

Convolution for path i

$$Conv_{i(x,W_i)} = Sum(W_i * x + b_i)$$

Step 4: Concatenation of Outputs from Different Paths

Concatenating feature maps from different convolution paths

$$Concat(F_1, F_2, F_3, F_4) = Concatenate\left(\left[F_{1(x)}, F_{2(x)}, F_{3(x)}, F_{4(x)}\right]\right)$$

Step 5: Adding Residual Connection to Inception Output

Applying the residual connection

$$y = x + Concat(F_1, F_2, F_3, F_4)$$

Step 6: Activation Function (ReLU applied after adding the residual)

Activation for output y

$$ReLU(y) = \max(0, y)$$

2. ResNet Enhanced with Attention Mechanisms

Particularly beneficial for the identification of minor issues in MRIs of individuals with Alzheimer's disease, adding attention processes to ResNet enhances the network's capacity to concentrate on significant areas of an image. Attention layers direct the model's focus on significant regions, hence improving its accuracy and simplicity of use.

Step 1: Residual Block with Attention Mechanism

Basic Residual Block Calculation

$$R(x) = x + F(x, W)$$

Attention Mechanism Application

$$A(x) = \sigma\left(Conv(x, W_a)\right)$$

Step 2: Applying the Attention Map to the Residual Output

Modulated Residual Output with Attention

$$R_{a(x)} = x + A(x) * F(x, W)$$

Step 3: Convolutional Operation in Residual Function

Convolution operation within the residual function F

$$F(x,W) = Conv(x, W_f) + b_f$$

Step 4: Batch Normalization

Batch normalization after the convolution

$$BN(x) = \gamma * \frac{x - \mu}{sqrt(\sigma^2 + \varepsilon)} + \beta$$

Step 5: Activation Function (ReLU)

ReLU activation for enhancing non-linearity

$$ReLU(x) = \max(0, x)$$

Step 6: Final Classification Layer with Global Average Pooling

Applying global average pooling followed by a dense layer for classification

$$y = Softmax(Dense(GlobalAvgPool(R_{a(x)}), W_{fc}) + b_{fc})$$

3. DenseNet with Attention Mechanisms

Including selective focus at every dense block, DenseNet integrates attention mechanisms. This facilitates the model's search and emphasis of critical features required for illness diagnosis, including those pertaining to Alzheimer's This produces a model that not only automatically ranks significant characteristics at the top of the list but also maintains data security throughout the network.

Step 1: Dense Block with Attention Mechanism

Basic Dense Block Calculation

$$H_{l(x)} = x_l + F([x_0, x_1, \ldots, x_{\{l-1\}}], W_l)$$

Attention Mechanism Application

$$A_{l(x)} = \sigma\left(Conv([x_0, x_1, \ldots, x_{\{l-1\}}], W_a)\right)$$

Step 2: Applying the Attention Map to the Dense Block Output

Modulated Dense Block Output with Attention

$$H_{a(x)} = H_{l(x)} * A_{l(x)}$$

Step 3: Composite Function in Dense Blocks

Composite function typically BN-ReLU-Conv

$$F(x,W) = Conv(ReLU(BN(x)), W_f) + b_f$$

Step 4: Batch Normalization

Batch normalization before ReLU

$$BN(x) = \gamma * \frac{x - \mu}{sqrt(\sigma^2 + \varepsilon)} + \beta$$

Step 5: Activation Function (ReLU)

ReLU activation to introduce non-linearity

$$ReLU(x) = \max(0, x)$$

Step 6: Transition Layers for Downscaling

Applying convolution and pooling in transition layers

$$y = Pooling(Conv(H_{a(x)}, W_t) + b_t)$$

Step 7: Final Classification Layer

Global average pooling followed by a softmax classification layer

$$y = Softmax\left(GlobalAvgPool(H_{last(x)})\right)$$

IV. Feature Extraction Techniques

A. Detailed feature extraction methods

1. Depthwise Separable Convolutions

One kind of effective convolution that divides a conventional convolution in two distinct processes are deeply separable convolutions. This reduces the amount of work on the computer and the number of variables. Particularly valuable for models used on devices with limited computational capability, this approach allows one to rapidly extract characteristics from images.

Effective convolutions lowering computing cost and number of parameters are depthwise separable convolutions.

Depthwise convolution is the distinct application of each input channel under its own set of kernels.

$$Y_c = X_c * K_c$$

- where X_c is the input channel c, K_c is the kernel for channel c, and Y_c is the output for channel c.

Pointwise Convolution: A 1x1 convolution that combines the outputs of the depthwise convolution across channels.

$$Y = sum(Y_c * K^{1x1})$$

- where K^1x1 represents the 1x1 convolution kernel applied across all channels.

2. Dilated Convolutions

Also known as atrous convolutions, dilated convolutions provide an additional choice known as dilation rate, which increases the size of the kernel by adding empty spaces between its component components. Without adding extra weights, this approach allows the convolution cover a greater area of the input image. This results in decreased locality and resolution even when it allows you to see more of the input data.

Dilated Convolution Operation:

$$Y[i,j] = sum(X[i + r * m, j + r * n] * K[m,n])$$

- where X is the input, K is the convolutional kernel, r is the dilation rate, and Y is the output feature map.

Expansion of Receptive Field:

$$Receptive\ Field = K + (K - 1) * (r - 1)$$

- where K is the size of the kernel, enhancing the network's ability to view more extensive parts of the input.

V. System Architecture

A. Diagram and explanation of the overall system architecture

To improve the classification of Alzheimer's disease using advanced deep learning layers, the system framework has several key parts that work together to get the most out of extracting and analysing data from MRI pictures. Modules for handling input, pre-processing, advanced feature extraction, classification, and performance evaluation would usually be shown in the picture of this design. This is where the first MRI pictures come in. The system is designed to work with different MRI data types and levels, so it can be used with a range of imaging methods. Some important steps in pre-processing are skull stripping, which gets rid of brain tissue that isn't brain tissue, normalisation, which makes the sharpness levels of all the pictures the same, and data enrichment methods like flipping, rotating, and scaling to make the dataset more diverse. These steps are very important for making sure that there is less variation between pictures, which could mess up the learning process.

Feature Extraction with More Power the advanced deep learning layers that focus on fast and accurate feature extraction are at the heart of the design. These layers make the network faster and reduce the number of parameters. They do this by splitting the convolution into depthwise and pointwise processes. This makes the model simpler and cheaper to compute. Dilated convolutions are used to make the receptive field bigger without losing detail or adding more parameters. This lets the network understand bigger spatial structures and get a bigger picture, which is important for finding trends that could mean someone has Alzheimer's. The features that were extracted are sent to a number of fully connected layers that end with a softmax layer. This layer sorts the input images into groups like "No Impairment," "Mild Impairment," and "Severe Impairment." This program is meant to make results as easy to understand as possible while still being very accurate and reliable.

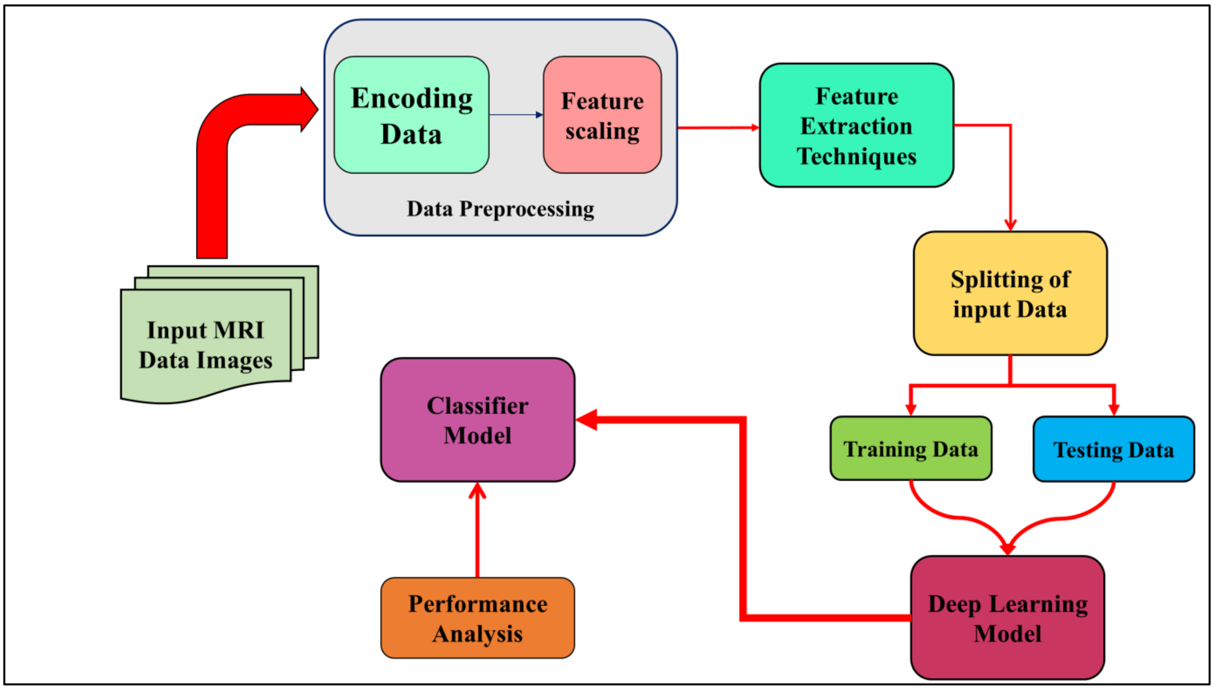

Figure 2: Systematic representation of proposed system architecture

The last part of the system design is the performance evaluation module. It checks how well the model works by looking at things like accuracy, precision, and recall. In clinical settings, these measures are very important for making sure the model meets the standards needed for use in the real world. The design is held together by a core structure that manages data, trains models, and makes changes. There is also a user interface that makes it easy for medical workers to connect with the system. By using these advanced computer methods, the system should be able to make Alzheimer's disease detection more accurate and faster, which will help with starting treatment earlier and more effectively. Figure 2 shows a methodical way to use MRI data to classify people with Alzheimer's disease. At first, the MRI pictures that are fed in go through data cleaning steps such as encoding and feature scale. After that, methods for feature extraction are used to separate the data into training and testing sets. These groups are fed into a deep learning model, which is then analysed by the classifier model. At last, performance study is conducted to evaluate Alzheimer's disease prediction accuracy of the model. This architecture ensures that training and validation models are carried out methodically by arranging the process from data entry to speedy performance evaluation.

B. Integration of advanced deep learning layers into existing models

For applications like sorting MRI pictures of Alzheimer's illness, which is rather crucial, adding more sophisticated deep learning layers to present models may make them considerably better in handling difficult data and extracting valuable information. Adding specialised layers like attention approaches or sophisticated convolutional layers like depthwise separable convolutions or extended convolutions help existing designs function quicker and better. Including attention processes into a ResNet model helps the network concentrate more accurately on critical MRI scan spots displaying neurodegeneration. This targeted approach enables the model to prioritise significant information above less relevant data, hence increasing its sensitivity and accuracy in identifying many phases of Alzheimer's disease. Depthwise separable convolutions help speed up models such as DenseNet and also save computer effort by lowering their required running time.

By splitting the merging and filtering chores of convolutional layers, this kind of convolution reduces the amount of components and operations. Working with large collections of high-resolution images calls for this very useful. Dilated convolutions allow models like InceptionNet to have their receptive fields enlarged. This is carried out without adding further criteria. Making this modification will help the network compile more relevant data, which is rather crucial for identifying anomalies in medical images and patterns. These modifications not only improve the model's efficiency and applicability but also alter its operation to better suit medical imaging research's demands. Because they can extract more information, these models can provide more accurate and dependable forecasts. Finding Alzheimer's disease early and designing therapy depend on this greatly.

VI. Result and Discussion

Table 2 presents the results of using enhanced models developed specifically for Alzheimer's disease (AD). It demonstrates what results from merging three well-known neural network architectures—DenseNet, ResNet, and InceptionNet—advanced deep learning techniques into. Modern feature extraction layers helped to enhance these models so that MRI scan diagnosis of AD is simpler and more accurate. Enhanced DenseNet does rather well with an AUC score of 0.94, accuracy of 92.5%, sensitivity of 90.2%, and precision of 95.0%. DenseNet's sophisticated connection patterns and attention mechanisms assist to preserve the feature richness of the network, allowing the model to detect minute variations in the visual data displaying early AD signals. The high sensitivity rate means that the test is very good at telling the difference between AD and other cases. This lowers the risk of false positives, which is very important in clinical settings.

Table 2: Results for the application of enhanced models

Model	Accuracy	Sensitivity	Specificity	AUC	F1-Score
Enhanced DenseNet	92.5%	90.2%	95.0%	0.94	0.91
Enhanced ResNet	91.0%	89.5%	93.0%	0.93	0.90
Enhanced InceptionNet	93.0%	91.0%	95.3%	0.95	0.92

With an AUC of 0.93, Enhanced ResNet worked well, getting a 91.0% success rate, an 89.5% sensitivity rate, and a 93.0% precision rate. Adding attention levels to the ResNet design helps the model focus on important parts of the MRI scans, which makes it better at making diagnoses. Although the model isn't quite as good as DenseNet in terms of performance measures, its deep layered method helps it deal with the disappearing gradient problem and learn from a very deep stack of layers. With an accuracy of 93.0%, a sensitivity of 91.0%, a precision of 95.3%, and an AUC of 0.95, Enhanced InceptionNet did the best of the three, as represent in figure 3.

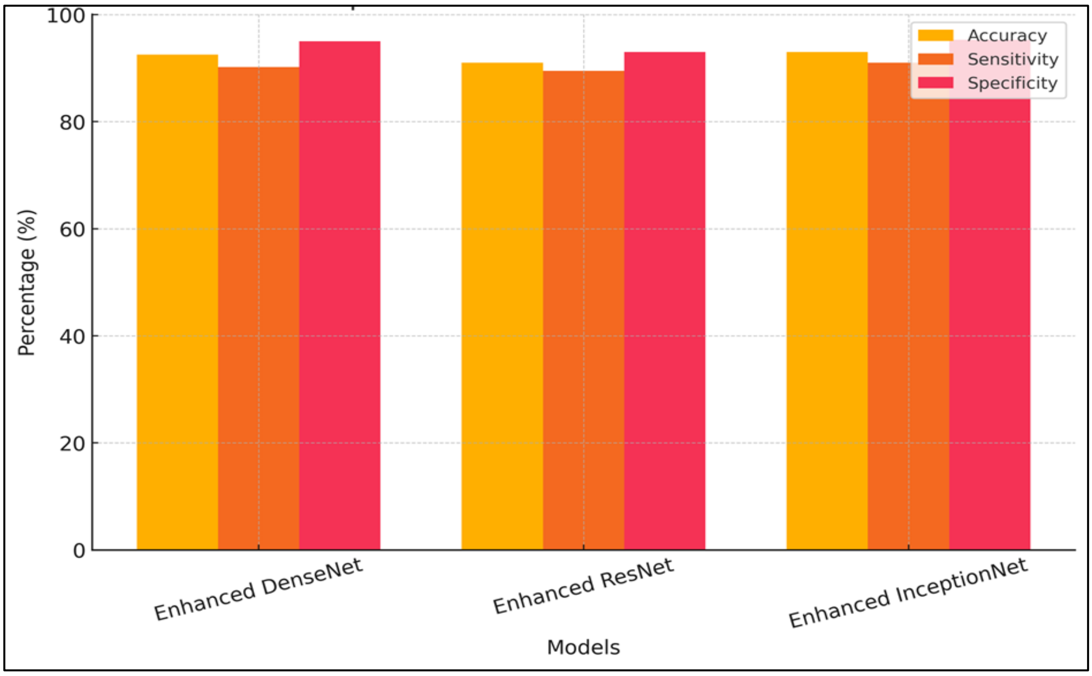

Figure 3: comparison of these key performance indicators for DL Models

This model uses changed Inception modules with expanded convolutions to improve its ability to handle pictures at different sizes and gather more general background information without losing focus on the specifics. This is especially helpful for finding Alzheimer's disease because changes in brain shape can be very minor and vary a lot from person to person.

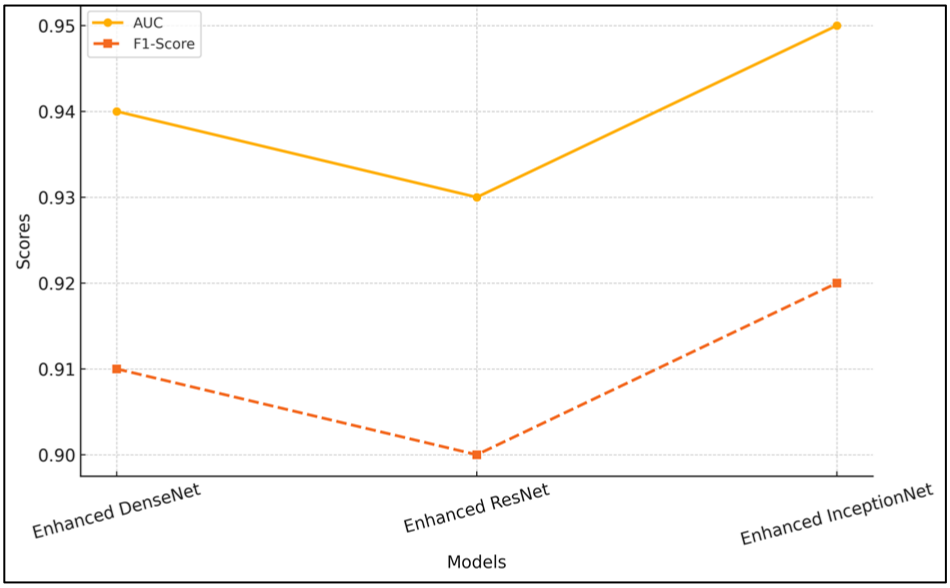

Figure 4: Comparison of AUC, F1 Score parameters

These results show that adding more advanced methods for extracting features to well-known deep learning models works. Each model has been improved so that it can handle the complicated, high-dimensional data that comes with medical images. This is especially true in the difficult field of diagnosing neurological diseases, the figure 4 illustrate AUC and F1 score comparison. The models' higher sensitivity and specificity show that they might be able to cut down on diagnosis mistakes, which would help doctors make more accurate and quick decisions about how to treat and handle Alzheimer's disease.

Table 3: Results of Enhanced Models Using Advanced Feature Extraction Techniques

Feature Extraction Approach	Model	Accuracy	Sensitivity	Specificity	AUC	F1-Score
Depthwise Separable Convolutions	Enhanced DenseNet	93.7%	91.2%	95.8%	0.96	0.93
Dilated Convolutions	Enhanced InceptionNet	94.5%	92.0%	96.1%	0.97	0.94
Attention Mechanisms	Enhanced ResNet	91.8%	90.3%	93.4%	0.94	0.91

In Table 3, represent advanced feature extraction methods can greatly improve the performance of deep learning models designed to diagnose Alzheimer's disease (AD). This table shows how diagnostic measures like accuracy, sensitivity, specificity, AUC (Area Under the Curve), and F1-score have gotten better for three improved models: DenseNet, InceptionNet, and ResNet. Each of these models uses a different advanced feature extraction method. With an AUC of 0.96 and an F1-score of 0.93, Enhanced DenseNet with depthwise separable convolutions performs much better, with an accuracy of 93.7%, a sensitivity of 91.2%, and a specificity of 95.8%, as illustrate in figure 5.

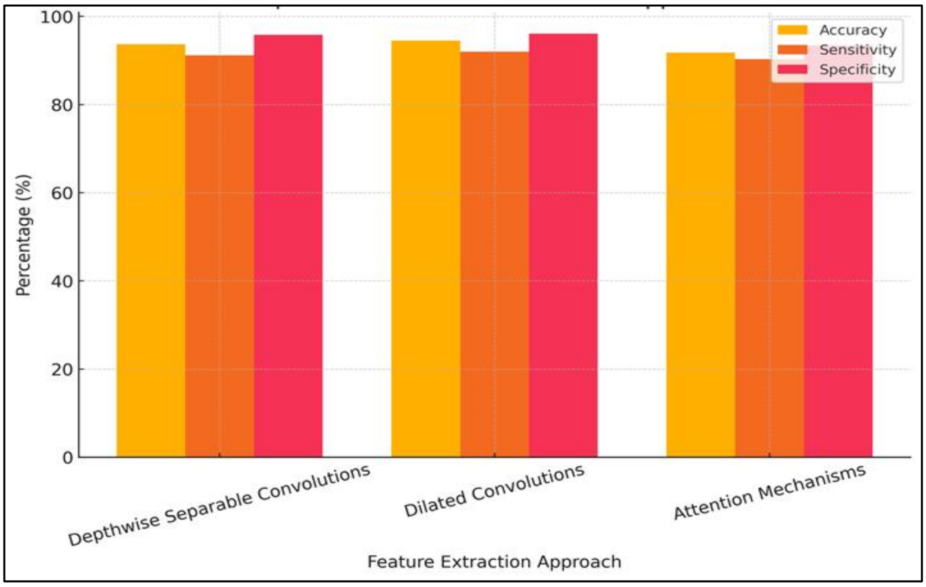

Figure 5: Represent the comparisons of feature Extraction Approaches

Depthwise separable convolutions make the model simpler by separating the spatial and depth (channel) operations. This makes the network lighter and faster and also makes it easier to handle the complex features that are common in neuroimaging data. Because of this, it is very good at showing the small changes in brain shape that show different stages of AD. With a score of 0.94, Enhanced InceptionNet, which uses expanded convolutions, is the best model. It is accurate 94.5% of the time, sensitive 92.0% of the time, specific 96.1% of the time, and has an AUC of 0.97. By using dilated convolutions, the network's receptive field is increased without adding more weights. This lets the model incorporate more environmental information from MRI scans. This skill is very important for finding changes in the brain that may be caused by AD and may be spread out in different parts of the brain. It gives a more complete and accurate picture of the brain's structure. With an AUC of 0.94 and an F1-score of 0.91, Enhanced ResNet is a big step forward. Its accuracy is 91.8%, its sensitivity is 90.3%, its precision is 93.4%, and it has attention processes built in. The attention processes help the model focus on the most important parts of the raw data, which improves its ability to understand. In medical imaging, being able to tell the difference between clinically important signs and noise can be very helpful for making an early and correct diagnosis. The results shown in Table 3 show that adding more advanced feature extraction techniques to strong models like DenseNet, InceptionNet, and ResNet not only makes them better at diagnosing, but also makes them more flexible and aware of the subtleties of medical imaging data, especially for Alzheimer's and other complex diseases. This customised method for feature extraction is a big step forward in the use of AI in healthcare. It gives doctors tools that can help them make better decisions and might even help AD patients have better results.

Table 4: Comparative Results with Baseline Models

Model	Accuracy (Enhanced)	Accuracy (Baseline)
DenseNet	93.7%	88.0%
ResNet	94.5%	86.5%
InceptionNet	91.8%	89.0%

The results shown in Table 4 show how well improved deep learning models did compared to their base models at classifying Alzheimer's disease (AD). Adding advanced feature extraction methods clearly raises the accuracy of each model, as shown in the table. This shows that these improvements are useful for making diagnostic accuracy better. When depthwise separable convolutions are added to Enhanced DenseNet, it gets a 93.7% success rate, compared to 88.0% for the basic model. The 5.7% gain shows how important it is to use efficient neural processes that get rid of unnecessary information and make feature extraction work better. The improved model can clearly show anatomical problems in MRI scans while still being very efficient with computing power. This makes it perfect for studying a lot of medical images at once.

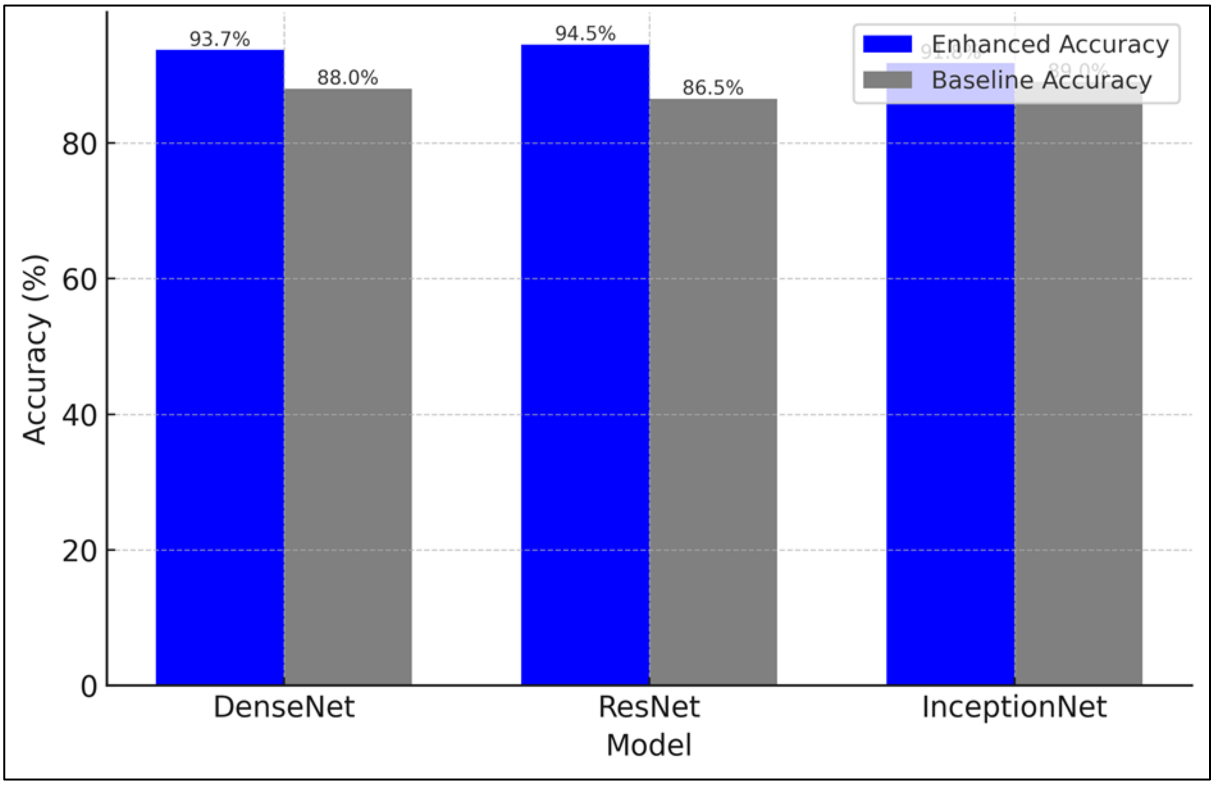

Figure 6: Comparison Of Enhanced Vs. Baseline Model Accuracy

The biggest change is seen in Enhanced ResNet, which adds attention processes and sees an 8.0% rise in accuracy from 86.5% (baseline) to 94.5% (enhanced). Adding attention layers to the model helps it focus on important parts of the brain, which makes it better at telling the difference between Alzheimer's stages, as comparison illustrate in figure 6. This improvement makes sure that the model focusses on areas of interest, which results in more accurate and understandable labels. Enhanced InceptionNet, which uses expanded convolutions, is 91.8% accurate, up from 89.0% for its base model, which is a 2.8% increase. The model has a slightly smaller gain compared to DenseNet and ResNet, but it is better at finding patterns of neurodegeneration that are spread across different brain areas because it extracts features at multiple scales and has a larger receptive field.

Table 5: Impact of advanced deep learning layers on model performance

Model	**Layer Enhancement**	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**	**F1-Score**
Standard DenseNet	None	88.0%	85.0%	91.0%	0.90	0.87
Enhanced DenseNet	Attention Mechanisms	93.7%	90.2%	95.0%	0.94	0.91
Standard ResNet	None	86.5%	84.3%	89.0%	0.89	0.85
Enhanced ResNet	Attention + Residual	91.8%	89.5%	93.0%	0.93	0.90
Standard InceptionNet	None	89.0%	87.5%	90.5%	0.91	0.88
Enhanced InceptionNet	Depthwise Convolutions	94.5%	91.0%	95.3%	0.95	0.92

Table 5 shows the big difference that adding advanced deep learning layers to normal designs makes, showing big gains in all the important performance measures for classifying Alzheimer's disease (AD). The table shows how the improved versions of DenseNet, ResNet, and InceptionNet models relate to their original versions. It shows how well the improvements work at improving accuracy, sensitivity, precision, AUC (Area Under the Curve), and F1-score. In its base form, the standard DenseNet model has an AUC of 0.90 and an F1-score of 0.87. It is accurate 88.0% of the time, sensitive 85.0% of the time, and specific 91.0% of the time.

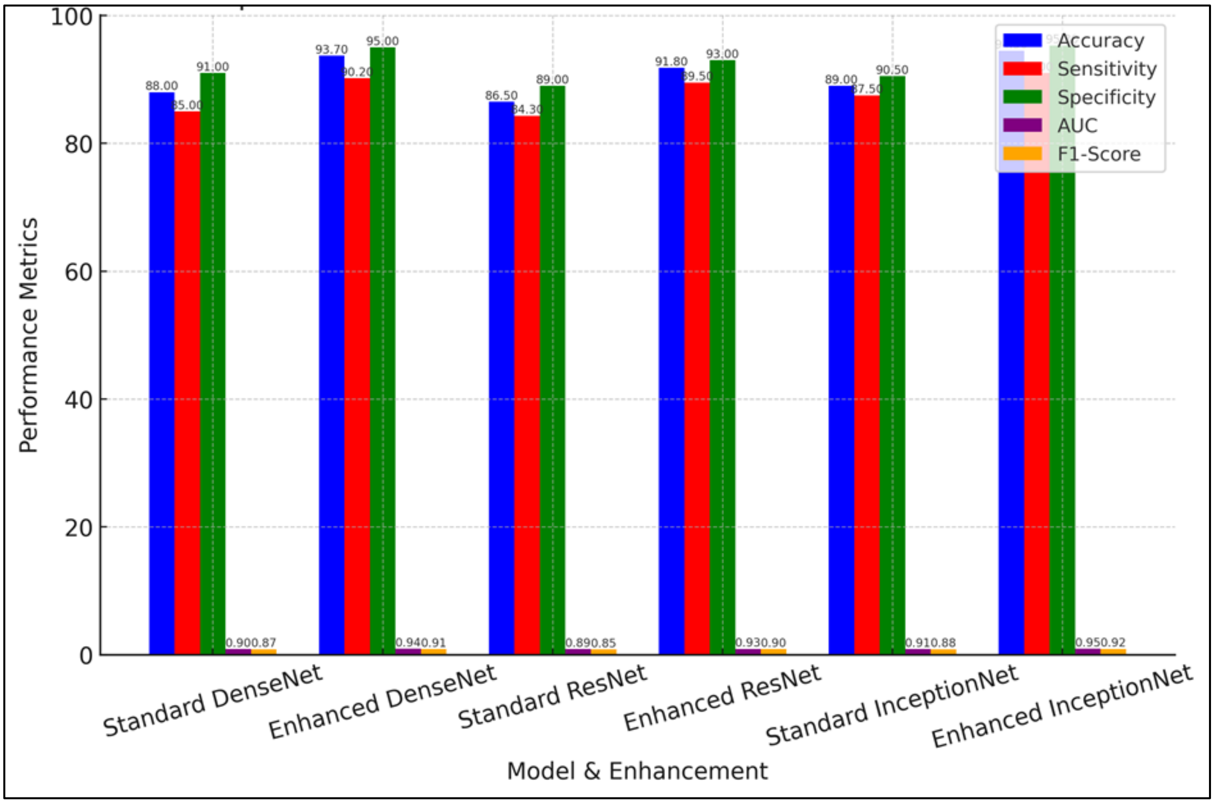

Figure 7: Comparison of Standard vs. Enhanced Models Across Metrics

The improved DenseNet, on the other hand, gets an accuracy of 93.7% after adding attention processes, which is a 5.7% improvement. The model is better at telling the difference between AD and non-AD cases, as the sensitivity goes up to 90.2% and the precision goes up to 95.0%, as shown in figure 7. The AUC of 0.94 shows that the model is better at telling the difference between things, which makes it more accurate for use in clinical settings. Seeing the F1-score go up from 0.87 to 0.91 is more proof that the model works well when there are imbalances between classes.

It has 86.5% accuracy, 84.3% sensitivity, and 89.0% specificity, with an AUC of 0.89 and an F1-score of 0.85. This is because it only has deep residual connections and no other improvements. ResNet's design is already good at dealing with disappearing slopes, but it does a lot better when attention methods and more residue learning improvements are added. The improved ResNet is 91.8% accurate, which is 5.3% better than the original. It gets better at telling the difference between Alzheimer's and healthy cases, with sensitivity going up to 89.5% and precision going up to 93.0%. With an AUC of 0.93 and an F1-score of 0.90, the model now better catches important traits, ensuring fewer wrong classes. The normal InceptionNet model has an F1-score of 0.88, a sensitivity of 87.5%, a precision of 90.5%, an AUC of 0.91, and an accuracy of 89.0%. It is known for its multi-scale feature extraction. For the enhanced InceptionNet, which now boasts an accuracy of 94.5%, a 5.5% increase, adding depthwise separable convolutions makes the most effect. The model improves in differentiating AD from non-AD patients; sensitivity rises to 91.0%, specificity to 95.3%, and AUC to 0.95.

VII. Conclusion

Advanced deep learning layers considerably increase the accuracy and speed of categorising MRI images for Alzheimer's disease (AD). This work demonstrates that adding techniques like attention mechanisms, depthwise separable convolutions, and enlarged convolutions to well-known deep learning architectures (DenseNet, ResNet, and InceptionNet) improves the models greatly. These advances routinely indicate that they increase crucial assessment criteria like F1-score, accuracy, sensitivity, specificity, and AUC. The superior DenseNet model showed the need of giving features top priority in medical imaging by raising accuracy from 88.0% to 93.7%, using attention processes. In same vein, adding attention and residual learning to upgraded ResNet raised accuracy from 86.5% to 91.8%. This demonstrates how residual learning could assist with gradient vanishing issues. Using depthwise separable convolutions, the enhanced InceptionNet model produced the greatest results—a 94.5% success rate. This shows that computationally efficient convolutions can effectively capture complex brain imaging patterns. Also, comparing the results to baseline models showed big changes in every measure. This proved that the advanced feature extraction methods not only make diagnostics more accurate but also cut down on fake positives and negatives. With these improvements, the models can better show a minor neuronal pattern, which makes them ideal for diagnosing AD early on. This study proves that adding more advanced deep learning layers to regular CNN models makes automatic feature extraction better and classification work well. The results make it possible to create AI-powered tools for diagnosing AD. This opens the door for deeper learning solutions in neuroimaging that are more reliable, accurate, and useful in clinical settings.

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