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Research Article

RESNET-53 for Extraction of Alzheimer's Features Using Enhanced Learning Models

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Abstract:

Detecting Alzheimer's disease typically involves a combination of medical and cognitive assessments, neuro imaging, and sometimes genetic testing. Machine learning and artificial intelligence (AI) techniques are being applied to analyze neuro imaging data, genetic information, and clinical records to develop predictive models for Alzheimer's disease risk and early detection. Many AI models, particularly deep learning models, lack interpretability. Understanding how a model reaches a particular diagnosis or prediction can be challenging, which is a concern in the medical field where interpretability and transparency are crucial. CNNs typically learn features directly from data without prior feature engineering. While this is an advantage, it may also limit the exploration of specific features or biomarkers known to be associated with Alzheimer's disease. Medical images often require pre-processing steps, such as normalization, registration, and segmentation, before feeding them into CNNs. The effectiveness of CNNs may depend on the quality and accuracy of these pre-processing steps. The proposed methodology combines both CNN-based feature extraction and integrates adaptive filtering techniques to leverage the strengths of each method. This hybrid approach can lead to improved Alzheimer's disease detection by enhancing image quality and extracting relevant features for diagnosis. The combination of filtering techniques and CNNs allows the network to focus on relevant features while filtering out noise and irrelevant information. The proposed methodology integrates Gaussian filter with bilateral filter to produce an adaptive filter. Bilateral filtering adapts to the local image structure and content. By using it in combination with Gaussian filtering, the model can adaptively filter different regions of the image, optimizing the smoothing and enhancement process based on local features. This can lead to more effective and discriminative feature learning. Using the traditional CNN approaches the feature extraction has got nearly 57.78% accuracy but with the proposed model the accuracy has improved to 94.24%.

1. Introduction

Main Alzheimer's disease is progressive, and its symptoms and progression can vary among individuals. Alzheimer's Disease (AD) detection using image processing techniques involves the analysis of neuroimaging data to identify structural and functional changes in the brain associated with the disease[1-16]. Feature extraction using segmentation is a common technique in image processing. Segmentation involves partitioning an image into regions or objects that correspond to meaningful areas of interest, such as objects, shapes, or structures. These segmented regions can then be used to extract relevant features. Threshold-based segmentation methods require choosing appropriate threshold values. Selecting the correct thresholds can be subjective and may require domain expertise. Image processing techniques may not account for the dynamic nature of the disease over time. Below section discusses the popular filters for performing segmentation on images

Bilateral filter

A popular image processing method is the BF that helps to smooth an image while preserving important edges and details. The key idea behind the Bilateral Filter is to combine spatial and range filtering benefits, allowing for more control over the smoothing process. The Bilateral Filter also considers the spatial proximity of pixels within a defined neighbourhood [17]. In range filtering consideration of the intensity or color similarity between pixels. Combining weights from the spatial kernel and the range kernel to calculate the final weight for each pixel in the neighbourhood. In filter processing for each pixel, calculate the weighted average of the pixel values in its neighbourhood, where the weights are determined by the combined spatial and range kernels. It defines a range kernel that assigns weights based on the similarity in pixel values. Pixels with similar intensity or colour values are given higher weights. In this, some operations are performed like spatial, range, mixing weights, and filtering processes. The merits are edge preservation, non-linear filtering, customizable parameters, and applications (table 1). The computation of the bilateral filter is presented in equation (1)

$$Bilateral\_Pixel(X,Y) = \frac{1}{N.F.} * \left(\sum_{i=1}^{n}\sum_{j=1}^{n} Pixel\_Intensity(X_i,Y_i) * e^{-\frac{X_i^2+Y_i^2}{2*\sigma^2}} * e^{-\frac{X_i^2}{2*\sigma^2}}\right) - \left(\sum_{i=1}^{n}\sum_{j=1}^{n} Pixel\_Intensity(X_{i+1},Y_{i+1})\right) - (1)$$

Where,

N.F. is normalization factor that ensures the weighted average is properly normalized.

σ is the standard deviation that controls the extent of spatial smoothing

While the bilateral filter can help in noise reduction, it can also smooth out fine details in the medical images. In Alzheimer's disease detection, subtle structural changes in the brain may be important indicators. Excessive smoothing can lead to the loss of such critical information.

Gaussian Filter

A Gaussian Filter, also known as a Gaussian smoothing filter or Gaussian blur, is a fundamental image processing technique used to reduce noise and perform image smoothing [18]. The Gaussian Filter is based on the Gaussian function, which is a continuous probability distribution. Two smoothing operations are performed kernel and convolution. In the kernel, the GF is discretized into a 2D matrix known as the GK. The size of this kernel is determined by the choice of standard deviation. In the convolution, for each pixel perform a convolution operation, which involves multiplying the pixel values in the kernel's neighbourhood by the corresponding values in the Gaussian kernel and summing up the results[19]. The smoothing effects were applied on GF to blur the image by replacing each pixel with an average of its neighbours, with the weights determined by the Gaussian distribution. GF is utilized mostly for noise reduction, edge preservation, & pre-processing. The computation of Gaussian filter is presented in equation (2)

$$Gaussian\_Pixel(X,Y) = \frac{1}{2\pi\sigma^2} * e^{-\frac{X^2+Y^2}{\sigma^2}} - (2)$$

Gaussian filters do not explicitly preserve edges in the image. While they tend to smooth transitions between regions of different intensity, they can also blur important edges and boundaries. This may impact the detection of structural abnormalities associated with Alzheimer's disease [13].

Traditional filters apply predetermined mathematical operations to images to extract specific features like edges, textures, or orientations. These features are hand-crafted and may require domain expertise to design. CNNs are often trained end-to-end, meaning they learn both feature extraction and classification (or regression) in a single integrated process [14]. The learned features are optimized for the specific task at hand. CNN-based feature extraction is highly flexible and adaptable to various tasks and datasets due to its ability to learn features directly from data. Traditional filters offer control but are limited to predefined operations. CNNs, especially pretrained models, are advantageous when limited labeled data is available. Traditional filters do not leverage transfer learning to the same extent.

Feature extraction methods using pre-trained models

The VGG16 & VGG19 models are deep convolutional neural networks known for their simplicity and effectiveness [15]. By removing the top classification layers to use them as feature extractors for image-related tasks (figure 1). VGG features can be extracted and used for tasks like image classification, object detection, and style transfer. InceptionV3 & InceptionResNetV2 are complex neural network architectures designed for efficient training and improved performance. These models are particularly useful for tasks like image classification, object recognition, and feature visualization [12]. A compact NN architecture called MobileNetV2 was created for devices that are mobile or embedded. It is pre-trained on various datasets and can be used for feature extraction in resource-constrained environments. BERT is a pre-trained model in the field of NLP. It is designed to understand the context of words in sentences.

EfficientNet is a family of efficient convolutional neural network architectures that balance model size and accuracy [11].

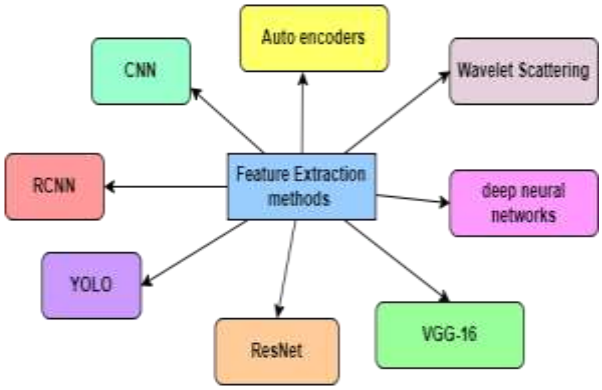

Figure 1: *Classification of Feature Extraction Methods*

2. Literature Survey:

Karim Aderghal et al [1] The newly developed approach focuses on a tiny ROI, such as the hippocampus area, employing CNN for automated categorization of brain images. LeNet-like network architecture is employed, and models are constructed and fused for classifying AD. The technique examines several transfer learning techniques, including sMRI, DTI, cross-domain methodology utilized in MNIST data set, and (iii) a hybrid methodology incorporating two kinds. The suggested technique, which makes use of glib CNN, is appropriate for the less resolving in both techniques. Even with tiny datasets, which are typical in medical image analysis, it still produces meaningful findings. In certain tasks, the efficiency of transfer learning increased the accuracy of determining the AD stage by more than 5 points. Cross-modal transfer learning, & a combination of the two utilising a shallow LeNet network are some of the transfer learning strategies that are compared. The method avoids 3D conv & full-brain utilisation by using the "2-D+" methodology previously devised for the hippocampus area. According to the interpretation of the data, filters taught on one modality have similar geometrical properties and only need modest adjustments when applied to another modality. The outcomes show that good performance may be achieved even with tiny datasets and few ROI slices. When compared to existing methods, the proposed methodology achieves good accuracy scores using a shallow convolutional network.

Atif Mehmood et al [2] focuses on the early detection of MCI using MRI in the treatment of dementia, particularly AD. Deep learning architecture, The lack of labelled datasets for the model's training is addressed by using particular techniques, such as layer-wise transfer for learning and tissue segmentation. The VGG design class with weights that have been trained is used in stages of transfer training to distinguish between several stages of cognitive impairment, including all four categories. The study draws on information collected in the ADNI database, which includes 85 NC clients, 70 EMCI patients, 70 LMCI patients, & 75 AD patients. To isolate GM tissue from brain pictures and help in diagnosis, tissue segmentation is done. Analysis of comparative research shows that the suggested model performs better when it comes of testing accuracy than current state-of-the-art models.

Liuqing Yang et al [3] DL methodologies in distinguishing related patients effected with AD, MCI, or no signs of dementia were seen utilising base brain MRI results. From structural MRI scans, DL algorithms extract characteristics that are then coupled to additional biomarkers to form an AD prognostic hallmark. The AD predictive signature offers enrichment options in AD clinical trial planning and assists in comprehending patient variability within a research cohort. Enrichment of clinical trials with patients showing fast disease progression is crucial for successful drug design in AD. The article demonstrates the use of DL-derived AD features combined a prognostic profile that accurately predicts the transition between MCI to AD after thirty-six months by combining it with other biomarkers. The study highlights the importance of using time-to-event data and Cox models instead of dichotomizing the disease progression, as it improves prediction performance. Intuitive score-play a significant role in prognostic score prediction concert, but subjective scoring methods and variations among physicians pose challenges.

AD has a significant global impact, affecting millions of people and incurring a substantial economic burden. Utkarsh Sarawgi et al [4] the presented architecture utilizes three different features in a multimodal ensemble approach to identify & grade AD based on MMSE scores. Initially the test was utilizing the ADReSS competition data set, related to the proper datasets with no biases against any one subject and is accessible through DementiaBank. The work highlights the effectiveness of using spontaneous speech as a source for robust inductive transfer learning models, showcasing generalizability through a task-independent feature space. To support deductive methods for AD classified & validation scores, the architecture makes use of domain knowledge. For MMSE score regression and AD classification, the system uses specialised ann having time properties. The provided method illustrates the value of utilising domain expertise and deductive transference for AD diagnosis and severity evaluation, as well as the possibility of multimodal techniques.

Yu-Ching NI et al [5] focuses on using Tc-99m-ECD SPECT brain perfusion pictures in normal clinics for objective evaluation of AD. The Inception v3 network framework is used in two-stage transfer learning, including pre-training using the ImageNet data set and ADNI database. Three-dimensional images are reorganized into ensemble learning and a two-dimensional sets for information augmentation are used to increase training precision. It is examined how well initial training variables for Tc-99m-ECD SPECT pictures can differentiate between AD and NC. The impact append on the little size in pre-training data from F-18-FDG PET images on model performance is analyzed. A deep learning algorithm utilising SPECT ECD perfusion pictures has been suggested, with pre-training on PET FDG metabolic imaging, shows increased sensitivity and accuracy in differentiating AD from NC. According to the study, a model developed for PET FDG metabolic monitoring may be applied to a limited portion of SPECT perfusion of the brain pictures, enhancing the practicality of using deep learning for objective recognition of AD in SPECT imaging.

Amir Ebrahimi et al [6] emphasises applying the ResNet-18 Methodology on MRI to identify Alzheimer's disease (AD). For AD identification in earlier investigations, 2D CNNs were applied to 2D image slices of 3D MRI images. To transfer information from 2D to 3D datasets, the proposed technique uses transfer learning in 3D CNNs. The dataset was derived from the ADNI contains MRI scans. Image pre-processing techniques such as intensity normalization and registration were applied to the MRI scans. Due to the little dataset, data augmentation is utilized for enhancing the classified performances. Transfer learning from ImageNet datasets, pre-training a ResNet-18 Methodology, was recommended to avoid overfitting and leverage knowledge from natural images. The fully-connected layer of the ResNet-18 Methodology was adjusted for AD detection, with a higher learning rate for weight and bias. To adapt ResNet-18 for 3D MRI scans, 2D filters were extended to 3D filters, and the remaining layers were adjusted accordingly. By replicating 2D filtering in the third dimension, the 2D ResNet-18's learnable parameters have been transferred into the 3D ResNet-18. Improved AD recognition precision based on the ADNI MRI datasets was achieved by using the Taguchi approach to determine the ideal set of variables to train the 3D ResNet-18.

Heta Acharya et al [7] AD is a progressive neurological affected which was a disorder and memory loss and thinking skills. The research focuses on classifying MRI scans of AD patients using transfer-learning Methodology, specifically VGG16, ResNet-50, and AlexNet, in combination with CNN. The proposed learning Methodology were tested on MRI images from a dataset at the Kaggle warehouse, with four categories. Transfer learning is a popular technique that utilizes pre-trained networks to reduce training time for neural network Methodology, especially when the available dataset is small. CNN is widely used in medical image analysis due to their effectiveness in extracting features from images. The VGG16 Methodology, initially trained on the ImageNet dataset, consists of 16 layers and can classify images into 1000 categories. ResNet 50 is a CNN architecture utilized in computer vision. It contains 50 layers and retrieve the issue of disappearing gradients through residual blocks. AlexNet was the first deep neural network to achieve significant improvement in ImageNet classification accuracy. It comprises 5 conv layers & three FC layers. AlexNet utilizes the ReLu, which is faster than the tanh function commonly used at the time. ReLU helped achieve faster training time and lower error rates. "Scattered pooling" refers to the effects of pooling layers in CNNs, where neighbouring groups of non-dispersing neurons are considered. This approach led to a decrease in error rates.

There is presently no treatment for the progressive neurological diseases Alzheimer's or effective treatment to slow its progression. Manu Raju et al [8] the proposed work utilizes transfer learning with the VGG16 Methodology and Fastai framework to perform multilevel classification of AD based on MRI. Pre-processing steps include intensity normalization and skull stripping of the MRI images obtained from Kaggle. The algorithm computes the brain affected region for each class and projects it onto MRI images using GradCam. GradCam helps ensure that classifiers correctly identify Alzheimer's disease based on the relevant brain regions, aiding in accurate diagnosis and reducing mislabels. The heatmap generated by GradCam indicates the main affected regions of the brain, including the hippocampus, amygdala, and parietal regions. The fully connected layers of the VGG16 Methodology trained on the ImageNet dataset are retrieved and fine-tuned for the classification task. The convolutional layers, responsible for learning lower-level features, require minimal modification as they are common for all images. A new untrained dense layer is inserted at the end of the VGG16 network, and the complete network is trained using the provided dataset. The categorical cross-entropy cost function is used for multiclass classification, and the SGD optimizer with Nesterov intensity is found to perform well for medical imaging. Fastai, a deep learning library, is utilized to enhance the performance and speed of the deep learning algorithms, offering high-level APIs and customizable lower-level APIs.

The automated recognition of various Alzheimer's phases, which might lessen the strain on the health care system. According to Rizwan Khan et al. [9], the suggested method aids in the early identification and prevention of Alzheimer's disease and enables prompt therapeutic therapy. The dataset used in the study consists of 315 T1-weighted MRI images obtained from the ADNI database. GM extraction is performed on the 3D voxel data of the MRI scans, and the resulting GM slices are used to train VGG architectures. The pre-trained VGG 16 & VGG 19 trained on the ImageNet database are utilized, and a layer-wise transfer learning approach is adopted with step-wise freezing of blocks (figure 4). Data pre-processing is crucial to enhance the contrast and pixel intensity of the MRI scans. Operations such as skull stripping, registration, normalization, and segmentation are applied using tools like the SPM12. The dataset is split in three parts of ratio 7:1.5:1.5 to evaluate the proposed approach. VGG 16 and VGG 19 architectures are employed as they have shown superior performance in feature extraction and image processing tasks. Transfer learning is utilized to leverage the pre-trained Methodologys' weights from the ImageNet database. The frozen convolutional base is combined with new fully connected layers for multi-class classification using the softmax function and categorical cross-entropy loss. Yi Li et al [10] has proposed a DL methodology for identifying AD at initial stage. The relationship between simple MRI biomarkers and aspects of AD progression supports the use of these indicators in the early detection and monitoring of AD. Image characteristics that represent the course of AD may be derived using a transfer learning approach based on the 3-dimensional in nature CNN Methodology centred on structural MRI. The augmented CNN Methodology shows higher prediction accuracy compared to the Image CNN Methodology in distinguishing stable and progressive MCI. CNN-derived image phenotypes have associations with early-stage markers of AD, such as lipid metabolites and histidine metabolite involved in tau phosphorylation & insulin resistance. The CNN-derived phenotypes show better associations with AD-related processes compared to clinical labels, cognitive labels, & picture summary measurements. The transfer learning technique improves the robustness of CNN Methodology and reduces overfitting. Case/control MCI is frequently left out of GWAS research, producing less accurate phenotypes, whereas CNN-derived picture phenotypes offer continuous and exact measurements.

Table 1: *Merits and Demerit Analysis on Different Approaches*

Ref	Algorithm	Merits	Demerits	Accuracy
[1]	CNN	Easy for implementation.	It works for particular dataset.	91.86 %
[2]	VGG19	Prediction of images take less time.	The images should have high quality.	98.73 %
[3]	VGG16	The performance was efficient.	The prediction accuracy was not accurate.	82.5%
[4]	Ensemble methods	Time-complexity is less.	Text analysis was not performed.	88.0%
[5]	CNN	The method was executed on multiple methods.	Pre-processing can be done for more efficiency.	86%
[6]	ResNet 18	Easy conversion of 2d to 3d filters using proposed method.	The 2d images are used for only tensor.	96.88 %
[7]	AlexNet	Compared with previous method proposed method has 12% increase in performance.	The issues with computer associates are not solved.	95.70 %
[8]	VGG16	The performance was high.	It can classify only images related data.	99%
[9]	VGG	It can efficiently identify the new features.	Proper comparison is not defined.	97.89 %
[10]	CNN, transfer learning.	CNN has performed accurately	Target labels are not identified accurately.	91%

2.1. Gaps Identified:

- The integration of various medical imaging modalities (e.g., MRI, PET, CT, genomics) remains a challenge. There's a need for research on effective fusion techniques to leverage the complementary information provided by multiple modalities.

- High-quality and diverse datasets are essential for training and evaluating deep learning models. Research is needed to address the scarcity of large-scale, annotated Alzheimer's disease datasets, especially longitudinal data that can capture disease progression.
- Understanding the progression of Alzheimer's disease is essential. Research gaps exist in developing models for longitudinal analysis of medical images to monitor disease progression and treatment effectiveness.

3. Proposed Methodology:

The proposed model to extract the features of the disease it performs the customization of the pre-trained model "ResNet50V2". Instead of passing the input images directly to CNN, the proposed model customizes few operations as discussed below

3.1. Input Pre-processing:

The input pre-processing is divided into two steps. The initial step performs "Zero Centring" on input images in the dataset. Next it performs "Adaptive Filtration" for reducing the noise in the images.

A. Zero Centring: Alzheimer's disease datasets may contain images with varying lighting conditions, contrast, and image quality. Mean subtraction can help mitigate the effects of these variations by centring the pixel values and making the data more consistent. The computation of zero centring is shown in equation (3)

$$New\_X_i = X_i - \sum_{i=1}^{n} \frac{X_i}{n} \text{ - (3)}$$

Where n is the number of pixels in the images

Mean subtraction can help reduce bias introduced by variations in image acquisition conditions. In Alzheimer's disease detection, where detecting subtle differences in brain images is crucial, reducing potential biases in the data is essential.

B. Adaptive Filter Design Using Integration Approach: Combining bilateral and Gaussian filters can be an effective preprocessing strategy for enhancing medical images, such as MRI or PET scans, when working on Alzheimer's disease detection or similar tasks (figure 2). This combination can help to reduce noise while preserving edges and structural details. Start by applying a Gaussian filter to the input image. This initial Gaussian filtering helps reduce high-frequency noise and provides some degree of smoothing. After applying the Gaussian filter, follow it with a bilateral filter. In the proposed algorithm, the model tunes the sigma value in the gaussian filter using the cross-validation approach. Tuning the sigma value in a Gaussian filter is a crucial step in image processing to achieve the desired level of smoothing while preserving important details. The sigma value determines the width of the Gaussian distribution used for convolution. A smaller sigma results in less smoothing, while a larger sigma leads to more extensive smoothing. The bilateral filter is designed to preserve edges while smoothing the image. It considers both the spatial and range domains, making it effective for retaining structural details while reducing noise.

Algorithm for BiGa Filtering Technique:

Input: Load the Images with 4 Class Labels, ALZ_4D

Output: Noise Reduced Images

Begin

1. K← 1 to 10
2. define sigma value in between 1 to 5 with a step value of 0.5&best_score←0
3. for i in K:
   for j in len(sig_value):
new_image←Gaussian_Blur(ALZ_4D[i],sig_value)
new_edges←Canny(new_image, aspect_height,aspect_width)
metric_score←new_edges/ j
4. if metric_score>best_score
sig_value= metric_score
5. for i in len(ALZ_4D):

New_ALZ_4D[i]←Guassian_Blur(ALZ_4D[i],sig_value)

New_ALZ_4D[i]←Bilateral_Filter(ALZ_4D[i], d=len(k)/i)

End

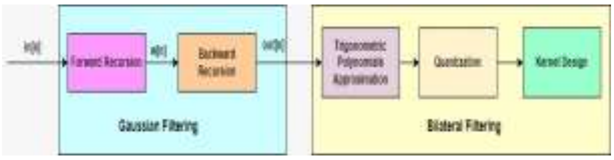

Figure 2: *Designing the Adaptive Filters as part of Pre-processing*

3.2. Need of frozen layers in pre-trained models

Select a pre-trained neural network model that is suitable for the task. Common choices include VGG16, VGG19, ResNet, Inception, MobileNet, and more. Load the pre-trained model weights and architecture. Remove the fully connected layers (often referred to as the classification head) at the end of the pre-trained model. These layers are specific to the original classification task and are not needed for feature extraction.

Frozen layers in pre-trained models play a crucial role in the field of deep learning, particularly in transfer learning scenarios. In deep CNN learned features are valuable and can be leveraged for new tasks without starting from scratch. However, to adapt the pre-trained model to a specific task, some layers need to be frozen while others are fine-tuned. Freezing certain layers of a pre-trained model helps prevent overfitting when the target task has limited data. A DNN requires a lot of computing and time to train from start. By freezing a substantial portion of the pre-trained model, significantly reduce training time and resource requirements. Freezing layers in a pre-trained model can improve convergence during fine-tuning. Pre-trained models often contain a wealth of knowledge about various aspects of the data. Pre-trained models with frozen layers are particularly useful when we have a small dataset for the target task.

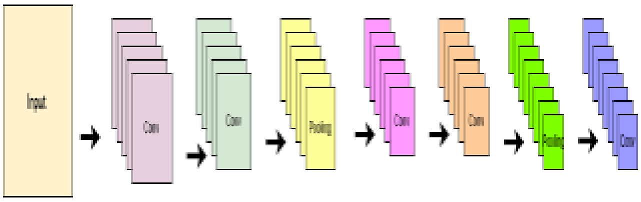

Figure 3: *Freezed Layers in ResNet-50V2*

In deep learning, freezing layers refers to the practice of preventing the weights and biases of certain layers in a neural network from being updated or fine-tuned during the training process. When i freeze specific layers in the model, i essentially lock their weights and biases in place. These layers become "frozen" and are no longer updated during training. During training, gradients are computed for the loss function with respect to the model's parameters. Gradients for the frozen layers are calculated but not used to update the weights and biases since they are fixed. Only the gradients for the trainable layers are used for weight updates through backpropagation. The gradient represents how much the loss changes concerning the parameter θ (θ includes the convolutional kernel weights, fully connected layer weights, and any other learnable parameters in the network). The computation of gradients loss is shown in equation 4

$$\frac{dloss}{d\theta} = 2 * (\frac{dX_i}{dx} - Truth)\,(dX_i * \sum_{i=1}^{n} \frac{X_i}{n}) - (4)$$

Using the loss function, among the existing variants of the ResNet, the proposed model has chosen “ResNet50V2” (figure 3). ResNet-50V2 retains the fundamental concept of residual connections (shortcut connections) introduced in ResNet. These connections allow for the direct flow of information from one layer to another, mitigating the vanishing gradient problem and enabling the training of very deep networks.

3.3. Finding optimal weights using transfer learning:

Using TL to find optimal weights is a powerful technique in deep learning, especially when limited data for a specific task. TL is an ML paradigm where information gained from one activity is used to another that is unrelated but yet important. When it comes to deep learning, neural networks are typically pre-trained on large datasets for tasks like image classification or natural language understanding. TL begins by choosing a model that is currently being trained on an initial function. The initial step is often feature extraction. Take the pre-trained model and remove its final classification layers. The remaining layers, known as the feature extractor, are retained with their weights frozen. Add fresh layers to the pre-trained methodology that are specifically designed for the target task. These new layers are randomly initialized, and the entire model, including the feature extractor and the new layers, is trained on the target dataset. The NN weights are changed as part of the optimisation process to reduce the size of the if that measures discrepancy between methodologies forecasts & the target dataset's ground truth labels.

3.4. Feature extraction using ResNet50V2

ResNet50V2 is a variant of the ResNet architecture, known for its outstanding performance in image recognition tasks. Feature extraction using ResNet50V2 involves utilizing the pre-trained layers of the network to retrieve meaningful feature in the image. Start by selecting the ResNet50V2 methodology. Typically obtain pre-trained ResNet50V2 models from popular DL libraries. Load the pre-trained ResNet50V2 model along with its weights. Most DL libraries provide simple APIs for this purpose. Ensure that load the model in "inference mode" or "evaluation mode," which means that the layers are not trainable. To perform feature extraction, typically remove the final classification layer. Extraction of features from the input images. Simply pass the image data through the model, and it will output feature vectors for each image. The extracted features can be used for various purposes, such as training a new classifier, performing similarity searches, or feeding into other machine learning models for downstream tasks.

A. Global Average pooling with mathematical formula

GAP also known as Global Average Pooling 2D, is a pooling technique commonly used in CNNs for feature extraction. It transforms a 2D feature map

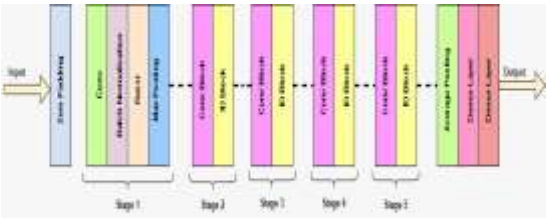

Figure 4: *Customized Layers of Transfer Learning*

into a single value for each channel, effectively reducing the spatial dimensions to a global scale. GAP is a methodology used at the final stage of a CNN architecture, typically before the final fully connected layers or classification layers. It helps in reducing the spatial dimensions of the feature maps and condensing the extracted information for classification or other downstream tasks. Three benefits are present dimension reduction, translation invariances, & fixed input size. The average value for each channel across the entire spatial extent of the feature map. The computation of global average in pooling layers is shown in equation (5)

$$GAP_C = \frac{1}{H*W} * C*(\sum_{i=1}^{n}\sum_{j=1}^{n} Input\_Pixel_{ijc}) - (5)$$

H – height of FM.
W - width of FM.
C – no. of channels.

GAP is a pooling operation that takes the average of all the values in a feature map. It is a non-parametric operation, meaning that it has no learnable parameters. This makes it a very efficient operation, as it does not require any training. It is often used as a replacement for fc layers in CNN. FC layers are typically used to classify the output of a CNN, but they can be computationally expensive and prone to overfitting. GAP can help to address these problems by reducing the n no. of parameter related to the methodology and making it more robust to variations in the input data. GAP does not have any parameters, so there is no need to tune any hyperparameters. First, the pooling window's size must be able to divide the feature map's size in half. Second, the pooling window should be large enough to capture the important features in the feature map.

B. Dense Layer: Dense layers can capture complex relationships between extracted features by learning a linear combination of them. This is important when the extracted features themselves may not be sufficient for the final task and need to be combined in a nonlinear way. Dense layers can be used for dimensionality reduction. They reduce the number of features while preserving the most important information. This can be particularly useful in situations where the raw feature dimension is very high or to prevent overfitting. The important features are extracted using the equation (6)

$$Imp\_Features(P) = \frac{e^{-\sum_{i=1}^{n} W_i P_i + b_i}}{\sum_{i=1}^{n} e^{-\sum_{i=1}^{n} W_i P_i}} - (6)$$

Figure 5 represents the usage of a pre-trained neural network for feature extraction, it's common to freeze some layers while adding custom layers on top to adapt the network to the specific task. Freezing layers means that their weights will not be updated during training.

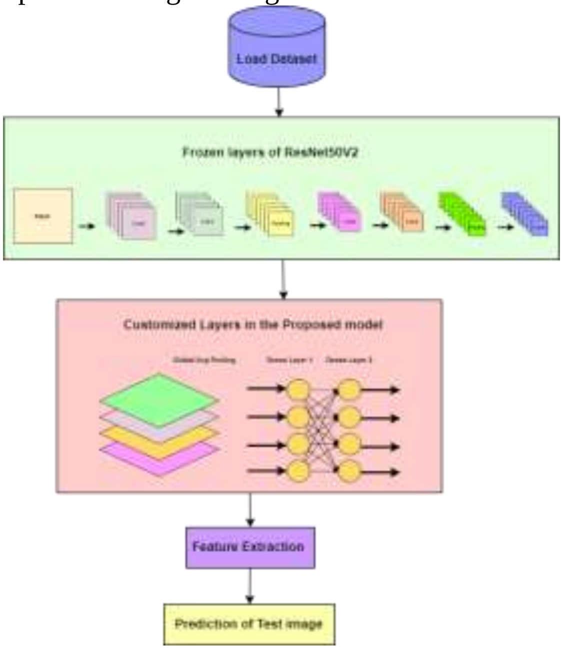

Figure 5: *Designing ResNet-53 for Feature Extraction*

4. Results & Discussion

Figure 6 represents the different filtration techniques applied on the input dataset. The bilateral filter is designed to preserve edges while smoothing the image. This initial Gaussian filtering helps reduce high-frequency noise and provides some degree of smoothing. Combination of these techniques has preserved edges and reduce frequency. Figure 7 presents the block structure of the ResNet 50 V2 for performing the pre-training task on the input dataset. Convolutional blocks with skip connections are a critical design element in ResNet architectures. They enable the training of very deep neural networks, improve feature learning, and enhance gradient flow, ultimately leading to better model performance, particularly in computer vision tasks. Figure 8 represents the parameter training with the customized layers in the proposed model. the GAP layer reduces the spatial dimensions while maintaining the channel dimension, and the subsequent Dense layer has 2048 units as specified. Figure 9 presents the epochs training with customized ResNet- 50 for feature extraction.

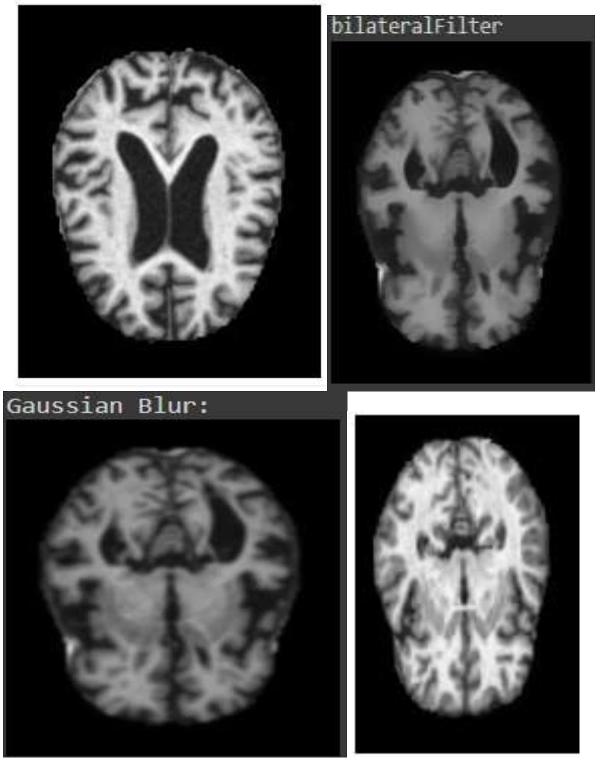

Figure 6: *Filtration Techniques for Pre-processing*

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 150, 150, 3)]	0	[]
conv1_pad (ZeroPadding2D)	(None, 156, 156, 3)	0	['input_1[0][0]']
conv1_conv (Conv2D)	(None, 75, 75, 64)	9472	['conv1_pad[0][0]']
pool1_pad (ZeroPadding2D)	(None, 77, 77, 64)	0	['conv1_conv[0][0]']
pool1_pool (MaxPooling2D)	(None, 38, 38, 64)	0	['pool1_pad[0][0]']
conv2_block1_preact_bn (BatchNormalization)	(None, 38, 38, 64)	256	['pool1_pool[0][0]']
conv2_block1_preact_relu (Activation)	(None, 38, 38, 64)	0	['conv2_block1_preact_bn[0][0]']
conv2_block1_1_conv (Conv2D)	(None, 38, 38, 64)	4096	['conv2_block1_preact_relu[0][0]']
conv2_block1_1_bn (BatchNormalization)	(None, 38, 38, 64)	256	['conv2_block1_1_conv[0][0]']

Figure 7: *Block Structure of ResNet-50V2*

This has increased the accuracy from 52% to 99.09% which is a great improvement with a smaller number of features. The loss of the training data is also almost giving raise to 0%. Figure 10 represents the extracted features with the customized ResNet-50v2. Most of the features are approximately equal to zero. These features might be ignored and continued for classification. Figure 11 represents the prediction of class labels. The dataset contains 4 class labels namely 1: "MildDemented", 2: "ModerateDemented", 3:

Layer (type)	Output Shape	Param #
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 2048)	0
dense_3 (Dense)	(None, 100)	204900
dense_4 (Dense)	(None, 4)	404

Total params: 205304 (801.97 KB)
Trainable params: 205304 (801.97 KB)
Non-trainable params: 0 (0.00 Byte)

Figure 8: *Customized Top Layers of ResNet*

```
Epoch 32/40
161/161 [==============================] - 1s 9ms/step - loss: 0.1183 - acc: 0.9719 - val_loss: 1.9571 - val_acc: 0.5231
Epoch 33/40
161/161 [==============================] - 2s 10ms/step - loss: 0.1218 - acc: 0.9651 - val_loss: 2.1961 - val_acc: 0.5629
Epoch 34/40
161/161 [==============================] - 1s 8ms/step - loss: 0.1237 - acc: 0.9604 - val_loss: 2.0487 - val_acc: 0.5199
Epoch 35/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0879 - acc: 0.9818 - val_loss: 2.1988 - val_acc: 0.5371
Epoch 36/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0733 - acc: 0.9885 - val_loss: 2.2225 - val_acc: 0.5496
Epoch 37/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0829 - acc: 0.9888 - val_loss: 2.3231 - val_acc: 0.5536
Epoch 38/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0681 - acc: 0.9932 - val_loss: 2.2157 - val_acc: 0.5381
Epoch 39/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0672 - acc: 0.9965 - val_loss: 2.2674 - val_acc: 0.5207
Epoch 40/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0551 - acc: 0.9909 - val_loss: 2.4199 - val_acc: 0.4844
```

Figure 9: *Epochs Training using Proposed Methodology*

```
[[[[0.          0.          0.          ... 0.          0.
    0.        ]
   [0.          0.          1.29054081 ... 0.          0.
    0.        ]
   [0.          0.          0.89779353 ... 0.          0.
    0.        ]
   [0.          0.          0.70658916 ... 0.          0.
    0.        ]
   [0.          0.          1.09550476 ... 0.          0.
    0.        ]]

  [[0.          0.          0.          ... 0.          0.
    0.        ]
   [0.          0.          0.          ... 0.          0.
    0.        ]
   [0.32600611  0.          0.          ... 0.          0.
    0.        ]
   [0.          0.          0.53682464 ... 0.          0.
    0.        ]
   [0.          0.          0.          ... 0.          0.
    0.        ]]
```

Figure 10: *Extracted Features of ResNet-53*

"NonDemented", 4: "VeryMildDemented". In the context of feature extraction, the dense layer can be used to transform the extracted features from lower layers of a neural network into a higher-level representation that is more suitable for the final task.

5. Conclusion

Feature extraction for Alzheimer's disease detection using customization of pre-trained models involves adapting a pre-trained deep learning model to extract relevant features from medical images. To prevent the pre-trained layers from being updated

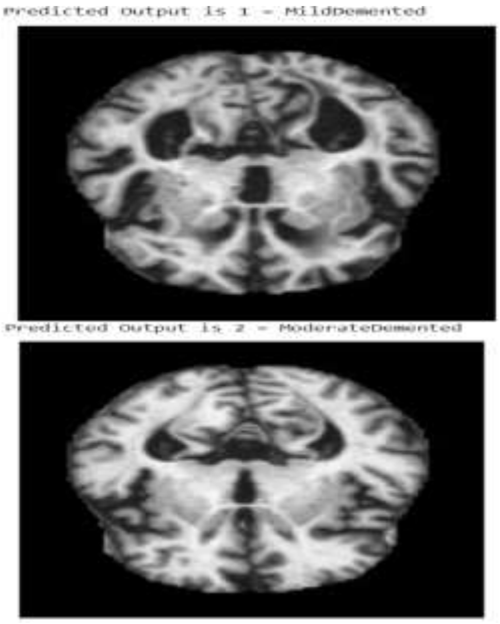

Figure 11: *Predicted Classes using ResNet-53*

during training and to retain the knowledge they've learned from ImageNet or other large datasets, freeze these layers. Add custom layers on top of the pre-trained model to adapt it for Alzheimer's disease detection. These custom layers should include Global Average Pooling (GAP) and one or more Dense layers. Adjust the number of units in the Dense layers to control the feature dimensionality. In future work, extending the use of transfer learning from other neurological disorders or diseases that share similarities with Alzheimer's disease. This can help in leveraging pre-trained models for related tasks and diseases.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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