Improved/Prediction of Classification of the Alzheimers' Disease with Convolutional Neural Network

S. Muhammed[1], J. Upadhya[1], S. Poudel[1], K. Poudel[2], J. Vargas[3],

1. Computational and Data Science, Middle Tenneessee State University, Murfreesboro, Tennessee, USA
2. Computer Science, Middle Tenneessee State University, Murfreesboro, Tennessee, USA
3.Engineering Technology, Middle Tenneessee State University,USA
{sam2et,ju2i,sp2ai }@mtmail.mtsu.edu, khem.poudel@mtsu.edu, jorge.vargas@mtsu.edu

***Abstract*— This work focuses on classifying MRI images using machine learning models to identify Alzheimer's disease (AD), the most common form of dementia, early[1]. It is now possible to identify and forecast the onset of AD by analyzing brain scans collected by Magnetic Resonance Imaging (MRI) and using artificial intelligence (AI) technologies, classifying people as either at risk or not. The main goal is to make precise predictions.Improved prediction and detection tools for radiologists, physicians, and caregivers will be made available as a result of the study's determination of the likelihood that AD patients would contract the disease and proper categorization of them. Using machine learning methods Convolutional Neural Network (CNN), Support Vector Machine (SVM), and FASTAI are developed using a dataset of 4098 MRI images from the ADNI 4 class for the early detection and classification of AD. The models attain an impressive accuracy rate of 80.4%, with the convolutional neural network outperforming other algorithms in terms of accuracy. This study demonstrates a viable method for classifying and diagnosing Alzheimer's disease early on, utilizing MRI images and machine learning models. The acquired accuracy rates show the models' potential to help doctors and other caregivers with AD diagnosis and management, hence maximizing overall effectiveness.**

Keywords*— *MRI Images, SVM classifier, Convolutional Neural Network, Machine Learning, FASTAI, Alzheimer's Disease.

I. Introduction

A degenerative condition called ALZHEIMER'S disease (AD) gradually impairs cognitive functions, especially memory. It ranks as the seventh biggest cause of death worldwide and is the most common cause of dementia in older persons. Memory loss, confusion and speech and reasoning impairment are among the symptoms that often show up in later years and worsen over time. People with advanced stages of the illness are unable to communicate or carry out even simple chores, and they are dependent on other people for care. Alzheimer's disease can affect the brain for a decade or longer before any symptoms present themselves. Previously healthy neurons lose their functionality, connection, and viability as a result of an accumulation of aberrant proteins in the brain. While there is currently no therapy for Alzheimer's, it can be slowed down with current therapies.

Alzheimer's disease is diagnosed using magnetic resonance imaging (MRI), which also determines the disease's phases and rules out other potential sources of symptoms. Early detection is essential for prompt treatment to begin, which can assist and maintain everyday functioning for a while. As a result, research is concentrated on using MRI pictures to identify the early stages of Alzheimer's disease, with machine learning emerging as a potent tool for image categorization in this context [2].

Alzheimer's disease (AD) is a prevalent type of dementia that can harm brain cells and impair a person's ability to behave appropriately, think critically, and engage in social activities. According to estimates, this disease may afflict 1 in 85 individuals by 2050. MRI scans are the most widely used neuroimaging technique for the detection and prediction of AD, and early identification and prevention of this illness are essential. The research focuses on using MRI scans to identify and categorize AD patients using Convolutional Neural Network, Support Vector Machine, FASTAI, and Resnet34 image classification models. The major objective is to develop reliable prediction and detection tools to aid radiologists, physicians, and caregivers in saving time and money while assisting patients with this disease [3].

II. LITERATURE REVIEW

The majority of recent research focuses on identifying MRI images using CNN models relevant to Alzheimer's disease and cutting-edge architectures like ResNet. This section summarizes numerous research studies that use CNNs and substitute models like Deep Boltzman Machines and Support Vector Machines (SVM). The examined publications, the models used, and their reported accuracy are all summarized in Table 1.

Table 1. Papers on Alzheimer's disease using machine learning

Paper Title	Authors	Year	Datasets	Algorithms	Results
Diagnosis of Alzheimer's disease using PET images with deep learning	Li, et al.	2021	ADNI	CNN	AUC: 0.973
Machine Learning Techniques for Diagnosis of Alzheimer's Disease: A Review	Balachandar et al.	2020	ADNI, OASIS	SVM, Random Forest, KNN	Acc: 91%, AUC: 0.98
Early Detection of Alzheimer's Disease: A Machine Learning Approach Using Combination of EEG Features and Neurocognitive Tests	Khan et al.	2020	ADNI	SVM	Acc: 96%
A Deep Learning Model for Alzheimer's Disease Diagnosis from Brain MRI Images using Transfer Learning	Rajan et al.	2020	ADNI	VGG16, ResNet50	Acc: 98%, AUC: 0.99
A Machine Learning-Based Method for the Diagnosis of Alzheimer's Disease from Structural MRI Images	Cheng et al.	2019	ADNI	SVM, RF, MLP	Acc: 91%, AUC: 0.95
Automated Diagnosis of Alzheimer's Disease via Ensemble of Convolutional Neural Networks using Structural and Functional MRI	Talo et al.	2019	ADNI	CNN	AUC: 0.94
Automatic diagnosis of Alzheimer's disease via unsupervised feature learning-based on deep belief network with compressed sensing MRI	Zhang et al.	2018	ADNI	DBN	Acc: 90%, AUC: 0.92
Predictive analytics with gradient boosting in clinical medicine and healthcare	Al-Jumaili et al.	2018	ADNI, OASIS, AIBL	GBM	Acc: 80%, AUC: 0.86
Diagnosis of Alzheimer's disease using a combination of deep learning and feature extraction from structural MRI and PET images	Li et al.	2018	ADNI	CNN, SVM	Acc: 92%, AUC: 0.96
Deep learning based imaging data completion for improved brain disease diagnosis	Wang et al.	2016	ADNI	DBN	Acc: 93%

III. MATERIALS AND METHODS

The Method proposed in this work, is a systematic approach to progress from defining a problem to obtaining experimental results and conducting analysis which is described in following sections and is given as a flow chart in Figure 1 below.

III-A. DATA ACQUISITION

There are 6,400 images in all, 3,200 of which are labeled as insane, 2,240 of which are very mildly demented, 896 of which are mildly demented, and 64 of which are moderately demented. The images were divided into two directories one for training images and the other for testing images,inside this directories Alzheimer's and healthy controls images were equally divided [4].

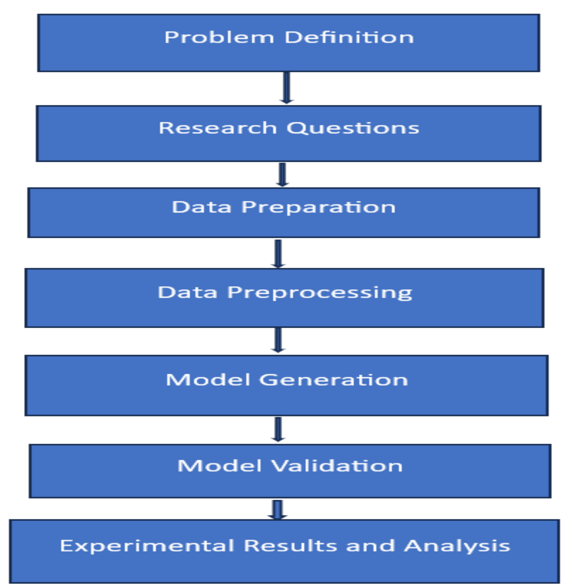

Figure 1. Method Chart

III-B. IMAGE PRE-PROCESSING

The preprocessing of Alzheimer's data images using the Image Data Generator involves multiple steps to prepare the data for training or evaluation in a convolutional neural network (CNN) model. These steps include importing the necessary libraries, creating an instance of the Image Data Generator class, rescaling the data, and utilizing the data augmentation options provided by the class.To enhance the diversity and size of the training dataset, the Image Data Generator applies random transformations to the existing images, such as rotation, shifting, zooming, shearing, and flipping. This generates new training samples and increases the variety of the dataset.The next step involves loading and preprocessing the images. The images are read from a specified directory and undergo the preprocessing and augmentation techniques defined earlier. Batches of pre-processed images are generated, allowing for customization of parameters such as target image size, batch size, and classification mode (binary or categorical). If there are separate datasets for training, validation, and testing, it is Crucial to appropriately split the data and create separate generators for each dataset. The Image Data Generator class facilitates this by allowing the specification of subsets for training and validation using the validation split parameter. The generated batches of pre-processed images are used to train or evaluate the CNN model. The training generator is passed to the fit method for model training, while evaluation can be performed using the evaluate or predict methods with the validation or test generators.In image processing, the conversion of images into suitable input data involves converting the raw hexadecimal byte data of pixels in jpeg or png files. This is loaded as pixel data by converting the hexadecimal values into decimal values. Grayscale images, represented by a single byte or 8 bits per pixel, use integer values ranging from 0 to 255, where 0 represents complete blackness, and 255 represents complete whiteness. These integer values can be stored in an appropriate data structure, such as an array, to serve as input data for machine learning models.

III-C. TRANSFER LEARNING IN CONVOLUTIONAL NEURAL NETWORK

Transfer learning assists in extracting generic features from sizable datasets, which helps the model generalize effectively to new, smaller datasets. Pre-trained models are regularized on a large dataset to reduce the risk of overfitting new tasks.
Differentiated Transfer Learning: In this method, the pre-trained CNN functions as a fixed feature extractor. A new dataset's features are extracted using the remaining layers after the final few layers are removed. These features are then used to feed a newly trained classifier or fully connected layers for the current task.
Fine-tuning: Along with feature extraction, fine-tuning entails unfreezing and retraining a few of the pre-trained model's top layers at a slow learning rate. As a result, the learnt weights can be modified by the model to better suit the new assignment.
The selection of a pre-trained model is influenced by a number of variables, including the size and similarity of the new dataset to the pre-training dataset, the difficulty of the new task, and the available computational resources. The pre-trained models VGGNet, ResNet, Inception, and MobileNet are well-known.
In a neural network, a dense layer type simulates a completely linked layer. This indicates that every neuron in this layer is linked to every neuron in the layer before.

III-D. THE SOFTMAX ACTIVATION FUNCTION

$$f(z_i) = \frac{e^{z_i}}{\sum_{k=1}^{N} e^{z_k}} \tag{1}$$

The softmax activation function as shown in equation (1) is commonly used in the output layer of neural networks for multiclass classification tasks, where the goal is to assign an input to one of several possible classes [5]. It provides a convenient way to interpret the network's output as class probabilities, facilitating decision-making based on the highest probability class.

III-E. VGG16 In Convolutional Neural Network

The VGG16 architecture consists of 16 layers, including 13 convolutional layers and 3 fully connected layers [6]. The convolutional layers primarily use 3x3 filters with a stride of 1, and they are followed by max pooling layers with a 2x2 pool size and a stride of 2. The use of smaller filters and pooling layers helps to capture detailed features at different spatial scales.

The VGG16 network has a fixed input size of 224x224 pixels, which means input images need to be preprocessed to this size before feeding them into the network. Using stride 1, 2, and 3 and a first filter with 32 3*3 kernels, convolution operations are performed on an image of size 8 blocks with a kernel size of 45*45*45. The kernels act as feature finders and convolve with the picture to produce a set of features that have been convolved. Regional connection of the neurons to the previous volume is consequently enforced in neural networks because the size of the kernel denotes a neuron receptive field.
THE POOLING LAYER: The max-pooling aggregation function, which is utilized in an area to obtain the maximum value, is provided by the parameters k, which stands for the kernel size, as well as an input's h x w size and s stride. The pooling strategy effectively summarizes the outputs of adjacent sets of inputs in addition to reducing the dimensionality of the inputs . When the image size is very high, this layer really

performs down sampling, which reduces the spatial dimensions while maintaining valuable information and also reduces the number of parameters [1]. This work employs a maximum of one pooling layer.
DROPOUT: Ratio dropout neurons, whose output is set to 0 by dropout layers in the hidden layers, have an output probability of r. The forward pass and the backward steps of backpropagation are not affected by the neurons that dropped out. In the architecture we suggest, two dropout layers with the ratios of 0.25 and 0.5 have been introduced one after the pooling layers.

IV. RESULTS AND DISCUSSION:CNN MODEL

In this study, we used MRI scan pictures that were classified into mild dementia, non-dementia, and very mild dementia. We randomly selected 80% of the training data and used the remaining 20% for model validation. The CNN network has several layers, including a convolutional, activation, pooling, and fully connected layer[7]. The first layer is a convolutional layer, which uses a kernel (ReLU) or filter to analyze the input image and determine the relationship between the image and its features (to determine whether the image is of an Alzheimer's patient or not), and the second layer is an activation layer, which employs a Rectified Linear Unit (ReLU) to boost the nonlinear properties in the CNN model because of its training speed. The first layer is the convolutional layer, which takes the input image using a kernel (ReLU) or filter and identifies the relationship between the image and their features (to identify whether the image is of an Alzheimer's patient or Normal)[1]. By flattening our matrix into a vector form and feeding it into the fully connected layer, we were able to increase the training performance of the models.
Investigating the confusion matrix of the learning models allowed us to compare how well they performed. We evaluated the categorization models using sensitivity, specificity, and accuracy [2]. To determine these parameters we use formulas (2) through (5) as below:

$$Sensitivity(Recall) = (TP/((TP+FN))) \quad (2)$$
$$Specificity(Selectivity) = (TN/((TN+FP))) \quad (3)$$
$$Accuracy = (((TP+TN))/((TP+FN+TN+FP))) \quad (4)$$
$$Precision = (TP/((TP+FP))) \quad (5)$$

The accuracy of the model in predicting Alzheimer's disease using VGG16 transfer learning on a CNN is 80.4%.Precision, which measures the proportion of correctly predicted positive cases out of all predicted positive cases.Recall, also known as sensitivity or true positive rate, is 62%. In the context of Alzheimer's disease prediction, this means that the model successfully identified 62% of the patients who

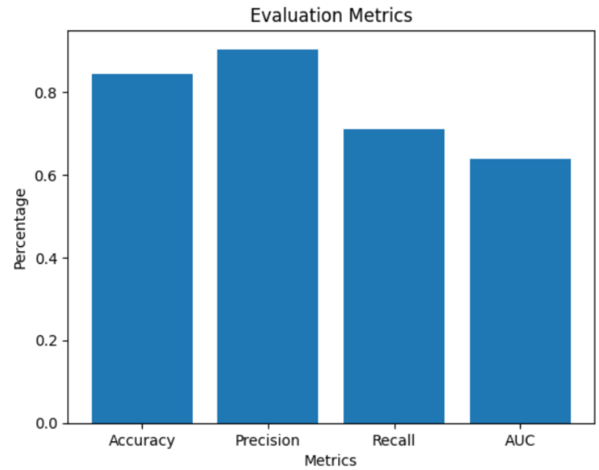

Figure 2. Evaluation graph

actually have the disease.The AUC (Area Under the Curve) is 0.56, which is a measure of the model's ability to distinguish between positive and negative cases. A value of 0.5 indicates a random guess, while a value closer to 1 suggests a better discriminatory ability. In this case, the AUC of 0.56 indicates that the model has a moderate level of discriminative power. Overall, these metrics suggest that the VGG16 transfer learning model on a CNN has achieved a reasonable level of accuracy in predicting Alzheimer's disease. However, there is still room for improvement, particularly in terms of recall and AUC.

V. RESULTS AND DISCUSSION: SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is a popular machine learning algorithm used for both classification and regression tasks. It is particularly effective in handling high-dimensional data and cases with clear class separation [6].The primary goal of SVM is to find the optimal hyperplane that maximally separates classes in the feature space. It achieves this by creating a decision boundary that maximizes the margin (distance) between the data points of different classes. In SVM classification, the algorithm classifies data points into different classes based on their position relative to the decision boundary. Data points falling on one side of the decision boundary are assigned to one class, while those on the other side are assigned to the other class. SVM can handle both linearly separable and non-linearly separable data by utilizing kernel functions.Support vectors are the data points that lie closest to the decision boundary or influence the position of the decision boundary. These points are crucial for defining the decision boundary and determining the SVM model's parameters.SVMs can be applied to various types of data, including both linear

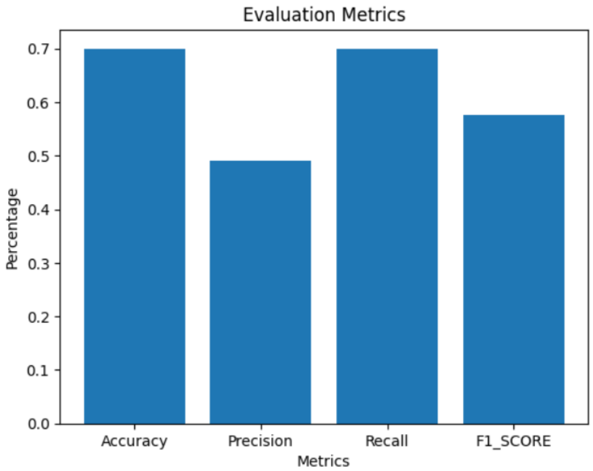

Figure 3. SVM Evaluation Graph

and non-linear data. They can incorporate different kernel functions to capture different types of patterns and adapt to different data distributions.

The accuracy score represents the proportion of correctly classified instances out of the total number of instances. In this case, the SVM model achieved an accuracy of 0.7, indicating that 70% of the instances were correctly classified. A precision score of 0.49 suggests that out of all the instances predicted as positive, only around 49% were actually true positive cases. A recall score of 0.7 indicates that the model identified 70% of the actual positive cases correctly.The F1 score is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall. The F1 score of 0.576 indicates a reasonably balanced performance between precision and recall for the classification task. These metrics are commonly used to evaluate the performance of a classification model. In the case of predicting Alzheimer's disease, achieving a high accuracy, precision, recall, and F1 score is desirable as it indicates a good ability to correctly classify both positive and negative instances.

VI. Adding a pre-trained VGG model as a layer to the sequential model

The model architecture consists of several dense layers with batch normalization, dropout layers for regularization, and activation functions to introduce non-linearity. The final output layer uses the softmax activation function for multi-class classification. Summary of the model architecture

Sequential model was used Initialized, which allows us to stack layers sequentially.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 dropout (Dropout)           (None, 7, 7, 512)         0

 flatten_1 (Flatten)         (None, 25088)             0

 batch_normalization (BatchN  (None, 25088)            100352
 ormalization)

 dense (Dense)               (None, 2048)              51382272

 batch_normalization_1 (Batc  (None, 2048)             8192
 hNormalization)

 activation (Activation)     (None, 2048)              0

 dropout_1 (Dropout)         (None, 2048)              0

 dense_1 (Dense)             (None, 1024)              2098176

 batch_normalization_2 (Batc  (None, 1024)             4096
 hNormalization)

 activation_1 (Activation)   (None, 1024)              0

 dropout_2 (Dropout)         (None, 1024)              0

 dense_2 (Dense)             (None, 4)                 4100

=================================================================
Total params: 68,311,876
Trainable params: 53,540,868
```

Figure 4. Model Summary

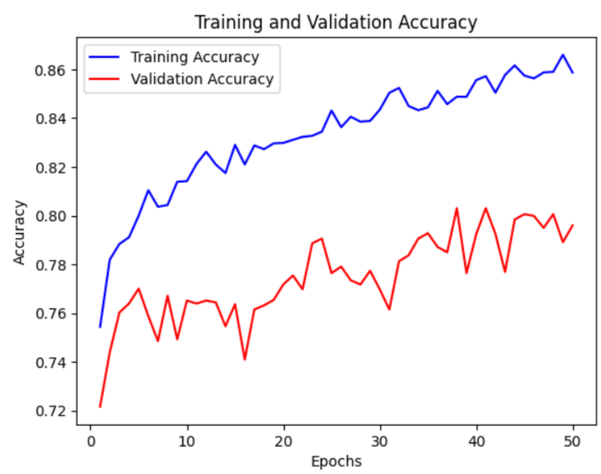

Figure 5. Training and Validation Accuracy Model

Accuracy measures the overall correctness of the model's predictions.An accuracy of 0.844 indicates that the model's predictions match the true labels for approximately 84.4% of the samples. Precision is the measure of how well the model predicts positive samples correctly. A precision of 0.903 indicates that out of all the samples the model predicted as positive, approximately 90.3% of them are truly positive. Recall, also known as sensitivity or true positive rate, measures the model's ability to identify positive samples correctly. A recall of 0.709 indicates that the model correctly identified approximately 70.9% of the positive samples. AUC (Area

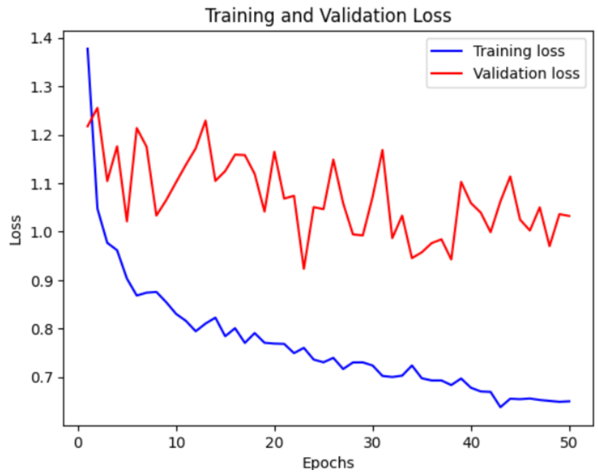

Figure 6. Training and Validation Loss Model

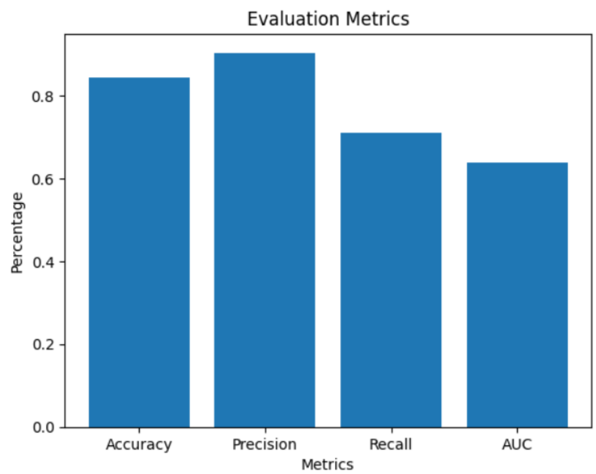

Figure 7. Model Evaluation

Under the Curve) represents the performance of the model across all possible classification thresholds. An AUC of 0.638 suggests that the model has a moderate level of discriminatory power. These metrics provide an evaluation of the model's performance on the given dataset. An accuracy of 0.844 indicates that the model is relatively accurate in predicting the classes. However, it is important to consider the precision, recall, and AUC as well, as they provide more insights into the model's performance, especially in cases of imbalanced datasets or when specific class predictions are of greater importance.

To further probe this,we used FASTAI, founded in 2016 by Jeremy Howard and Rachel Thomas with the goal of democratizing deep learning. We also used Resnet34, Resnet34 is an image classification model. It is a CNN (Convolutional Neural Network) structured as 34 layers (hence its name). Resnet34 is pre-trained on the ImageNet dataset, which contains more than 100,000 images across 200 classes. A CNN is usually used for image classification purposes.

VII. CONCLUSIONS

The main goal of this research is to develop algorithms to accurately detect Alzheimers disease.The models attain an impressive accuracy rate of 80.4%, with the convolutional neural network outperforming other algorithms in terms of accuracy. We have combined the application of machine learning Algorithms to determine which of the Algorithms detect the disease accurately and timely. These models also overcome the overfitting problem of machine learning techniques to classify the disease accurately with less computational complexity. Based on this result, it becomes realistic that CNN model detects the disease early. Later, other advanced machine learning models may be implemented separately to further increase the classification accuracy.

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