International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 10-No.4 (2024) pp. 879-889
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

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

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Article Info:

DOI: 10.22399/ijcesen.519
Received : 16 October 2024
Accepted : 26 October 2024

Keywords

Neuro Imaging
Gaussian Filter
Bilateral Filter
Feature Extraction
Neural Networks

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

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[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.

1.1. 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 [17]. In range filtering consideration of the intensity or color similarity between pixels. In filter processing for each pixel, calculate the weighted average of the pixel values in its neighborhood, 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. The merits are edge preservation, non-linear filtering, customizable parameters, and applications. The computation of the bilateral filter is presented in equation (1)

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

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.

1.2. Gaussian Filter

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1.3. 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. 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].

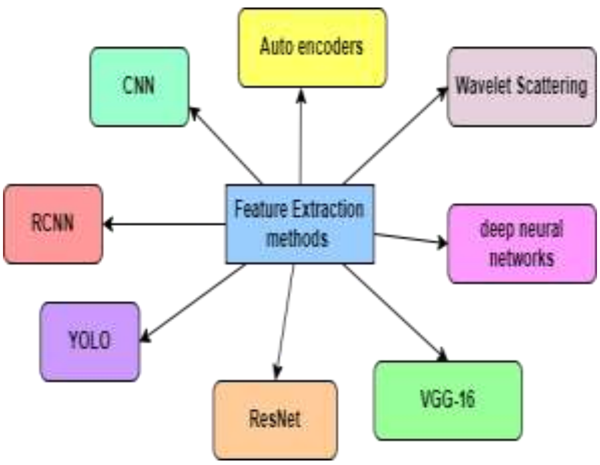

Figure 1: *Classification of Feature Extraction Methods*

2. Literature Survey:

Karim Aderghal et al [1] The newly developed approach focuses on a tiny ROI, 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 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. 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] 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 work highlights MMSE score regression and AD classification, the system uses specialized and having time properties. Yu-Ching NI et al [5] focuses on 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). 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 proposed learning Methodology focuses on "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.

Manu Raju et al [8] the proposed work utilizes GradCam helps ensure that classifiers correctly identify Alzheimer's disease based on the relevant brain regions, aiding in accurate diagnosis and reducing mislabels. 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 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 transfer learning technique improves the robustness of CNN Methodology and reduces overfitting.

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)

$New\_X_i = X_i - \sum_{i=1}^{n} \frac{X_i}{n}$ - (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. This combination can help to reduce noise while preserving edges and structural details. Start by applying a Gaussian filter to the input image. 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
         Best_score+=2*new_edges+metric_score
         Metric_score=new_edges+best_score/2
        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
```

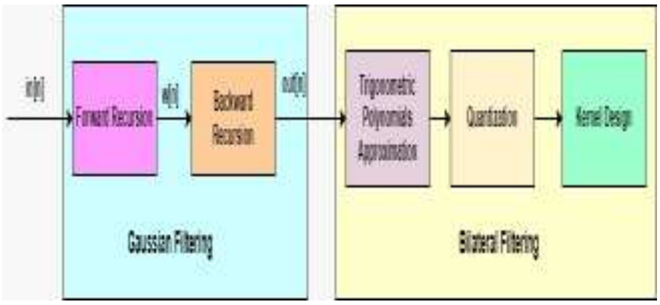

Figure 2: *Designing the Adaptive Filters as part of Pre-processing*

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. Freezing certain layers of a pre-trained model helps prevent overfitting when the target task has limited data.

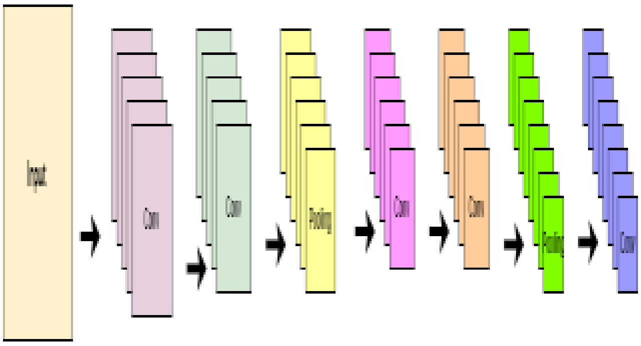

Figure 3: *Freezed Layers in ResNet-50V2*

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

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

Using the loss function, among the existing variants of the ResNet, the proposed model has chosen "ResNet50V2". 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. 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.

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.

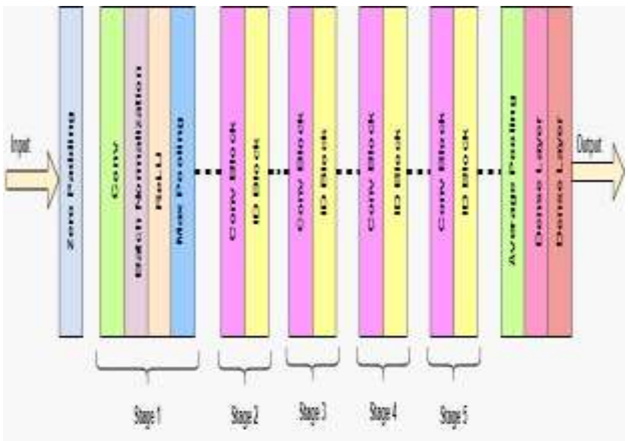

Figure 4: *Customized Layers of Transfer Learning*

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 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)

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

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. 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. 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.

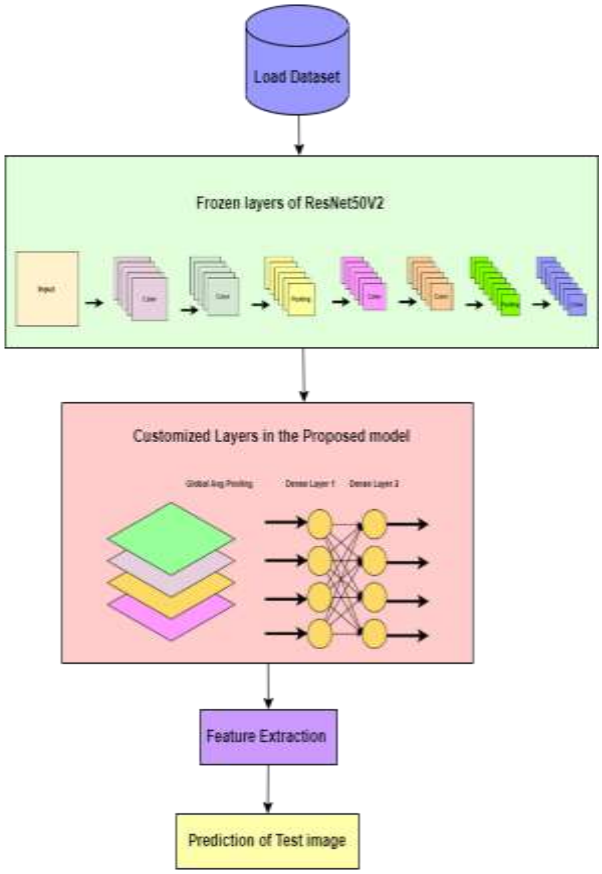

***Figure 5:** Designing ResNet-53 for Feature Extraction*

4. Results & Discussion

Figure 6: *Filtration Techniques for Pre-processing*

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.

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*

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.

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*

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.

```
Epoch 32/40
161/161 [==============================] - 1s 9ms/step - loss: 0.1183 - acc: 0.9719 - val_loss: 1.9571 - val_acc: 0.5211
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: 0.9814 - val_loss: 2.1968 - 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: 0.0601 - acc: 0.9932 - val_loss: 2.2157 - val_acc: 0.5301
Epoch 39/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0472 - acc: 0.9965 - val_loss: 2.2474 - val_acc: 0.5207
Epoch 40/40
161/161 [==============================] - 1s 7ms/step - loss: 0.0551 - acc: 0.9909 - val_loss: 2.4199 - val_acc: 0.4840
```

Figure 9: *Epochs Training using Proposed Methodology*

Figure 9 presents the epochs training with customized ResNet- 50 for feature extraction. 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%.

```
[[[[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.          1.09559476 ... 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*

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 the classification.

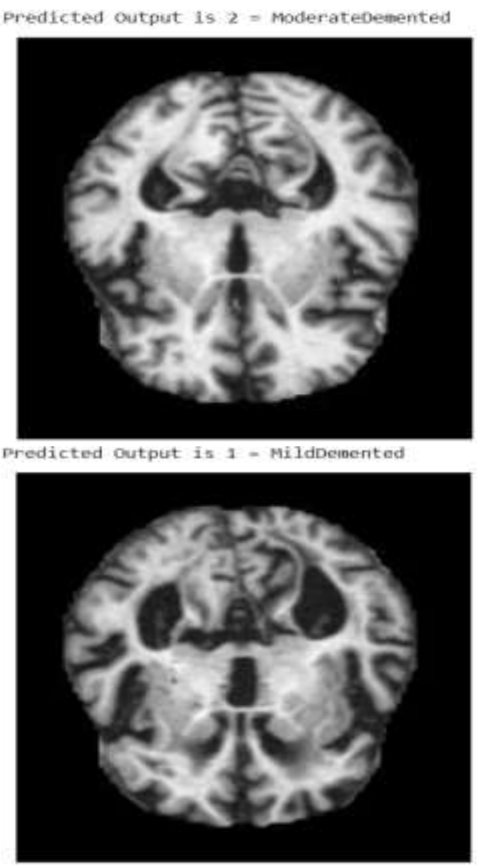

Figure 11: *Predicted Classes using ResNet-53*

Figure 11 represents the prediction of class labels. The dataset contains 4classlabels namely1:"MildDemented", 2: "ModerateDemented",3:"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 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
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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