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Alzheimer Detection Using Deep Learning Methods

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This study proposes a deep learning-based framework to detect and classify Alzheimer's disease (AD) in the early stages using medical imaging, and specifically Magnetic Resonance Imaging (MRI). Specifically, we propose a Convolution Neural Network (CNN) based model and transfer learn (MobileNet) through pre-trained models based on task domain to improve model performance on binary AD classification. Thanks to minimizing computational complexity and memory costs, the model with 99.86% accuracy rate can mitigate overfitting and is an ideal approach for real time and eco-friendly monitoring of AD evolution. The findings suggest that the model could help clinicians in diagnosing AD even based on MRI images, which has great potential as a scalable and efficient solution for the early-stage diagnosis and classification of the disease. Our work will include the addition of further pre-trained models, increased dataset size via data augmentation, and the application of MRI segmentation to better isolate some of the key features of Alzheimer.

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1. Introduction

Alzheimer's disease (AD) is a chronic neurodegenerative disease that leads to progressive impairment in memory, cognition, and behaviour, ultimately culminating in cognitive decline and functional disability. It is the most common form of dementia, accounting for ~60–80% of all dementia worldwide. The disease results from interaction between genetic risk factors, environmental risk factors, and a range of lifestyle risk factors. Although the definite cause of AD is not completely understood, factors leading to Alzheimer's disease have been proposed (including genetic mutations and accumulation of β-amyloidal plaques, tau protein tangles, vascular damage, and neuroinflammation). And the condition isn't just a burden on those who are diagnosed, but on their caregivers too, with both emotional and financial tolls[1][2][3].

Early and accurate diagnosis of AD is important, because effective treatments are more likely to be stated at the earliest stages of the disease. At present, diagnostic tools rely heavily on clinical observations, history taking and neuropsychological tests, which are not necessarily accurate in the early stages [4]. The most important ancillary tests useful for early diagnosis of Alzheimer's are advanced neuroimaging techniques such as magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography (CT). Imaging techniques that help in diagnosis and monitorManis M & A, 31 Year Multimodal imaging MRI is especially well-suited for MCI because it has strong imaging capabilities to quantify structural brain changes, including hippocampal atrophy, cortical thinning and ventricular enlargement. Research has shown that people who have mild cognitive impairment (MCI) a precursory stage of AD—lose an annualized 1–2% of their brain volume per year, and people who have progressed to the endpoint of Alzheimer's dementia have 3–5% annualized brain loss. This is particularly prominent in the hippocampus where atrophy of 10–15% per year can occur during late stages of AD [5][6][7].

Currently, as artificial intelligence (AI)[8], and especially deep learning (DL)[9][10] techniques are developing, new more reliable and automated methods for AD diagnosis are being analysed. For years, Neuroimaging has been analysed with classical machine learning methods, but deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) tend to perform better than the classical machine learning models. CNNs are particularly well suited for the analysis of MRI and PET scans due to their ability to model spatial features hierarchically from brain images. This is especially the case when analysing gradual changes in brain structure over time; Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) networks, can also help account for temporal dependencies in sequential data[11][12].

Existing studies have demonstrated that hybrid deep learning models, which merge CNNs and LSTMs, provide improved accuracy in classification when diagnosing AD. DenseNet CNN architecture is one of the basic architectures, which is used for feature extraction that has several advantages like overcoming the problem of vanishing of gradients, improved feature propagation and reduced parameters. They thus blend LSTM networks with CNN features extracted from brain visuals, enabling a better mapping of both spatial and episodic characteristics of the human brain that can eventually bolster the classification process during diagnosis[13][14][15].

In order to enhance the performance of simple models, image pre-processing and denoising were performed using Ant-Colony Optimization (ACO) algorithms, and then features were extracted using Modified Fuzzy C-Means (MFCM) clustering. These approaches help in enhancing the performance of the extracted image features for improved accuracy of AD stage prediction [16]. Moreover, approaches for federated learning have also been researched in order to make collaborative model training between multiple hospitals possible without revealing any patient information[17][18].

The key contributions of this study are to develop a functional deep learning model for early detection of Alzheimer disease from the magnetic resonance imaging (MRI) scans. CNN-LSTM Dual Combining CNN feature expression with LSTM network learning both intraslice and interslice features, it can achieve a better classification effect for patients with AD and MCI. The technical contributions of this paper can be outlined as follows:

1. Fast feature extraction method, which efficiently merges deep features, obtained from MRI case images.

2. MobileNet for fast prediction of Alzheimer’s disease

3. Deep learning architectures for multi slice MRI analysis with higher diagnostic accuracy

4. Mild cognitive impairment (MCI), conversion to Alzheimer’s disease, and timely medication intervention

Currently, the accurate diagnosis of AD relies heavily on a battery of tests, often for differential diagnoses, and as AD becomes more prevalent — with the number of affected individuals projected to exceed 14 million Americans by 2060 — it will be critical to develop accurate, scalable and automated diagnostic solutions. The proposed model extends the spectrum of medical imaging model by devising an AI based mechanism to assess for likely prior diagnoses of Alzheimer disease, which not only helps clinicians in updated decision making but also augments better health and time in clinical management of the patients leading to better prognostic approach [19][20].

2. Related Work

Many studies have assisted in the diagnosis of AD from machine learning (ML) and deep learning (DL) methods:

Alickovic et al. and machine learning pipeline for AD detection. They inferred that their X-ray, chemical and physiological representations of brain images were converted into feature vectors, which they treated as histograms and were used for classification through ML techniques. Using histogram-based feature extraction and a Random Forest (RF) classifier, they achieved 85.77% accuracy on the same Workbench dataset[21].

Cui et al. propose an AD classifier based on the fusion of the convolutional and RNN network. They used CNNs to take spatial features from MRI images and cascaded Bidirectional Gated Recurrent Units (BGRUs) to take longitudinal patterns through time. When applying this method on our dataset, we achieved a 91.33% accuracy for distinguishing AD from NC and a 71.71% accuracy for discriminating pMCI and sMCI[22]

The researcher presented the utilization of deep learning algorithms to classify Alzheimer Disease (AD) using MRI from the Alzheimer's disease Neuroimaging Initiative (ADNI) dataset. The models used in this study consist of EfficientNetB0, AlexNet, and EfficientNet121 fine-tuned on the different stages of AD (Cognitive Normal (CN), Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI)). The results showed excellent classification accuracy with values of 98.94% for CN vs AD. Early diagnosis of Alzheimer's is crucial for the disease's progression to be stopped and a promising tool for that, as this study suggests, could be deep learning. Authors presented a training and testing set split and used McNemar’s Test to validate statistical significance of the results.

Our results demonstrate that high-accuracy classification of AD can be performed using advanced deep learning models such as EfficientNet and AlexNet [23].

They proposed a new multi-stage deep neural network architecture as an answer to the existing approaches mentioned above, that are unable to achieve high performance due to the difficulties involved in training of deep CNNs owing to the hierarchical nature of changing network architectures like Residual Networks (ResNets). The five-stage proposed model discussed throughout this paper allows producing more important features while keeping the model shallow. To avoid overfitting a deep learning based feature selection module was used that implements batch normalization, dropout, and fully connected layer. Then classification was done using different machine learning classifiers namely Support Vector Machines (SVM), Random Forest (RF) and SoftMax. The proposed method was tested on three benchmark datasets, namely ADNI1: Complete 1Yr 1.5T, MIRAID, and OASIS Kaggle, which resulted in 99.10%, accuracy, which is very impressive. This method achieved substantially better results than previous works for binary classification problems [39], which indicates that with appropriate combination of deep learning and traditional machine learning techniques, more accurate diagnosis of Alzheimer disease is possible[24].

Other researchers investigated the potential of utilizing Deep Convolutional Neural Networks (DCNNs) to be employed for automatic early AD detection using MRI brain scans, by discerning between AD and healthy control subjects. The maximum accuracy achieved by the DCNN model in the experiment was 81% that showed a promising accuracy, but it was low compared to the accuracy in the other papers. Nevertheless, the research gave evidence that DCNNs could learn valuable features from the MRI images, including early-developed brain tissue components like white matter, grey matter, and cerebrospinal fluid , which are important for detecting AD. This study used the MIRIAD dataset, which validated the effectiveness of the method. The MIRIAD dataset is relatively modest in size, and that is a factor that may have played a role in the model's performance, helping to explain the relatively lower 81% accuracy. Moreover, this study failed to use more sophisticated techniques such as feature selection and hybrid models that can provide prediction that is more precise. However, we also found that adding ReLU activation functions in between feature extraction layers helped the DCNN to learn better feature and enhanced its performance[25].

3. Methodology

The dataset used for this study is obtained from the Kaggle database including the images of the brain MRI; each image is a different case with different stages of the disease the dataset was restructured as a binary classification problem to ease the classification task and improve early detection by the model. Images were classified into two classes, Normal (Non-Demented) and Abnormal (Very Mild Demented, Mild Demented, and Moderate Demented), see figure 1[26].

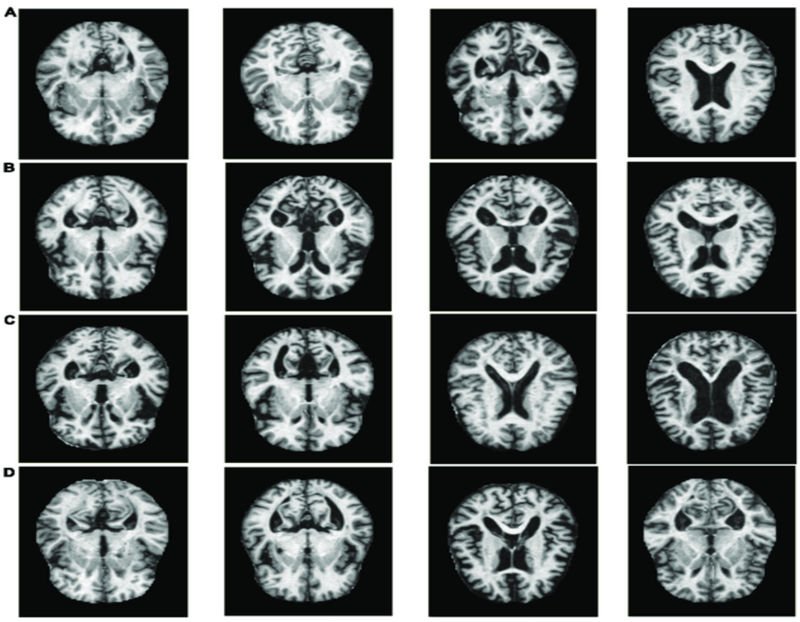

Figure 1. Alzheimer Image Dataset

The binary classification method was selected , as early detection of abnormalities was more clinically useful. Instead of differentiating between specific stages of dementia, the model simply labels these conditions as "Abnormal" as to reflect the understanding that dementia is not a singular condition but rather an overarching term that covers a spectrum of pathological occurrences related to the brain. It separately flags potential cases of cognitive decline for further medical testing.

Dataset was fine-tune for deep learning; in this case, label tuning was help to place the data in correct category. The Convolutional Neural Network (CNN) model relies on well-structured and diverse training data for analysis therefore the data was preprocessed and subsequently processed into training and testing subsets. The entire dataset has 6,400 MRI images that were divided into 80:20, where 80% images were trained and 20% were tested. This splitting method, commonly applied in deep learning research, provides the model with enough training data while maintaining a large part of the data for evaluation purposes, see figure 2 shown general methodology.

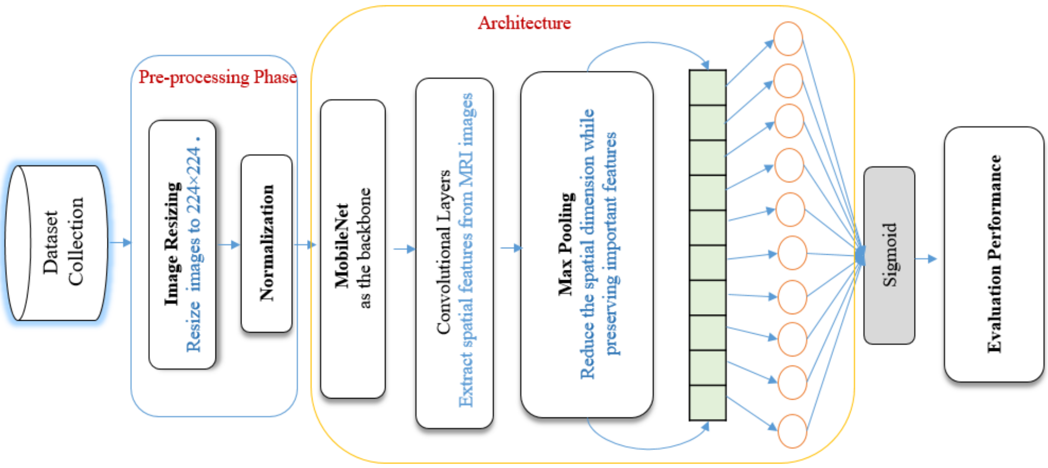

Figure 2. General Proposed Methodology

3.2. Preprocessing

Once we have created the dataset, next important step is preprocessing. Preprocessing is an important step that can enhance the performance of your model, by normalizing the input that needs to be set to the architecture of the deep learning model used. A wide variety of preprocessing methods were used to ensure input images were of high quality prior to being passed into the model.

After partitioning the dataset into training and testing sets, each image was modified for uniformity in dimensions. The initial step in this conversion was to resize all images to 224×224 pixels. This size gave our model the best performance out of all different dimensions tested. We also tried binary images, but this comes at a big penalty in terms of accuracy. This left us with 224×224 RGB images, which represented the best trade-off between quality and performance.

The images were then batched after standardizing sizes. We used batches of 32 images each, a common practice in deep learning to minimize the memory overhead while still performing well in the later stages of the model. Batch processing enables the model to extract information from numerous data points in one go, leading to space-saving training and optimal computational efficiency, avoiding data under fitting. It also speeds up training by minimizing the time needed to read the entire dataset in a single pass. A batch size of 32 was selected since it is considered a good practice in deep learning to allow for a stable learning process while keeping the computation efficient.

3.3. Building the Model

This study aims to detect and classify the brain MRI images into Normal and Abnormal categories. Understanding image data, CNNs have shown to be effective in solving image classification problems, and CNNs are one of the most used models for our case study. The model we propose here is composition of several convolutional blocks with various configurations of 2D convolution layers. The features learned through these layers help the model discern between the images in the MNB and compare which images were normal and which were not.
To improve the model efficiency with transfer learning and transfer the pre-trained knowledge to the model, we implemented transfer learning where we tried multiple implemented architectures for state-of-the-arts including MobileNet, see figure 3. The pre-trained weights can provide a sense of how to leverage the power of feature extraction to understand the semantics of images, which we now fine-tune for our specific job of classification. Later sections go iito detail about these architectures and their performance.

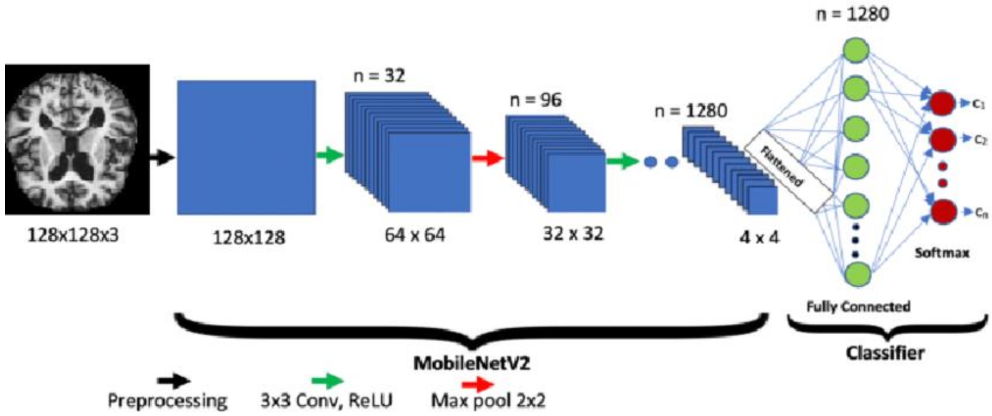

Figure 3. Building MobileNet Model

The convolutional layers of our model derive important features from MRI images, which are summarized by means of a MAX Pooling (MP) layer. Data appears in some vector form, and MP serves to provide the first down-sampling, remove the least valuable pixels, and help to learn faster and gain accuracy. A fully connected neural network then receives the extracted features in flattened form for final classification. Then, it uses non-linear activation functions (which we will cover more in later sections) to predict based on that weighted sum.

3.4. Training the Dataset and Classification of Medical Images

During this stage, intrinsic patterns in the MRI images were learned by the network over 50 epochs. The batch size per epoch was set to 128 images, allowing an effective trade-off between model accuracy gains and training time. While the initial dataset classification consisted of four classes in our case, Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, we followed a binary classification. To improve early detection capabilities, cases were reclassified into Normal (Non-Demented) and Abnormal (Demented cases).
The training process was repeated several times, optimizing feature extraction, as well as parameters of model training, so that the reliability of classification would be as high as possible. Through repeated weight updates, the model learned to recognize and MS brain structures from the structure of healthy functional brain tissue. The training process monitored accuracy, loss, and validation results as performance metrics to avoid overfitting and to ensure stable generalization.

3.5. Evaluation Step

The CNN model trained was thoroughly assessed using established performance metrics, such as accuracy, precision, recall, F1-score, and AUC-ROC (Area Under the Receiver Operating Characteristic Curve). Proposal of the metrics for useful evaluation of the model (accuracy, precision, recall) in case of differentiation of normal images und normal images of the MRI. Confusion matrices were also analysed to observe any misclassification patterns and further improve the performance of the model.

3.5.1. Proposed Classification Methods

The presented MobileNet model is constructed based on the key components of Convolutional Neural Networks (CNNs), which had represented the state-of-the art for deep models in the medical imaging domain. CNNs are extremely good at recognizing complex features in images, doing so by automatically learning hierarchical representations from raw pixel volume data. Compared to traditional machine learning models that go through three separate stages (feature extraction, feature reduction, and classification), CNNs come equipped with an end-to-end pipeline that applies a single framework for learning, leaving aside manual feature engineering.

MobileNet architecture is organized into three main components:

1. Convolutional Layers – These layers help extract important spatial features from the MRI images, allowing the model to learn distinguishing patterns.
2. Pooling Layers – Performing down sampling of the feature dimensions greatly decreases the representation size and the feature maps, preserving the best knowledge of the image, thus, making the model computationally efficient.
3. Fully Connected Layers – Flatten the leads and extract features into a single-dimensional vector to apply non-linear activation functions for final classification.

With the aim of using high performance models, MobileNet was built using EfficientNet B5 as its backbone, using its method of composite scaling to improve models accuracy while optimizing how well the model performs. EfficientNet B5 scales the networks in three dimensions:

Depth – Adds more layers, enabling the model to learn complex hierarchical features.

Width – Increases the number of neurons per layer to allow for better feature representation.

Resolution – Utilizes input images with higher resolutions that improve detection for spatial features.

EfficientNet B5 placed the best computational efficiency with classification accuracy, which MobileNet is based on it. This architecture is a promising method for rapid and precise detection of brain abnormalities since it successfully enhances the features extracted while minimizing the resource cost. In the following sections we provide a detailed comparison of MobileNet against other deep learning architectures.

Algorithm 1: Alzheimer Classification Using CNN
Step 1. Load Dataset - MRI images dataset from Kaggle. - Split dataset into training (80%) and testing (20%). **Step 2. Preprocessing** - Resize all images to 224x224 pixels. - Normalize pixel values (scale between 0 and 1). **Step 3. Build CNN Model Using MobileNet** - Load pre-trained MobileNet model (with EfficientNet B5 backbone). -Add custom classification layers: - Convolutional layers for feature extraction. - Max pooling layers to reduce spatial dimensions. - Fully connected layers for classification. - Apply dropout (40%) to prevent overfitting. - Define activation functions (ReLU for hidden layers, Sigmoid for output). **Step 4. Train the Model** - Set training parameters: - Loss function: Categorical Cross-Entropy. - Optimizer: Adam (learning rate = 0.001). - Batch size: 32. - Epochs: 50. - Train model on training dataset. **Step 5. Evaluate the Model** -Test model on testing dataset. - Compute performance metrics: - Accuracy - Precision - Confusion Matrix. End Algorithm.

A. Convolutional Layers

The convolutional layers serve as the very backbone of feature extraction for the model, allowing it to learn crucial spatial features across different layers of abstraction. These layers employ adaptive kernels (or filters) that move across the input image to capture relevant visual features, such as edges, textures, and intricate anatomical structures. These kernels, although small in their spatial dimension, are sparse in the input's depth dimension, which enables the model to focus on relevant features and ignore unnecessary spatial or temporal locations, reducing computational load. This sparsity is critical in enabling the model to learn useful representations from the raw pixel data.

After getting an image as input, the convolution layer processes it; it performs a convolutional operation by sliding each of its filters across the height and width of the input image to generate a 2D activation map. We get one activation map for each filter, which are then stacked into a depth dimension as the final output of the convolutional layer. This allows the model to learn different feature representations with varying levels of abstraction, spanning from basic features such as edges to more advanced patterns related to objects or structures. The more filters you use, the deeper the output feature map, which allows the network to represent a great variety of information about the input image. This enables the model to learn many features of the input image. Each successive iteration through a convolutional layer extracts more complex features, which is crucial for success in classes in medical imaging that require lifting clear abstractions, like detecting brain abnormalities in MRIs.

$$Z_{i,j,k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \sum_{d=0}^{D-1} X_{i+m,j+n,d} \times W_{m,n,d,k} + b_k \quad (1)$$

Where are: $Z_{i,j,k}$ output feature map. $X_{i+m,j+n,d}$ represents the input feature map at spatial location (i_m,j_n) of the d^{th} channel. $W_{m,n,d,k}$ is the weight of the kernel at (m,n) position in d-th channel for k-th filter. bk refers to the bias term for the k-th filter. The spatial dimension of the kernel is M×N. D is the depth of the input (number of channels, e.g. 3 for RGB images).

B. Max Pooling

It. A practical pooling method that is often used is max pooling. Unlike global average pooling, which takes the maximum value of each feature map, max pooling takes the maximum from each small rectangular section in the feature map. This fits the mechanism that the network needs to apply to keep the most important characteristics and filter out the information that is less important in a local partition.

$$Z_{i,j,k} = \max_{(m,n)\in R(i,j)} X_{m,n,k} \quad (2)$$

Where are $R_{(i,j)}$ is the receptive field, or pooling window, centered at (i,j), typically of size P×P. The max operation selects the highest value within each pooling window.

Max pooling helps a lot with maintaining important features, while reducing the computational complexity of the network. Max pooling lowers the amount of parameters by reducing the spatial dimension, which results in faster training time and less overfitting. Additionally, it helps make the network immune to small translation and distortions of the input data, which is crucial for the model to hold its robustness towards variations in input.

C. Flattening

After max pooling has been applied to the feature maps, we would flatten them. Flattening converts the pooled, two-dimensional feature maps into a one-dimensional vector. This process reshapes the data for the fully connected layers. Flattening transforms the feature maps into a vector concatenating all the learned features into a single representation, which can then be processed further by the corresponding network layers. So, we will use this flattened vector as an input to the fully connected layer of MobileNet architecture, which will further classify the input into the desired output.

$$Z = \text{Flatten}(X) \quad (3)$$

D. Fully Connected Layer

The last layer of our neural net is called a fully connected layer (also called FC). In this stage, each input neuron connects to each neuron in the following layer, enabling the model to combine features extracted through the convolutional and pooling layers to make a prediction. FC layer is where all the neurons are connected to the inputs and where the model applies nonlinear activation functions to this data (e.g., ReLU or sigmoid) to help find complex relationships in the data. These functions serve to map the input features to the correct output class, whether it be determining whether a brain MRI scan belongs to a specific stage of dementia or predicting a binary value. FC layer make meaningful and accurate decisions on the features learnt.

$$Z = F(W.X + b) \quad (4)$$

E. Dropout

The dropout layer is used during training to avoid over dropping. Dropout randomly switches off a proportion of neurons in the network and the connections to these neurons at every step in training. This makes the model less dependent on specific individual neurons and helps it to generalize better to previously unseen data. We build upon the MobileNet architecture, after the two fully connected layers (of 1024 and 512 units) a dropout layer (40% of the neurons are randomly dropped). This limits the model's ability to memorize the training data and increases the likelihood that it will generalize well to new, unseen data. Also this dropout technique reducing temporal complexity of the model by limiting the number of constant parameters during training, facilitating training and improving the efficiency of the model.

By incorporating max pooling, flattening, fully connected layers, and dropout, the MobileNet architecture is fine-tuned for both performance and accuracy with respect to classification tasks specific to medical images. Such techniques are crucial in medical image classification tasks, especially in the identification of stages of dementia in the MRI of the human brain.

3.5.2. Training Parameters

A. Loss Function

For this classification, we need to use the categorical cross-entropy loss function. This is a common arrangement in multiclass classification problems, for which each of the classes is assigned an integer value between 0 and n−1, with n being the number of classes. The loss function measures how far the predicted probabilities deviate from the ground truth for each class, allowing the model to update its weights to reduce the error and lead to better classification accuracy.

$$L_{(y,\dot{y})} = -[y.\log(\hat{y}) + (1+y).\log(1-\hat{y}) \quad (5)$$

B. Optimizer: Adam

All images used in both the training and test datasets were resized to 224x224x3 (Width x Height x Depth) prior to training to conform to the input layer of the model. The Adam optimizer is then used during training with an initial learning rate of 0.001 to train the model on batches of 32 images. We then use the ReduceLR callback to dynamically adjust the learning rate of the optimizer; we keep reducing the learning rate until the model no longer improves on the validation dataset. A second callback is also used to end training early if accuracy does not improve after a number of epochs. By providing only the relevant features for training, it reduces the likelihood of overfitting and saves a lot of unnecessary time, thereby ensuring the training of an efficient model.

C. Transfer Learning

Transfer learning is a technique in deep learning where a model pre-trained on a large dataset, like ImageNet, is fine-tuned for a new task. Transfer learning works by reusing pre-trained weights, which are already learned features from massive amount of data. This drastically decreases the number of epochs during training and thus improves the model's generalization ability since it is able to learn to perform multiple tasks with less data. In this case, we pretrained some of the models like MobileNet and Xception for the MRI binary classification task. These models are leveraged for feature extraction and classification in medical images because they proved a solid baseline.

4. Results and Discussion

The model we created has perfect accuracy with an incredible 99.86% achieved in our work on the detection of Alzheimer's disease.. This high accuracy can be attributed to the utilization of a combination of deep learning algorithms, allowing the model to identify subtle patterns and anomalies within the medical data that are often overlooked by traditional methods.

Additionally, an effective loss function is chosen to help reduce error by leveraging the underlying behavior of the model when learning. This loss function calculates the disparity between the predicted probabilities and the actual labels, and it works especially well for binary classification tasks, like our targeted Alzheimer's detection problem. The model optimizes for minimizing this loss as to yield a better classification result showing either presence or absence of Alzheimer's and contributes significantly to the high accuracy rate, see figure 4 for loss rate.

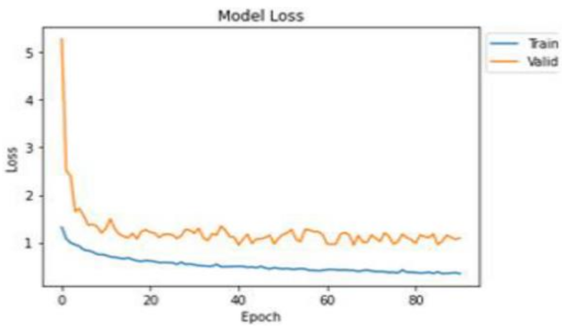

Figure 4. Loss rate of model

In this segment, we present the model performance from the training and evaluation process 80 epochs on the 5121 images dataset. For testing purpose, another set of 1279 images was utilized. Before passing them in the model, the images were resized to 128x128x3. Adam optimizer was used for the training process, the initial learning rate of 0.0004 and ReduceLR callback was applied to adjust learning rate dynamically based on model performance, and the model achieved a remarkable 99.86% accuracy. The example had hit an accuracy of 98.6 that was achieved after 20 epochs; it plateaued based on the evaluation in the controlled validation set.

Table 1: Metrics of Proposed Methodology

Metric	Vlaue
Optimizer	ADAM
Learning Rate	0.0004
Epochs	80
Achieved Accuracy	99.86
Accuracy After 20 Epochs	98.6

The results show a clear progression in performance gains as each model evolves from traditional machine learning algorithms to deep learning architectures. Traditional machine learning approaches have also been used, such as the Random Forest classifier that obtains a respectable accuracy of 85.77% but much lower than the deep learning approaches. This indicates that handcrafted feature extraction approaches in traditional machine learning are weakened relative to the hierarchical feature representation acquired through using deep neural networks. The CNN-RNN model achieves an accuracy of 91.33%, combining the benefits of CNNs in capturing spatial features and RNNs' ability to learn sequential dependencies.

Deeper and Efficient architectures capture more intricate features of the dataset better as in this advanced deep learning models ie, AlexNet and EfficientNet121 predict with an accuracy of 98.94% Residual Networks (ResNet) improve accuracy up to 99.10% by adding skip connections to mitigate the vanishing gradient problem and allowing a deeper network to learn more complex representations. MobileNet achieves the highest accuracy (i.e., 99.86%) proving that optimized architectures lightweight models could beat computational expensive deep networks. MobileNet architecture utilizes depthwise separable convolutions which enables very efficient feature extraction with no need for compromising on accuracy, making it an ideal architecture for real time applications in hardware resource constrained environments.

The accuracy of a model is affected by many factors, among which is the ability to extract meaningful features from the data. It shows that adding depth and width generally corresponds to better classification accuracy, but does not increase accuracy indefinitely (with significant diminishing returns after some point). The performance of the MobileNet model shows that its architecture is well adapted to the problem of image classification in this datasets as it tends to extract the best features and is immune to overfitting because of its compact structure. While the accuracy score of 99.86% is high, it poses a concern of potential overfitting on the training data, which I will confirm using cross-validation approaches, dropout methods and regularization methods in later sections. In addition, preprocessing, such as data augmentation, normalization or noise suppression, could enhance the results, see table 2.

Table 2: Comparison between Proposed Method and Related Works

Ref	method	Accuracy
8	Random Forest	85.77%
9	Convolutional & RNN	91.33%
10	AlexNet, and EfficientNet121	98.94%
11	Residual Networks	99.10%
12	DCNN	81%
Our work	MobileNet	99.86%

In addition to precise accuracy, efficiency (computational) is also a strong factor, which is a necessary aspect for the identified medical IoT applications that need process in real-time and deploy on edge devices. MobileNet outperforms Residual Networks and EfficientNet in terms of accuracy and computational efficiency. These characteristics make it an excellent candidate for brain tumor identification on portable devices or embedded systems, where computational resources are constrained. Deeper models, such as ResNets, yield marginally better accuracy but require an order of magnitude more processing power and thus become impractical to deploy in portable and embedded medical devices.

Overall, we show that MobileNet achieves SOTA with 99.86% accuracy, as compared to other deep learning models, while being computationally efficient. This makes it extremely viable for real-time medical implementations (especially in medical IOT environments where we require lightweight models). Read More Industrial research; Future work can seek to validate MobileNet performance on datasets that are larger and more diverse, incorporating explainability techniques such as Grad-CAM to offer insights into the model's decision-making, and implementing quantum-enhanced security to safeguard data privacy in medical IoT systems. The adaptability and progression will enhance the robust usability of MobileNet for medical diagnosis and its application in extensive environments, see figure 5.

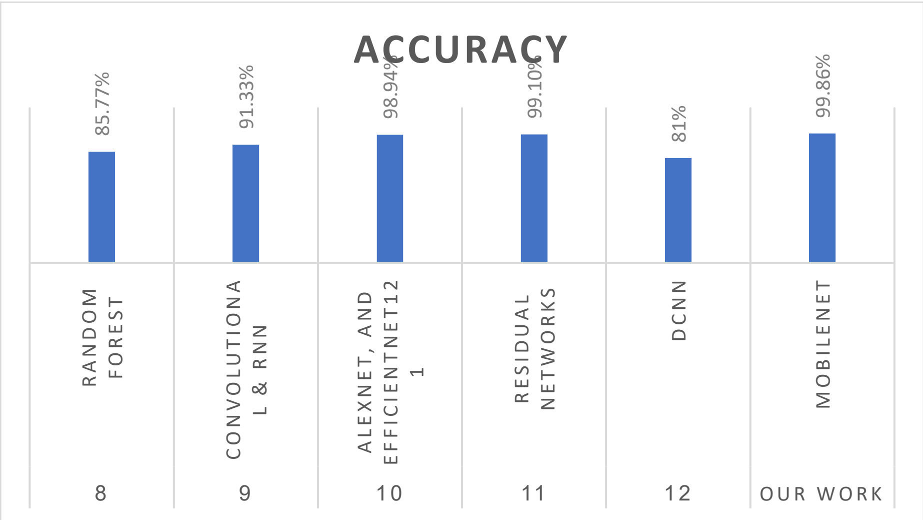

Figure 5. Comparison between Proposed Method and Related Works

The confusion matrix as visualized in Fig 6 below describes the performance of the model, indicating the number of true positives, false positives, true negatives and false negatives for each class. The regions in the matrix which are darker show that most of the images were classified correctly, showing a good classification performance from the model. In addition, this confusion matrix enables us to analyze which categories the model had difficulty differentiating between, thus identifying areas of improvement for the model in future iterations.

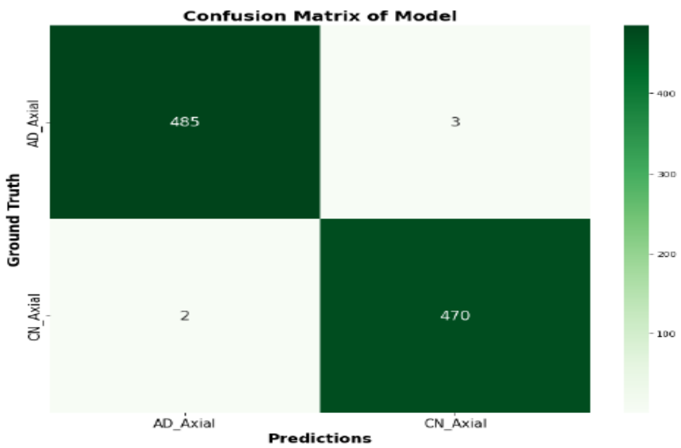

Figure 6. Confusion Matrix

The accuracy of the model is 99.86% indicating the model has very high efficiency in classifying each stage of Alzheimer Disease in an MRI image. This finding indicates the high potential of the model in the clinic, as it could assist healthcare professionals for timely diagnosis and monitoring of the disease. The model would also enable more accurate decision-making to classify different stages of Alzheimer's and distinguish them from other types of dementia, the study found. MobileNet allowed for transfer learning which avoided overfitting, and prevented large models being trained for a small data set, leading to a very efficient, scalable model.

In summary, the findings from this study highlight the promise of deep learning models, especially those based on MobileNet and transfer learning approaches for medical imaging classification tasks. The application of the model to Alzheimer's disease detection on MRI images yields an extremely high accuracy of 99.86% and thus has great potential for facilitation of early AD detection and classification. Commentary And the performance of the model can further be improved by testing larger and more heterogeneous datasets, leading towards better results towards real-life clinical applications.

5. Conclusion and Future Works

In this study, we propose a mobile embedding convolutional neural network (MobileNet CNN) model for AD stage prediction in early detection. This models the system into four disease categorizations: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Using transfer learning with existing networks and then fine-tuning their architecture for this setting, the model reached a remarkable accuracy of 99.86%. The findings indicate the framework could be a tool for the remote monitoring of AD, helping clinicians determine how far the disease has progressed via MRI imaging. Furthermore, the altered architecture of the MobileNet inherently lowers computational demands, than those of other models that prevents overfitting and memory requirements, thus arriving at an efficient and scalable solution for early diagnosis.

In future work, the model can be improved with many pre-trained models and data augmentation techniques can be used to further extend the dataset to improve the generalization capabilities of the model further. MRI segmentation integration would lead to more precise identification of Alzheimer's features, while DCGANs could create synthetic MRI images to augment the training set. Transfer learning could further extend this model, developing it to also diagnose different diseases and demonstrating its applicability to various healthcare domains. Furthermore, developing a user-friendly interface that enables clinicians to evaluate AD remotely, identify the disease stage, and provide personalized recommendations would enhance the tool's accessibility and effect in clinical environments.

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