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Transfer Learning-Based Approach for Early Detection of Alzheimer's Disease

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ABSTRACT
Alzheimer's disease is one of the world's main health concerns today. People with Alzheimer's disease who are diagnosed early have the best chance of receiving effective therapy. It's critical to catch the sickness as early as possible. Magnetic resonance imaging is one way to define Alzheimer's disease by finding structural abnormalities in the brain (MRI). We propose that machine learning, specifically trained convolutional neural networks (CNNs) with transfer learning capable of making predictions about similar brain imagery, can aid in early detection. CNN enables the extraction of MRI properties and classification as Alzheimer's disease or normal brain. We used the VGG19 architecture to categorize patients as having no signs of Alzheimer's disease or having signs of very mild, mild, or moderate Alzheimer's disease. Based on a transfer learning methodology, this method correctly classifies MRI images into four phases of Alzheimer's disease with an accuracy of 85 percent.
Keywords: Alzheimers Disease, Transfer Learning, VGG19, MRI, CNN.

I. INTRODUCTION

ALZHEIMER'S Disease (AD) is a progressive neurologic disorder that causes the brain to shrink (atrophy) and brain cells to die. The onset of Alzheimer's disease is usually slow, and the early symptoms can be attributed to aging or common forgetfulness. The patient's cognitive abilities, including the capacity to make decisions and carry out daily chores, degrade as the disease progresses. There is currently no cure for the disease; however, a set of rules can be followed to help slow its progression. However, it is apparent that Alzheimer's disease is not a fast-moving condition, but rather a slow-moving degenerative process that can take decades to manifest into a form that interferes with daily tasks. According to A.J Mitchell et al., this suggests that those with Mild Cognitive Impairment may be in the early stages of Alzheimer's Disease. [3] With an annual conversion rate of 5-10%, this change is significant. As a result, an accurate diagnosis will be critical in improving their patients' quality of life.

The motive for developing new technologies to aid in the fight against Alzheimer's disease is clear, not only from an ethical standpoint but also due to the growing number of Alzheimer's cases in our society.

Today, 50 million people worldwide suffer from dementia, with Alzheimer's disease accounting for

two-thirds of the cases [1]. Alzheimer's disease has surpassed cancer as the most dreaded disease in the United States, with a new case reported every three seconds [2]. We offer a model that performs near-perfect classification to demonstrate how transfer learning might aid in disease early detection and classification.

II. RELATED WORKS

Since 1994, researchers have been utilizing MRI data alone to detect the development of Alzheimer's disease using a variety of machine learning algorithms [4]. The researchers started by deciding which biomarkers they wanted to look at. A biomarker is a measurable indicator of the health of a biological system. On the other hand, hippocampal volume is regarded to be inadequate as a predictor of progression from mild cognitive impairment (MCI) to Alzheimer's disease (AD) [5]. As a result, further factors must be investigated, and current research has indicated that significant changes also occur in many other cortical areas [6]. Machine learning and deep learning techniques are effective in aggregating spatial data from MRI images and categorizing them.

Instead of using only one slice and input from diverse sources, a deep neural network incorporates data from several levels of the brain scan. Scanning techniques would increase the network's performance. Plant et al. (2010) employed feature selection to achieve 92 percent accuracy in binary Alzheimer's disease classification [7].

III. DATASET AND FEATURES

Our data comes from a Kaggle project that used MRI brain pictures. A large number of images and their consistency were the key factors for choosing this data collection. They are black and white images with a size of 224x224 pixels. The data consists of nearly 6400 images, of which 5000 images were used for testing and 1200 images were used for training. All four categories of images are included in the data: non-demented, very mildly demented, mildly demented, and moderately demented. Each image shows a clipped backdrop of 2D MRI cross-section of the brain.

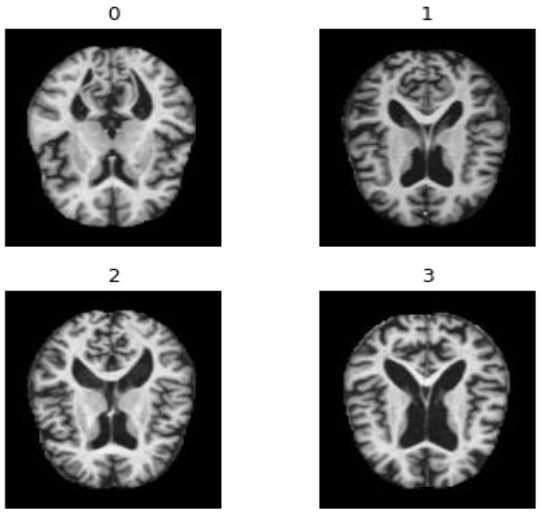


Fig. 1 : MRI Images from the Dataset

As illustrated in Figure 1, the dataset contains MRI pictures of nondemented, mildly demented, very mildly demented, and moderately demented patients.

IV. METHODOLOGY

We decided that adopting transfer learning from a pre-trained network would be the ideal strategy because developing and training a deep neural network from scratch is quite expensive. We can download various classification networks whose weights are trained on the imageNet dataset using Keras and TensorFlow. The model's early convolution blocks have already been optimized to find the common low-level properties of all natural photos incredibly effectively. In order to strengthen the network even further, we trained all of the convolutional layers in our scenario.

A. CNN:

CNN is a type of deep neural network (DNN) that is frequently used to analyse visual data [8]. For image recognition and categorization, ConvNet or CNN is a powerful Neural Network Algorithm. A CNN is a feed-

forward network that filters an array of pixels as inputs [9, 10].

There are many filters in the convolution layer that perform convolution operation. A filtered picture is created by passing an image through a filter, and the process is known as convolution [12]. After that, the tensors are max-pooled, and the output is sub-sampled to reduce the size of the image. As a result of the above technique, the number of parameters decreases, lowering complexity [13].

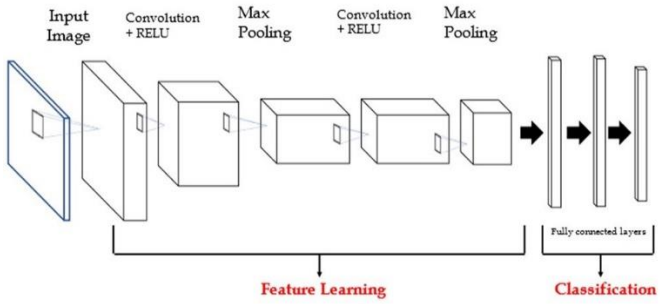


Figure 2: Architecture of Convolutional Neural Network [11].

The feature extraction procedure, which is the first layer of a CNN, is done with Convolution Layers. Some filters are applied to the image data, which is a grid-like pattern or matrix, for feature extraction. To produce a feature map of neurons, all of the filters are convolved with each input image. Between the filters and the inputs, dot manufacturing happens, and the outcome of each convolutional layer becomes simpler. Instead of a fully linked neural network, we get fewer shared parameters, which minimizes the model's complexity and improves its efficiency.

B. **Pooling:**

The convolutional layers apply learned filters to the input in a systematic way to build a feature map that contains all of the input's summary features. Any minor change, such as rotation, cropping, or flipping, could cause this. The most common solution is to use a layer of pooling [14]. Each feature map is worked on individually by the pooling layer, resulting in the equal number of new pooled feature maps. The size of the feature map changes to 2 by 2 pixels with a stride of 2, and the feature map is always reduced by a factor of two, lowering the number of pixels in each feature map. The pooling function used is max pooling, in which the output is sub-sampled to make a smaller picture, and the number calculated is the greatest value from that particular feature map. As a result of the above method, the number of parameters decreases, lessening the complexity [15].

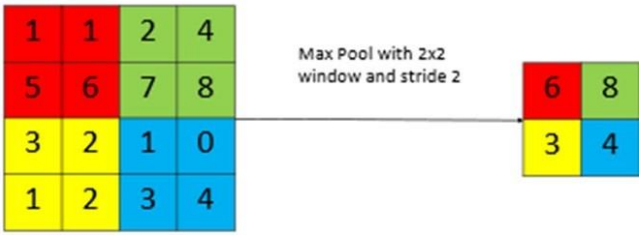


Fig 3: Max pool Operation in CNN [16].

C. **Transfer Learning:**

Transfer learning is a machine learning research challenge in which a previously trained model is reused on a new issue, allowing deep neural networks to be taught with less data and less time [17]. Keras' pre-trained models work well for transfer learning, but there is one catch. Humans, objects, and animals have all been taught to discern between these models. However, in our situation, every image is of a brain, and we need to identify characteristics that differentiate them by class. VGG19's first two layers, which are made up of 40 pre-trained layers, will suffice. Hopefully, this will allow us to use VGG19's incredible feature identification capabilities without having to look for specific items.

VGG Net is a simple CNN architecture that stands out among the rest. VGG's architecture may be defined in a few words. We must stack the convolutional layers as the filter sizes grow larger. That is, if layer 1 has 10 16 filters, layer 2 must contain at least 16 filters. Another notable feature is that in any VGG architecture, all filters are 3x3 in size.

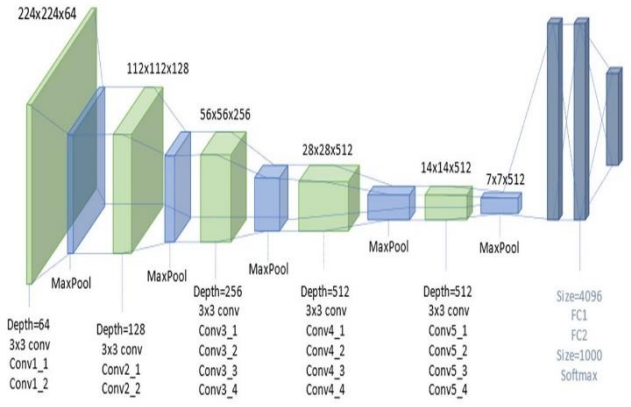


Figure 4: VGG19 Architecture [18]

VGG19 has 19 layers, with the numbers 16, 3, 5, and 1 representing Convolution, completely connected, Max Pool, and SoftMax, correspondingly [19]. The network may be loaded from the ImageNet database, which contains over a million photos, with a previously trained sort of the network. As a consequence, the model of picture inputs with a resolution of 224x224 has learned rich characteristic representations for a wide variety of images [20]. With the SoftMax activation function, the number of nodes in the final fully linked layer equals the number of classifiers. The SoftMax function is defined as shown in Eq. 1

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \; for\; i = 1, \dots, K \; and \; z = (z_1, \dots, z_K) \in R^K \qquad (1)$$

This formula determines the conditional probability of each class given the model's input (image). A conditional probability has been calculated for each categorization. The model predicts picture classification by picking the class with the highest conditional probability.

The original VGG19 network was updated by adding new fully linked layers to the network's untrained end. Using our training set, we then restricted the entire network. We picked categorical cross-entropy as our loss function because it is commonly utilized for multiclass classification tasks. The categorical-cross entropy can be calculated using Eq. 2

$$H(p,q) = -\sum_{x} p(x) \log\big(q(x)\big) \qquad (2)$$

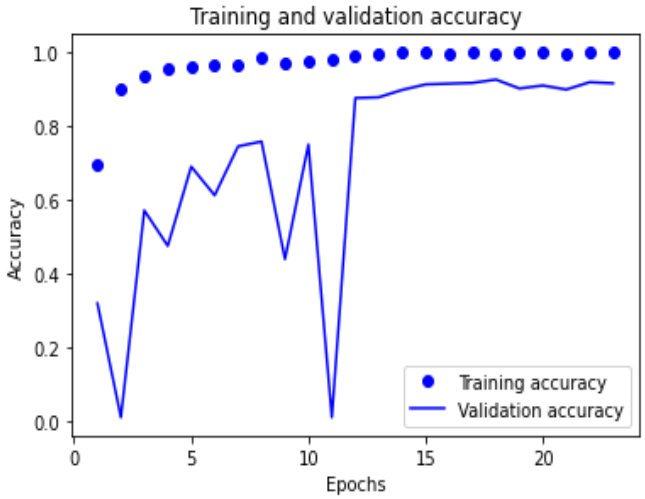
Where the true distribution is p, and the computed distribution is q.

D. Optimizer and Learning Rate:

We'll use the Adam optimizer because it's the best optimizer for most circumstances right now. I tried adjusting the learning rate while working on this model, but both raising and reducing it produced terrible results. Similar results were obtained by putting the optimizer on a learning schedule. Finally, I applied the Adam optimizer which seems to improve the model's performance.

V. EXPERIMENT AND RESULTS

The model did not follow a linear route to this conclusion during the training phase, as can be seen here, with some noise in the validation accuracy and loss. Using the accuracy and loss plots we have created; we can see that our model is very overfitted and does not generalize well. The accuracy of the model rapidly hits 99%, but these gains do not translate to validation accuracy, which can fluctuate greatly. No amount of regularization, batch normalization, or dropout seems to satisfactorily reduce this overfitting (at least without negatively affecting the validation accuracy).



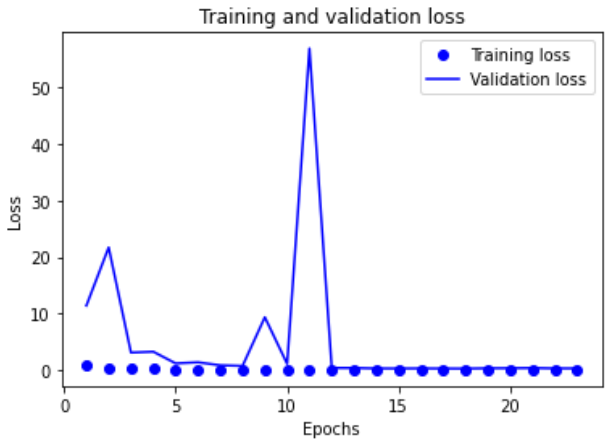


Figure 6: Accuracy and Loss of testing/training

No amount of regularisation, batch normalisation, or dropout appears to mitigate this overfitting satisfactorily (at least without negatively affecting the validation accuracy). This is due to our transfer learning of the GVV19 model. The GVV19 model is a double-edged sword in this case: in testing, it significantly enhanced the model's accuracy from roughly 50% to 78 percent. It was, however, tough to get it passed this phase. It could be beneficial to employ more Conv2D layers in future revisions.

Our model performs best when predicting Class 0 (no Alzheimer's) and poorest when predicting Class 3 (Moderate Alzheimer's), according to our confusion matrix. When an inaccurate prediction is produced, it looks that the real label is likely to be one stage away (e.g., if the model predicted an image of Very Mild Alzheimer's, the actual label was most likely No Alzheimer's or Mild Alzheimer's). It's easy to blame this on the fact that each stage of the sickness causes slow or subtle alterations, but it's vital to remember that our beginning social class disparity is likely to blame. Without initially addressing the imbalance, it's difficult to make any clear conclusions.

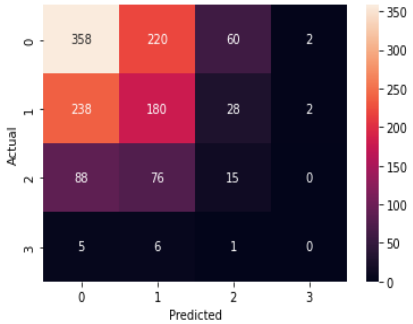


Figure 7: Confusion Matrix and Accuracy

E. Combining Alzheimer's-Positive Classes:

We can combine our Alzheimer's-positive classes to better balance our classes. Here there are two classes dementia and nondementia, this turns our problem into a binary classification problem, identifying whether or not a brain has patterns related to Alzheimer's. the dementia class consists all the three positive class very mild, mild and moderate. Due to this in some tests, this raises our accuracy as high as 85%, but in many tests, the results are nearly identical to our previous model. In either case, Because Alzheimer's manifests differently depending on the stage of the disease, it is useful to identify which stage a person might currently be experiencing. A better solution is to add more observations to our underrepresented classes.

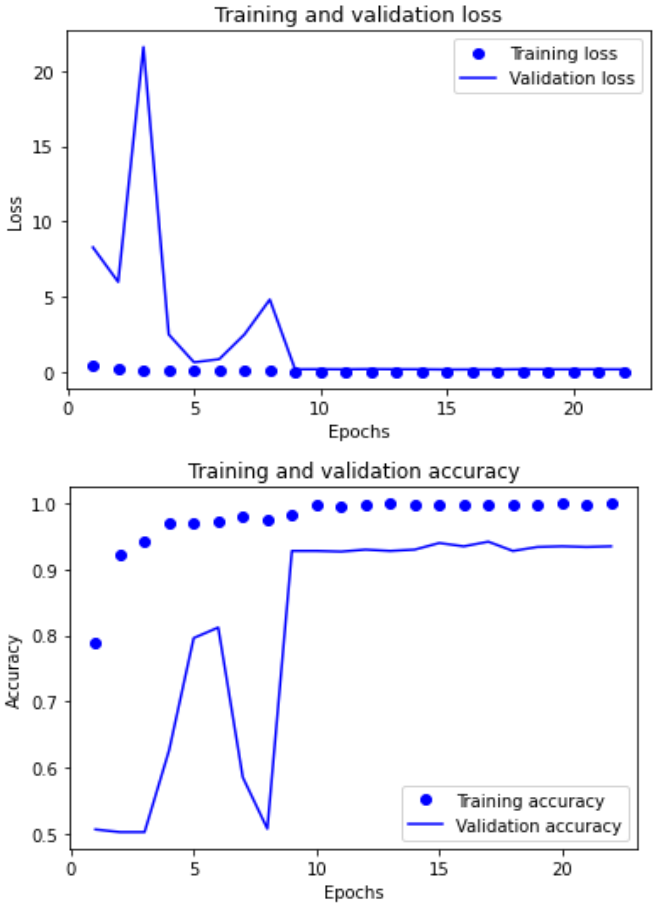


Figure 7: Accuracy and Loss of testing/training

We compared the performance of our proposed method with some state-of-the-art approaches, as shown in Table I. The comparative study and the provided accuracy are based on the testing dataset. We compared the performance of our proposed method with some state-

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TABLE I: COMPARISON OF THE ACCURACY OF THE PROPOSED METHOD WITH OTHER METHODS

Methods	Network	Accuracy
[21]	DNN	67%
[22]	CAE	80%
[23]	Inception	81%
Proposed method	CNN Transfer Learning	85%

From Table I, D. Manzak and G. Sentinel [23] used the Deep Neural Network (DNN) for the detection of AD and they obtained 67%. Also, Martinez-Murcia, Ortiz, Gorriz, Ramirez, and Castillo-Barnes [24] have applied the Convolutional Autoencoders (CAE) and they obtained 80%. Cortical images are applied to different deep networks including ResNet and Inception in [25] and achieved 81%. Our method outperformed the above methods with 85.79% testing accuracy. This efficiency is due to the use of Transfer Learning by using knowledge acquired from the VGG19 architecture for the classification of images from the Oasis dataset.

VI. CONCLUSION

We used the VGG19 baseline model to detect Alzheimer's disease using MRI data in this study. With the help of this we classified whether the patient is demented or non demented and also if demented, we predicted the stage of dementia. Our current methodology infers throughout the full MRI image. The method's good results have backed up the theory that Alzheimer's disease traits aren't recognized in specific brain regions, but rather aggregate and hidden features existing across the brain.

The team would like to investigate feature extraction on specific brain regions in the future. In the future, more data from more patients will be collected to ensure that the model's accuracy remains consistent. To solve the problem of insufficient training data, several strategies are utilized in the literature, which the team would want to investigate more in the future by considering 3D MRI images.

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