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Alzheimer's Disease Detection using Deep Learning Network

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***Abstract*—** Alzheimer disease (AD) is an advanced neuron disorder in brain. This disorder primarily affects memory, thinking process and behavior. One of the earliest symptoms is unable to remember newly learned information. Then memory impairment becomes more severe and affects daily activities also in life. Alzheimer disease progressively effects cognitive functions such as reasoning, judgment, and language. AD person may have troubles in finding words, solving problems and making decisions. People with AD may experience changes in behavior and personality.AD patients may become anxious, confused, agitated, or withdrawn. As the disease advances, individuals may struggle with performing routine activities. AD is characterized by the accumulation of abnormal protein deposits in the brain due to two reasons. Amyloid plaques, au tangles. Identifying the area caused by protein deposits exactly we require an optimized finding techniques. Deep learning models, such as Convolutional Neural Networks (CNNs), can analyze MRI and PET scans to detect patterns indicative of Alzheimer's. These scans provide detailed structural and functional information about the brain. Deep learning models can automatically learn relevant features from raw data. This is particularly useful when dealing with complex datasets like medical images. Deep learning models can classify brain images as either indicative of Alzheimer's disease or healthy. This involves training models on labeled datasets to distinguish between different classes (AD vs. non-AD). In this research study we have trained DENSENT, ALEXNET, RESNET, VGG-series, Google Net and our proposed Network. The results with proposed net got quite better than existing networks with accuracy of 96% approximately.

Keywords—Deep learning, Image Data generator, Efficient Net, imbalanced data.

I. INTRODUCTION

Alzheimer's Disease (AD) stands as one of the most pressing health challenges of our time, profoundly impacting millions of lives worldwide. As a progressive neurodegenerative disorder, AD gradually impairs memory, cognitive function, and behavior, ultimately leading to significant functional decline. Initially described by Alois Alzheimer in 1906, the disease has since emerged as a major cause of dementia among older adults, affecting approximately 50 million people globally.

The hallmark pathological features of AD include the accumulation of beta-amyloid plaques and tau protein tangles in the brain, which disrupt neuronal communication and lead to widespread brain cell damage. These biological changes manifest clinically through a spectrum of symptoms, beginning with subtle memory loss and progressing to severe cognitive impairment and functional dependency.

Beyond its profound impact on individuals, Alzheimer's Disease places immense emotional and economic burdens on families and caregivers. As the population ages and life expectancy increases, the prevalence of AD is expected to rise dramatically, presenting significant challenges for healthcare systems worldwide.

While research has advanced our understanding of AD's underlying mechanisms and potential treatments, effective disease-modifying therapies remain elusive. Current management strategies focus on symptom alleviation and support, underscoring the urgent need for continued research into early detection, prevention, and ultimately, a cure.

This introduction sets the stage for exploring the complexities of Alzheimer's Disease, highlighting the critical need for concerted efforts in research, care, and public health to confront this devastating condition.

For CNN[34] model training and improving identification of AD, Convolutional Neural Networks have been used frequently by researchers due to its accuracy and flexibility of techniques. Neural network has been predominantly utilized exhibition of Computer vision errands applied across different areas like self-driving vehicles, clinical imaging, horticulture, producing, and so on. Together with the accessibility of large information, and with expanded figuring abilities are the dominating justifications behind the new achievement. Image acquisition is the starting and most important step in creation of computer vision algorithms. If obtained image is insufficient, the ideal errand of desirable task may be impossible to do. Each of these methods use Convolutional-networks along with immense number of layers and these consists of very large amount of parameters which should be tuned. Consequently they command a big quantity of data to enhance overall performance and

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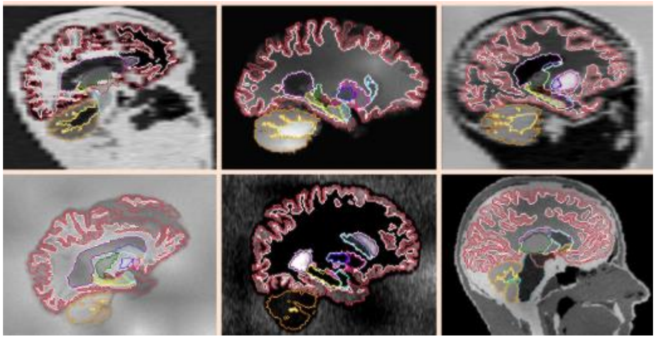
generalization ability. Data availability of AD is one of the biggest drawback at present. Whereas the quantity of seen statistics data is developing at an exponential rate, many datasets be afflicted through various forms of imbalance also.

II. Related Work

Deep learning approaches [4] show impressive results in a variety of object recognition problems from recent years. Image Net Large Scale Visual Recognition Challenge is a well-known object recognition competition in which all participants competed against each other on a scale for detection of object and image categorization. Several new approaches have been identified and detected for this task which define as ADs classification.

Deep Learning [6] is comparatively new concept which is used for years in the field of medical imaging like “classification of breast tissue,” “detection of cerebral micro bleeds,” “classification of brain images,” and “segmentation of CT liver images” . The specific tasks such as visual recognition of objects, identification, and separation, deep CNNs are at present the most appreciated by computer vision researchers. Unlike conventional NN which receive vector input, CNNs operate on volumes, which is one of its advantages over ANNs. The term “parameter sharing” refers to the practice of more than one neuron in a given entity map using the same weights. Contrary to ANNs, neurons were linked; local connectivity refers to the idea that each neuron is attached to a specific section of an image. Currently, people are building CNN from the ground up because it is uncommon to have a sizable database. The classification method for our three-way categorization issue – MCI vs AD Cognitively Normal: should be created by domain adaptation using a cutting-edge CNN method, VGG16. The Oxford VGG has built the 16-layer network known as VGG16. It took part in the 2014 ImageNet Large Scale Visual identication (ILSVI) ImageNet competition. One of the earliest architectures to push to 16 layers and use tiny (3x3) convolution filters to probe the depth of the network.



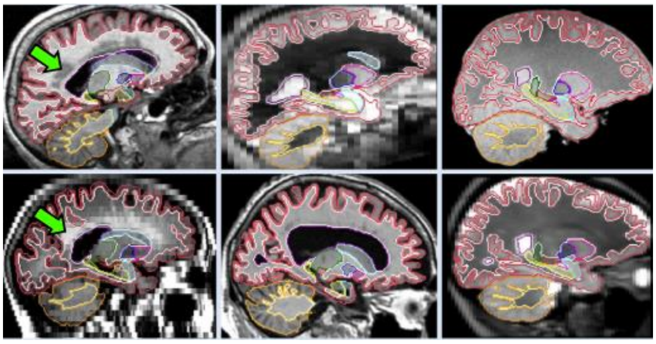


Figure1: Brain MRI Scan Images of Alzheimer’s Disease

A. *LeNeT used for AD Images training*

LeNet is one of the modern network for image processing. LeNet (LeNet-5) consists of two parts: (i) a convolutional encoder consisting of two convolutional layers (ii) a dense block consisting of three fully connected layers.

The basic units in each convolutional block are a convolutional layer, a sigmoid activation function, and a subsequent average pooling operation. Each convolutional layer uses a 5×5 kernel and a sigmoid activation function. These layers map spatially arranged inputs to a number of two-dimensional feature maps, typically increasing the number of channels.

The first convolutional layer has 6 output channels, while the second has 16. Each 2×2 pooling operation (stride 2) reduces dimensionality by a factor of 4 via spatial down sampling. The convolutional block emits an output with shape given by (batch size, number of channel, height, width).In order to pass output from the convolutional block to the dense block, flatten of each example in the minibatch is required. In other words, we take this four-dimensional input and transform it into the two-dimensional input expected by fully connected layers: as a reminder, the two-dimensional representation that we desire uses the first dimension to index examples in the minibatch and the second to give the flat vector representation of each example. LeNet’s dense block has three fully connected layers, with 120, 84, and 10 outputs, respectively. n-dimensional output layer corresponds to the number of n possible output classes.

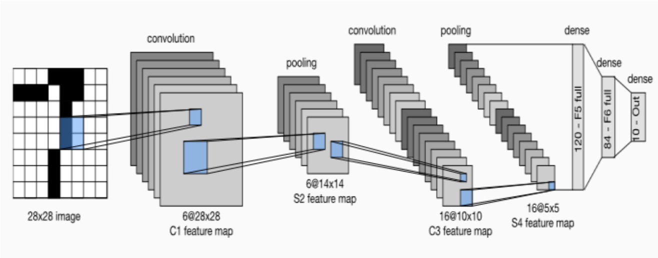


Figure2: LeNet Architecture used for AD Images

B. *AlexNet for Alzheimer’s Disease Images training*

AlexNet’s first layer, the convolution window shape is 11×11. A larger convolution window is used to capture the object. The convolution window shape in the second layer is reduced to 5×5, followed by 3×3. In addition, after the first, second, and fifth convolutional layers, the network adds

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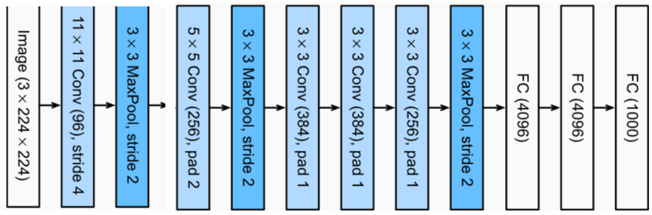
max-pooling layers with a window shape of 3×3 and a stride of 2. Moreover, AlexNet has ten times more convolution channels than LeNet.



C. VGG Network for AD Images training

Like AlexNet and LeNet, the VGG Network can be partitioned into two parts: the first consisting mostly of convolutional and pooling layers and the second consisting of fully connected layers that are identical to those in AlexNet. The key difference is that the convolutional layers are grouped in nonlinear transformations that leave the dimensionality unchanged, followed by a resolution-reduction step. Grouping of convolutions is a pattern that has remained almost unchanged over the past decade, although the specific choice of operations has undergone considerable modifications. The variable arch consists of a list of tuples (one per block), where each contains two values: the number of convolutional layers and the number of output channels, which are precisely the arguments required to call the VGG_block function.

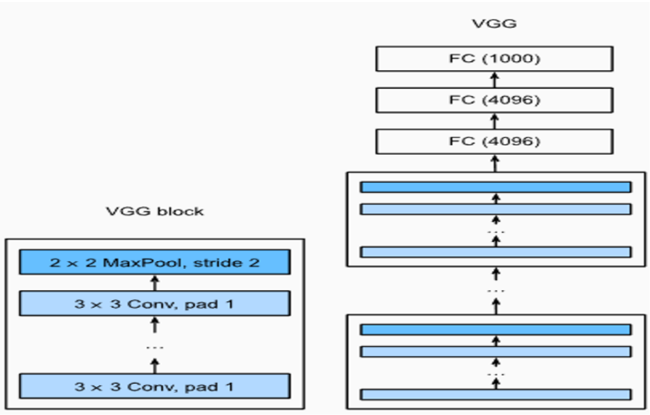


Figure4: VGG Network Architecture used for AD images training

D. Google Net Architecture for Alzheimer's Disease Images training

Inception Block:

The inception block consists of four parallel branches. The first three branches use convolutional layers with window sizes of 1×1, 3×3, and 5×5 to extract information from different spatial sizes. The middle two branches also add a 1×1 convolution of the input to reduce the number of channels, reducing the model's complexity. The fourth branch uses a 3×3 max-pooling layer, followed by a 1×1 convolutional layer to change the number of channels. The four branches all use appropriate padding to give the input and output the same height and width. Finally, the outputs along each branch are concatenated along the channel dimension and comprise the block's output. The commonly-tuned hyper parameters of the Inception block are the number of output channels per layer, i.e., how to allocate capacity among convolutions of different size.

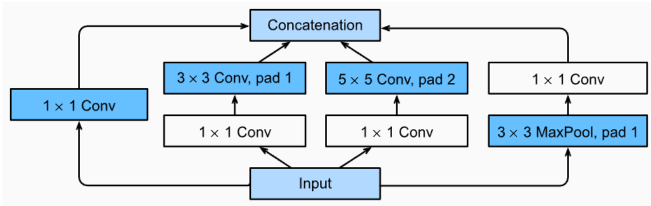


Figure5: Inception Block used in Google Net

GoogLeNet uses a stack of a total of 9 inception blocks, arranged into three groups with max-pooling in between, and global average pooling in its head to generate its estimates. Max-pooling between inception blocks reduces the dimensionality. At its stem, the first module is similar to AlexNet and LeNet. The GoogLeNet model is computationally complex. The large number of relatively arbitrary hyper parameters in terms of the number of channels chosen, the number of blocks prior to dimensionality reduction, the relative partitioning of capacity across channels, etc. Much of it is due to the fact that at the time when GoogLeNet was introduced. Automatic tools for network definition or design exploration were not yet available.

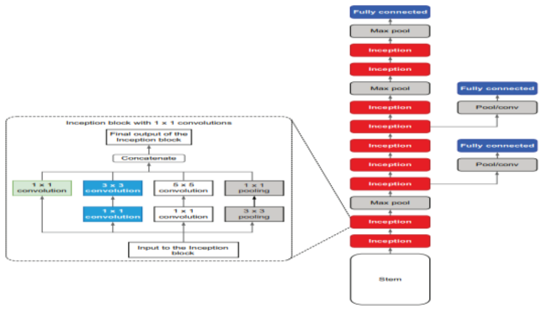


Figure6: GoogleNet Architecture used for AD images training

E. Residual Network (RESNET) Architecture for Alzheimer's Disease detection

ResNet has VGG's full 3×3 convolutional layer design. The residual block has two 3×3 convolutional layers with the same number of output channels. Each convolutional layer is followed by a batch normalization layer and a ReLU activation function. Then, we skip these two convolution operations and add the input directly before the final ReLU activation function. This kind of design requires that the output of the two convolutional layers has to be of the same shape as the input, so that they can be added together. If we want to change the number of channels, we need to introduce an additional 1×1 convolutional layer to transform the input into the desired shape for the addition operation

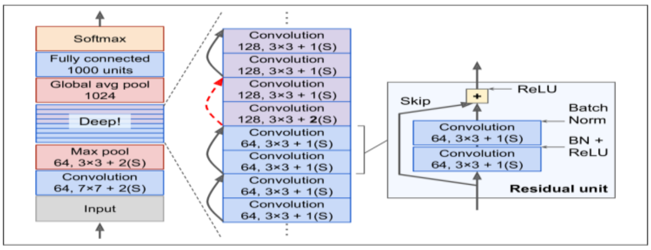


Figure6: ResNet Architecture used for AD images training

The first two layers of ResNet are the same as those of the GoogLeNet we described before: the 7×7 convolutional layer with 64 output channels and a stride of 2 is followed by the 3×3 max-pooling layer with a stride of 2. The difference is the batch normalization layer added after each convolutional layer in ResNet. GoogLeNet uses four modules made up of Inception blocks. However, ResNet uses four modules made up of residual blocks, each of which uses several residual blocks with the same number of output channels. The number of channels in the first module is the same as the number of input channels. Since a max-pooling layer with a stride of 2 has already been used, it is not necessary to reduce the height and width. In the first residual block for each of the subsequent modules, the number of channels is doubled compared with that of the previous module, and the height and width are halved.

F. DenseNet for Architecture for Alzheimer's Disease

DenseNet uses the modified "batch normalization, activation, and convolution" structure of ResNet. A *dense block* consists of multiple convolution blocks, each using the same number of output channels. In the forward propagation, however, we concatenate the input and output of each convolution block on the channel dimension. Lazy evaluation allows us to adjust the dimensionality automatically. DenseNet first uses the same single convolutional layer and max-pooling layer as in ResNet. similar to the four modules made up of residual blocks that ResNet uses. DenseNet uses four dense blocks. As with ResNet, we can set the number of convolutional layers used in each dense block.

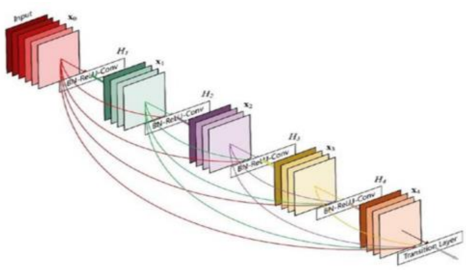


Figure7: ResNet Architecture used for AD images training

III. Proposed Model

In this research work, we have built our customized network and trained on the same dataset[38] along with above discussed existing networks. Our Model has built like below with different combinations of layers with ReLu activation function in convolutional layers. Softmax is used for output layers since we are building the model for multi classification. Dropout hyper parameter also used in layers to suppress disturbing parameters with maximum fifty percent.

```
model = Sequential([
    Rescaling(1.0/255, input_shape=(img_height, img_width, 3)),

    Conv2D(32, 3, padding="same", activation='relu'),
    BatchNormalization(),
    MaxPool2D(),

    Conv2D(64, 3, padding="same", activation='relu'),
    BatchNormalization(),
    MaxPool2D(),

    Conv2D(128, 3, padding="same", activation='relu'),
    BatchNormalization(),
    MaxPool2D(),
    Dropout(0.15),

    Conv2D(256, 3, padding="same", activation='relu'),
    BatchNormalization(),
    MaxPool2D(),
    Dropout(0.20),

    Conv2D(512, 3, padding="same", activation='relu'),
    BatchNormalization(),
    MaxPool2D(),
    Dropout(0.25),

    Flatten(),
    Dense(1024, activation="relu"),
    BatchNormalization(),
    Dropout(0.5),
    Dense(num_classes, activation='softmax')
])
```

Figure8: Customized model for Ads Image training.

IV. Results and Discussion

Dataset [38]used for the model building is image dataset with 18755 images splitted into train and test datasets as 13142, 5322 respectively. The size of image is 180X180 with 3 channels. Total number of classes in this dataset are 5, classified as 'AD','CN','EMCI','LMCI','MCI'.

The platform we used for experimentation is Google Colab with TPUv2, which is a free service utilized. The frame work for experimentation used is Tensorflow

When the DenseNet trained on the above dataset, with pertained parameters on ImageNet dataset the model achieved the accuracy 0.9383.

The confusion matrix for the above trained model is

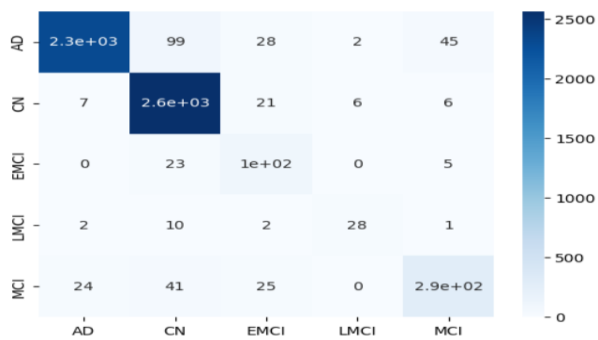


Figure 9: Confusion matrix of DenseNet on AD dataset.

And DenseNet valuation on test dataset with hyperparameters like epoch: 50, Optimizer: Adam, Loss

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function: categorical cross entropy is as given below

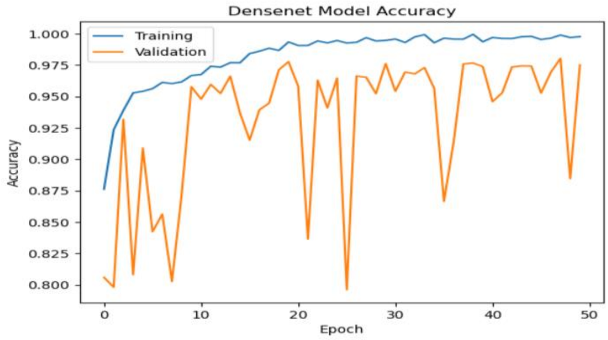


Figure 10: Training and Validation accuracy of DenseNet on AD dataset.

The experimental results of VGG19 given less accuracy when compared with DenseNet. VDD 19 did not use pertained parameters. This network achieved the accuracy of

85.54%.

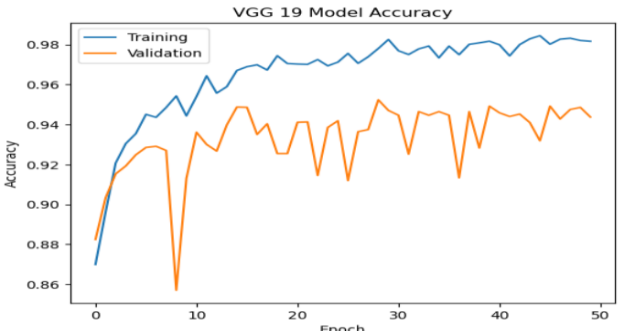


Figure11: Training and Validation accuracy of VGG19 on AD dataset.

For AlexNet, LeNet and GoogleNet, the performances are very low and less than 50%. These are existing and ancient networks used for very low contrast images. These model's performances were not compared with modern Networks performances.

In ResNetV2 the model has given the performance as 93.11 percentage, more than what we have achieved with previous models.

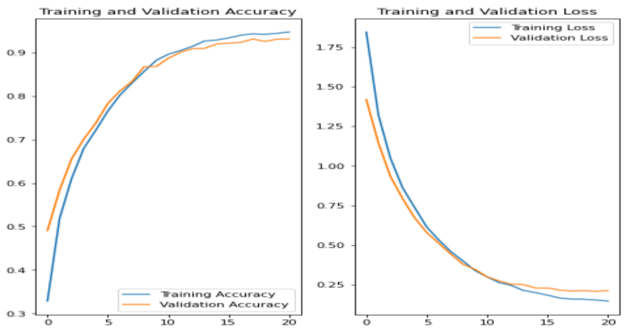
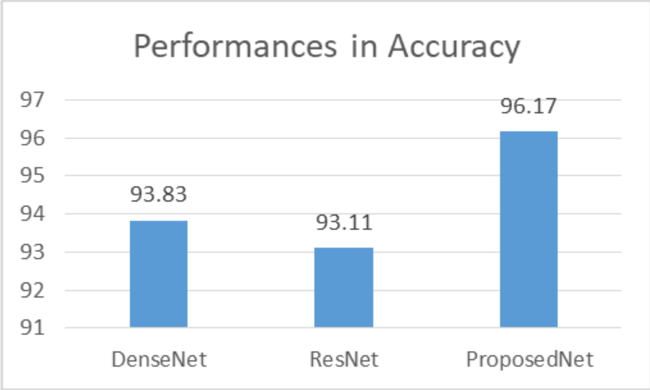


Figure12: Training and Validation accuracy of ResNetV2 on AD dataset

Proposed Network shown in Fig8 trained on the same environment, with same GPUs, with 20 epochs achieved good results. It has given 96.17% of accuracy. Comparison of all network performances are given below



V. Conclusion and Future Work

In this research work we approached and proposed a network to improve accuracy for finding the Alzheimer's Disease along with other deep learning models. In the first approach we have identified imbalanced dataset which is available in kaggle and we have utilized this as an objective for our work. For this the image data generator techniques is used to balance the data by random rotating, random shifts, and random zoom process the new images are generated and data is balanced. After balancing the data we have applied various deep Learning Networks to identify Alzheimer's Disease and also improve its accuracy. Finally by using TPU environment from Colab we have reduced time.

In future we can extend accuracy for further by using a a huge and various different. Apart from this some extra identification and detection methods are utilized to compare disadvantages as well as advantages to the proposed method. small gpu instance for various kind of models on different Further, we can make a level up to install applications on mobile which is very useful for patients.

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