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# MobileNetV1-Inspired Deep Learning Framework for Early Detection and Staging of Alzheimer’s Disease Using MRI

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**Abstract:**

*Alzheimer’s disease is one of the most common neuropathological diseases worldwide, with approximately 46.8 million individuals suffering from Alzheimer’s disease, with ramifications for caregivers and economies. Various studies describe Alzheimer’s as a progressive disease and focus on the need for early detection to allow for timely intervention and treatment options. Cognitive tests are typically used to evaluate early detection for Alzheimer’s, but MRI brain scans are the main detection method for Alzheimer’s diagnosis. Several studies have looked for abnormal brain conditions based on Alzheimer’s disease and dementia disease detection from features extracted from medical images. Methodological approaches to deep learning for brain structure segmentation and Alzheimer’s disease classification are becoming more common due to their better performance on larger datasets and their ability to outperform established machine learning models. The use of deep learning techniques in this study is based on a ‘‘brain MRI scan classification framework’’ for a more precise, efficient, and automated classification of Alzheimer’s Disease stage. The suggested deep learning model uses a convolutional neural network (CNN) architecture with depth-wise separable convolutions based on MobileNetV1 to allow for computational efficiency, pattern recognition, and robust feature extraction assistance. The study employed 6400 MRI images from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, categorized as non-demented, mildly demented, moderately demented, and severely demented. The model achieved an overall accuracy of 98% on the test dataset, demonstrating an ability to identify the discrete classes of Alzheimer's disease progression. The average test loss score was remarkably low at 0.0543, demonstrating an effective reduction of the differences between the predicted value and actual value. The model obtained precision scores of 0.95, 0.97, 1.0, and 1.0. The precision score indicates accuracy in the predictions from the classes. The macro and weighted average precision scores were 0.98, which indicates consistency in the precision across all classes.*

***Keywords:*** *Alzheimer’s, MRI, CNN, MobileNet v1, deep learning, medical imaging*

## I. INTRODUCTION

Dementia, a degenerative type of disease, was first discovered by Alois Alzheimer in 1907 and was subsequently named Alzheimer's Disease (AD) accordingly [1]. In the years that followed, the consequences of AD on global health have only become more apparent. In 2015, the World Alzheimer's Report predicted that AD would increase substantially by 2030. The report suggested that approximately 74.7 million people would be affected by AD in 2030, compared to 46.8 million counted in 2015 [2]. The implications of the increasing prevalence of Alzheimer's Disease go beyond individual.

health. In the 2019 Alzheimer's Association Report, around 5.8 million Americans were estimated to be living with AD, and as mentioned is expected to increase to 13.8 million and potentially more in the next century. AD has been the sixth leading cause of death in the USA, with an estimated 121,000 deaths [3]. It is a large economic burden worldwide, affecting every aspect of society. The economic impact of living with Alzheimer's Disease (AD) is predicted to surpass $2.0 trillion USD in 2030. This raises awareness about the medical and economic consequences while reemphasizing that AD requires considerable examination on both a larger level and at the individual level [4].

According to the World Alzheimer Report, it is forecasted that the prevalence of Alzheimer's disease will significantly increase by 2030, which will significantly threaten individuals and create an economic burden. Specifically, the world economic cost of Alzheimer's disease will exceed $2.0 trillion USD by 2030, demonstrating the need for effective diagnosis and treatment as a priority. Alzheimer's Disease is a progressive neurodegenerative disease. It mainly affects cognitive processes, thereby resulting in memory loss and changes in thought and behavior [5]. Alzheimer's dementia first presents itself as Mild Cognitive Impairment (MCI), whereby some patients progress to AD at a rate of 8-15% annually [4]. Early diagnosis, particularly at the higher end of the continuum, such as with MRI, can significantly improve the rate of recovery for patients, 29-55% [6], versus a considerably slower rate of progression recorded after AD has fully developed. Although Alzheimer's disease and the neurodegenerative disease process are incompletely irreversible [1], some medicalized treatment expertise may slow the neurodegeneration once the progression has been established to bridge the gap for symptomatic treatment of patients, if timing diagnosis and treatment options earlier in the continuum. Lastly, these early diagnosed options available may not only lessen the burden on the economy of the world, but most importantly, enhance the quality of life for both the patient and the caregivers.

Given the importance of timely and accurate diagnosis of neurological diseases like Alzheimer's, it has been widely studied by examining the pathological areas of the brain using many different modalities. The American Academy of Neurology (AAN) [2] recommends, for example, magnetic resonance imaging (MRI) and Computed Axial Tomography (CT) in this regard. In practice, the diagnosis of Alzheimer's disease consists of a combination of clinical history, physical examination, and neuropsychological tests that assess cognitive functioning [1].

Although the application of MRI for diagnostics over the years has been widespread, brain MRI analysis remains a manual process that is labor-intensive and error-prone [7] across many images. Therefore, an automated segmentation method is warranted to provide a more confident and competent segmentation solution. Recent advances using computational methods on MRI to support segmentation, visualization, and registration of large datasets, in particular, have shown considerable promise and have value in supporting clinicians with qualitative diagnostics.

This work makes several key contributions, including the development of a MobileNetV1-based convolutional neural network (CNN) architecture specifically designed for the early detection of Alzheimer’s disease using MRI data. It also includes a comprehensive performance evaluation on a large, multi-class dataset, demonstrating high classification accuracy and low error rates. Additionally, the study incorporates preprocessing and augmentation techniques to address class imbalance and improve the model’s generalizability. This study aims at the development of such a deep learning model that would assist in the diagnosis of AD using MRI scans during its primitive stages. Specialized examination is required for the analysis of MRI scans for AD, which prolongs the diagnosis due to the unavailability of and curtails some level of inaccuracy due to human error. The automated technique proposed in this study targets this problem. It is due to the rapid spread and prevalence of this disease, in addition to the economic burden it poses, that various research programs have been funded for easier and more efficient ways of AD diagnosis.

## II. LITERATURE REVIEW

S. Kumar et al. reviewed some 64 papers published in 2020 and concluded that during the past 5 years, a considerable rise has been witnessed in AD dementia modeling using ML techniques with relevant neurological data [9]. M. Tanveer et al. reviewed papers between 2005 and 2019 and found SVM to be the most popular, suitable for interpretability and not getting stuck in local minima, but found NN-based models to be more robust and versatile in capturing high-dimensional data [18]. A study done for AD Diagnosis on MRI data relied on the extraction of concatenated features in order to make a classification of MRI Scans, achieving an accuracy of 98.87 percent, 98.99 percent recall, and 98.95 percent precision [10]. Similarly, Gowhar Mohiuddin Dar et. al. implemented a comprehensive study on ResNet 50, VGG 16, and MobileNet pre-trained models, and their evaluation concluded with a 96.6 percent accuracy for the MobileNet models. The aforementioned models were adopted as being pretrained and were fine-tuned on MRI data with 4 classes [11].

Sharmat et al. used the ADNI Dataset and concluded with a modification of the Inception V3 Model with RMS prop optimizer and a learning rate of 0.00001, achieving a test accuracy of 98.67 percent [12]. A. Franic and I.A. Pandian found that an ensemble of Mobile Net yields 91.3% accuracy, while individually, both scored around 89% accuracy [15]. H. Ji et al. developed three base CNNs and their ensemble output, which yielded a test accuracy of 97.65% [15]. C. Kavita et al. trained several models and performed a comparative analysis on them, and found the best accuracy to be 83% the ML models were Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting [17]. X. Zhou et al. concluded that Generative Adversarial Networks were optimal at augmenting and aiding the AD diagnosis, but specifically for 1.5 Tesla scanned images [8]. W. Feng et al. used 3D CNN, 3D CNN with SVM, and 2D CNN, whereas 3D CNN with SVM showed an accuracy of 95.74%, which was best among the three, while the rest performed under 90%. [19]. B. A. Mohammed et al. made a hybrid of Alex Net and ResNet-50 and two more such models, where both mentioned models were independently attached to SVM. t-SNE was used to reduce dimensionality of the OASIS dataset, where AlexNet + SVM performed well and scored an accuracy of 94.8%.[20].

Vrooman et al. incorporated the use of traditional K-Nearest Neighbor techniques in order to classify the different segments of the brain, such as gray matter, white matter, and cerebrospinal fluid. The researchers manually labelled 12 datasets of brain MRI scans before training them in a case of supervised learning. Once a sufficient accuracy had been reached, the results were validated against 59 individuals with dementia and AD. In this methodology, cerebral tissue probability maps undergo a process of rigid registration to a designated reference coordinate system in order to create a training set for the KNN classifier. Training is limited to samples automatically extracted from the dataset to be segmented. This is accomplished through the application of a threshold to the probability maps, followed by the implementation of an automatic outlier sample rejection scheme. Management of large datasets of MRI scans is a time-consuming and laborious process owing to the huge capacity required to store them, and further image processing and labelling are required. The primitive research carried out on the automated diagnosis from MRI images mainly consisted of brain segmentation using threshold techniques and even artificial neural networks in the late 20th century [21]. Despite giving promising results in brain segmentation, their implementation requires either interactive threshold selection or manual labeling for training the physiology and even the location of the segments. Therefore, in order to counter these challenges, various scientists experimented with a variety of techniques. Wells et al. employed the use of a Parzen window coupled with interactive training in order to attain probability density distributions that were conditioned for each class [22]. The research was furthered by continually iterating the estimation of the tissue-based classes for optimum results. Simultaneously, EM approaches were also utilized to estimate class distributions in the MR bias field by scientists at Harvard University [7].

A deep convolutional neural network was developed by Zhang et al. to segment isointense brain segments [232]. These segments pertain to scans taken during early childhood, which may represent a marker for the future development of the disease. Due to similar intensity levels in T1 and T2 MR images during this age, differentiating between white and gray matter is quite troublesome. The study demonstrates the superiority of CNNs in infant brain tissue segmentation and outlines a path for future improvements and exploration. It stands out from the conventional approaches as it seeks to provide accurate segmentation labels by capturing highly nonlinear mappings between inputs and outputs [12]. Yet the findings provide valuable insights for improved computational models for accurate and quantitative tissue segmentation [23]. In a nutshell, the convolutional neural networks are one of the most significant and popular network architectures when it comes to image classification and diagnosis [24].

## III. METHODOLOGIES AND TECHNIQUES

All the pictorial data used in this research were retrieved from Kaggle, an open-source database. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset was used [2]. Various factors were considered during the selection of the dataset, like the database being large and diverse enough for minimal ambiguity during training, the images taken were from MRI scans only, and no interventional modality was used; image quality was also taken into consideration, and lastly, a labelled dataset was selected. The dataset is meticulously curated from various reputable sources, including websites, hospitals, and public repositories, to ensure a diverse and representative collection, comprising a total of 6400 MRI images. The dataset used in this study was divided into four groups or classes; about 50% of the dataset comprised brain MRI scans from non-demented patients, while the other half of the dataset was divided into mildly demented patients (14%), moderately demented (1%), and very demented patients (35%), as represented in Figure 1. The resizing of images facilitates uniformity and streamlines the data for analysis. The primary objective of sharing this dataset is to facilitate the development of an accurate classification framework for Alzheimer's Disease. Researchers can leverage this dataset to explore and innovate in the field, contributing to advancements in Alzheimer's diagnosis and treatment.

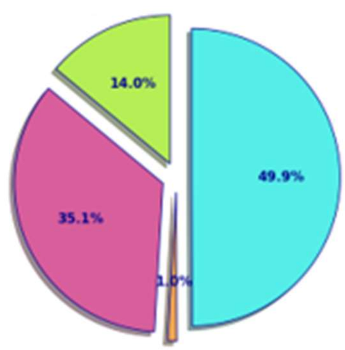



**Figure 1: Distribution of Alzheimer's MRI Images**

An essential step during preprocessing involves the normalization of pixel values into a standard range. Pixel intensities for all images, as seen in Figure 2, are normalized into a standard range so pixel intensities across all images achieve greater convergence during training. This was achieved using the equation:

$$P_n = \frac{P}{Q}$$

Where;
P = pixel intensity value
$P_n$= normalized pixel intensity value
Q = Maximum pixel intensity in an image

The intensity values in the model were rescaled to the range of [0, 1]. Normalization has two essential purposes in neural network models. First, normalization provides numerical stability, keeping the network's values close together for stability and consistency. Second, neural networks generally perform better when the data are standardized within a certain interval. Normalization allows for a smoother and more efficient training process because the pixel values are homogenized so that the model can efficiently learn the meaningful patterns and features in the image data. Moreover, normalization is an essential, effective preprocessing technique and optimizes the input data for subsequent model training. The classification framework, for detecting Alzheimer's Disease, ultimately benefits from the normalization of the data before the model development.

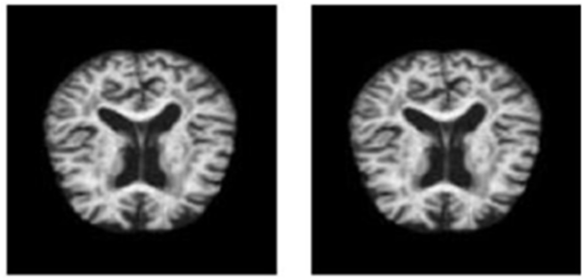


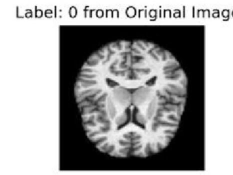
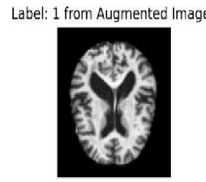
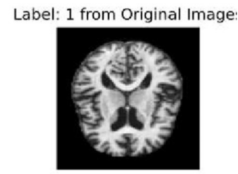
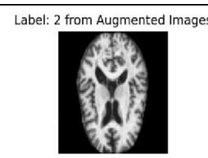
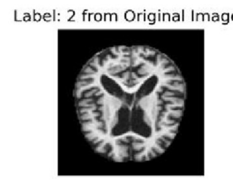
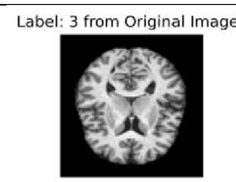
**Figure 2: image from the dataset (left), and the resulting image obtained after normalization (right)**

For the dementia classification framework to be solid, we must generalize the model. One way in which we can accomplish this is by reducing class imbalance. Data augmentation tools were set up to run rescaling, shear, zoom, and horizontal flip functions on an unaltered dataset of preprocessed Magnetic Resonance Imaging (MRI) images for their analysis. This latter dataset consisted of grayscale images that were also resized to be 128 x 128 pixel images. The purpose of augmentation was to eliminate imbalances by generating additional images for classes with insufficient representation. Subsequently, an augmented dataset was created, wherein the augmented images were carefully organized into a directory similar to the original dataset. This augmentation process was conducted with a discerning approach, ensuring that the resulting dataset adheres to the desired size specifications for each class. The augmented dataset classes were divided into Mild Demented and Moderate Demented Images.

Table 1 exhibits images that were generated and original images as well for the two augmented classes, Mild and Moderate Demented Images.

It is a common observation that machine learning models, although being transparent in their working, may not necessarily be able to capture the dimensional depth that big datasets and tasks pose, as seen in cases [13-19]. Therefore, CNNs are preferred for computer vision problems. Convolutional Neural Networks (CNNs) are used as a deep learning approach to extract features of an MRI image. The primary objective is to enhance the effectiveness of recognizing typical patterns within the images, with a specific focus on detecting Alzheimer's Disease (AD). CNN allows for the detection and efficient learning of hierarchical features from the data. Its importance lies in the fact that medical data requires scrutiny structurally to ensure no feature is overlooked. Such a level of precision and accuracy is not humanly possible and is extremely prone to error and negligence. CNN allows nuanced patterns to be traced multiple times in layers, reducing the chances of negligence significantly.

**Table 1: Examples of augmented images generated from corresponding original images from each class**

| Class No. | Class Name | Generated Image | Original Image |
|---|---|---|---|
| **0** | ***Non Dement ed Images*** | N/A |   |
| **1** | ***Mild Dement ed Images*** |   |   |
| **2** | ***Moderate Dement ed Image*** |   |   |
| **3** | ***Very Mild Dement ed Images*** | N/A |   |

The neural network structure is based on the MobileNetV1 model, which is designed for mobile applications, with a primary focus on computational efficiency and producing a lightweight model. The model is aimed at processing image data in devices with limited computational capabilities, allowing it to be widely implemented while avoiding complex computational architectures. The model is still robust enough to extract relevant features for certain medical images.

Some of the core design principles leveraged from the MobileNetV1 are depth-wise separable convolutions, which help with computational efficiency while maintaining model capacity to learn complex spatial dependencies. The MobileNetV1 model was developed using depth-wise separable convolutions. Traditional convolutional layers apply one filter across all channels of each input feature map, which subsequently outputs a feature map. In MobileNet's depth-wise separable convolutional methods, each input channel receives a filter that only operates on the grouped depth-wise input and outputs an individual feature map. The 1x1 convolutions are then used to combine the depth-wise outputs across the output channels. By separating the convolutions into two stages, the model can learn meaningful spatial features that populate the individual sample channels to compose meaning based on the given patterns and representation.

Other features incorporated in the model are batch normalization, ReLU activation, and strategically placed average pooling layers. This enables the devised model to not only discriminatively extract complex features but also be computationally efficient while doing so. Global average pooling serves as a spatial summarization mechanism, contributing to the model's adaptability and interpretability. Figure 3 shows the workflow for Alzheimer's MRI Image classification using deep learning. This figure depicts the entire Alzheimer's MRI image classification process, starting with dataset acquisition and image augmentation, then moving on to CNN-based feature extraction and deep learning for multi-class classification, and finally evaluating performance using precision, recall, and F1-score metrics.

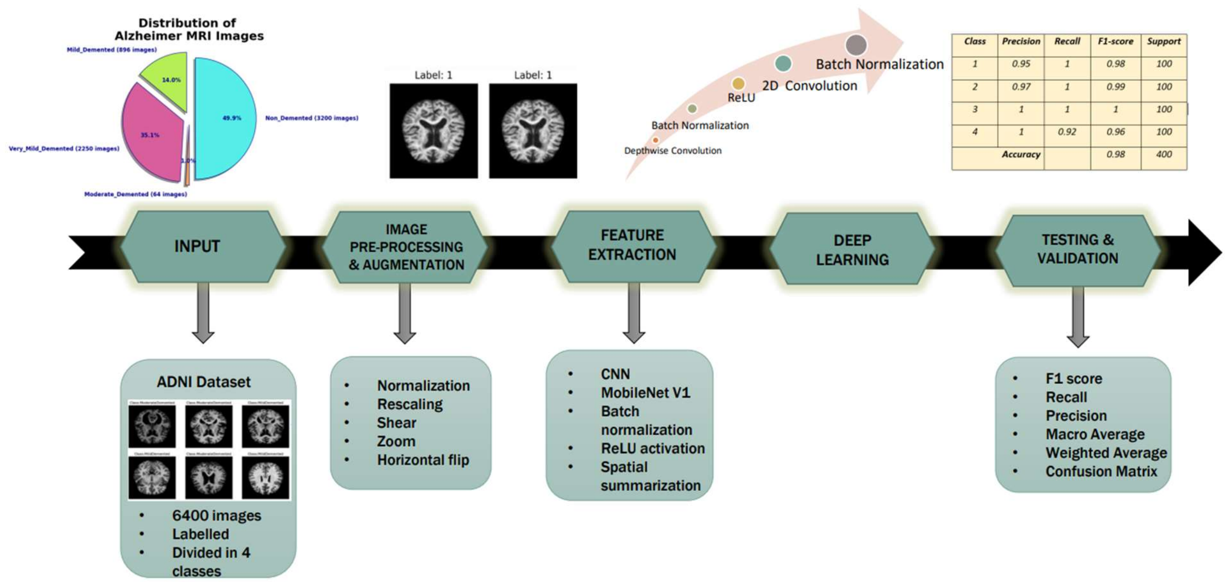



**Figure 3: Workflow for Alzheimer's MRI Image Classification Using Deep Learning**

## IV. RESULTS AND DISCUSSION

After fine-tuning the VGG16 architecture, the algorithm was able to subtly recognize structural changes in the brain that indicated the possibility of Alzheimer's disease. As evident above, the model was trained by minimizing the categorical cross-entropy loss through stochastic gradient descent. The test dataset resulted in an average loss of approximately 0.0543 over 13 batches. This can be considered a significantly low error when comparing the predicted values to the true values. Using these figures, the model's accuracy for detecting Alzheimer's pathology was calculated to be 98%, which lies within a satisfactory range of correctness of the model's predicted classifications. These quantitative metrics provide a preliminary understanding of the model's performance.

The results were also represented using a confusion matrix in Figure 4. The explanation behind this choice is that it offered a clearer understanding of the model's performance on specific classes rather than across the epochs. The confusion matrix illustrated very few misclassifications, with most of them between classes that have slight distinctions. Otherwise, almost all instances were classified correctly.

Table 2 exhibits a classification report that shows the precision, recall, and F1-score values of the model, exemplifying the model's ability to balance precision and recall, which is crucial for having a reliable Alzheimer's detection system. Class 1 has an F1-score of 0.98, which shows it was able to balance precision to recall well. Classes 2 and 3 have F1-

scores of 0.99 and 1.00, respectively, demonstrating high precision and recall. Lastly, class 4 has an F1score of 0.96, which has the lowest recall value but was able to balance out due to the high precision.

**Table 2: Classification Report**

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| **1** | 0.95 | 1 | 0.98 | 100 |
| **2** | 0.97 | 1 | 0.99 | 100 |
| **3** | 1 | 1 | 1 | 100 |
| **4** | 1 | 0.92 | 0.96 | 100 |
| | ***Accuracy*** | | 0.98 | 400 |

In addition, both Macro Average and Weighted Average provide summary performance statistics that give us different impressions of the general performance of the model. Macro Average is used here because it assesses performance equally for an item on a per-class basis, while the Weighted Average weights the number of samples for a class, which helps ensure performance of the model was assessed equally in the presence of the dataset imbalance. Both macro-average and weighted-average were 0.98, which emphasizes the reliability of the model's performance and identifies the model as resourceful across all classes while acknowledging the class size imbalances.

The precision scores of the model indicate a high level of accuracy in predicting positives, as we see precise predictions made from each class. Class 2 and Class 3 have a perfect representation, indicating that we had perfect positives, which means all of the instances predicted as Class 2 and Class 3 are correct. Class 1 performed at 0.95 precision, indicating 95% of the instances predicted as Class 1 were true positives. Class 2 performed at 0.97 precision and Class 3 100% precision, again indicating a high level of accuracy in detecting positives in their respective classes. Class 4 also has a perfect precision score of 1.00, meaning it had perfect positives as well.

In summary, this study adds to the body of knowledge for the diagnosis of Alzheimer's Disease, using a systematic approach with detailed imaging and novel architectures of neural networks. As reported by The World Alzheimer's Report, it is projected that the incidence of AD will rise enormously by 2030 and not only pose a risk to the health of individuals, but also put a significant economic burden on society. It is suggested that the economic impact will exceed USD 2.0 trillion. This demonstrates the urgent need for accurate diagnostic tools and treatment for Alzheimer's Disease.

This study uniquely employs a CNN to extract features from an MRI image dataset composed of 13 batches of images. CNN is particularly suited for this study since the layered architecture aims to simplify imaging features into an efficient detection model. Additionally, based on the MobileNetV1 architecture, CNNs are also particularly well-suited for extracting pertinent information from images. This is beneficial for this study since one needs a reliable detection of complex anatomical features of the brain, along with relatively subtle changes from Alzheimer's disease, to replicate a diagnosis.

Overall, the fine-tuned VGG16 architecture produced beneficial results with a low entropy loss of 0.054 and fantastic test accuracy of 98%. Different visual and graphic representations of the results display the intuition and reliability of the results, as well as indications of areas of potential improvement. The Model's precision, recall, and F1-score values represent the model's ability to provide a balance between accuracy and sensitivity across varying classes.

Figure 4 presents the confusion matrix. The confusion matrix displays the model's performance in classifying across four classes throughout the dataset. The confusion matrix demonstrates good accuracy overall, with low misclassification throughout the four classes, especially the fourth class (which has some class overlap). Overall, the model shows high predicted reliability in Alzheimer's stage determination.

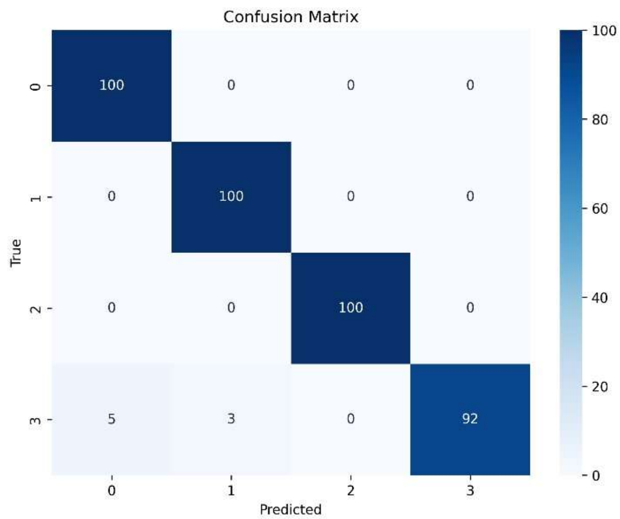



**Figure 4: Confusion Matrix for Alzheimer's MRI Classification Model**

## V. CONCLUSION

With the increasing prevalence of Alzheimer's Disease over time, the demand for early, effective caregiving methods and treatments is vital. At the same time, in literature, successive studies have shown that AD is a progressive disease and early intervention can improve global disease burden. Convolutional Neural Networks (CNNs) have demonstrated great success in medical image analysis towards early detection of AD. The architecture, modeled after MobileNetV1, is uniquely developed and should uniquely excel at real-world constraints by offering great computational efficiency and the capacity to keep pace with the rapidly increasing number of Alzheimer's disease (AD) cases. The paper emphasizes entropy loss as the main measurement of performance and error, but it would be necessary to develop the measurement system into a stronger version by adding more metrics for reports. The model can be made interpretable for ease of integration into clinical environments through methods such as Grad-CAM. Evidence can also be provided using other loss metrics, such as Hinge loss and Log loss. Additionally, it is important to validate with other neurological diseases presented with changed anatomical structures, so that misdiagnosis does not take place due to the complexity of the brain structure. The data would only be trained on MRI datasets of AD-affected and healthy brain scans; it would not incorporate non-AD neurological pathologies to understand how estimates might vary.

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