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A Fine-Tuned Resource-Limited Deep Learning Approach for Alzheimer's Diagnosis

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Abstract— Automated Alzheimer's Disease (AD) Diagnosis anticipates perfect and timely medical aid to Dementia affected patients. Nowadays, the AD diagnosis using the Deep Learning (DL) architecture leads to the early diagnosis of the disease. This paper proposes a thirteen-layer Convolutional Neural Network (CNN) architecture that integrates five sets of convolutional layers with batch normalization to enable efficient hierarchical feature learning, followed by max pooling to reduce computational complexity. A dropout layer is employed to reduce overfitting in this model by dropping 50% of neurons during training, and finally, fully connected layers are incorporated for identifying multiple classes of dementia images. The Adam optimizer is used to expedite faster training, also yields stable convergence. The proposed model is validated on two popular databases, the OASIS and ADNI databases, to evaluate high diagnostic accuracy with limited resources. The proposed model reports diagnostic accuracy of 92% and 68%, and computational time of 53 minutes and 62 minutes, respectively, for the OASIS and ADNI databases, which are found to be more promising and robust than other conventional pre-trained DL models, including DenseNet, EfficientNetB3, MobileNet, and ResNet152. Finally, the proposed approach has been ideated as a mobile application for easier usage by patients and pathologists.

Keywords— Dementia classification, convolutional neural networks, early detection, resource utilization.

I. INTRODUCTION

Alzheimer's disease (AD) mainly affects aged people who are over sixty years, and it is the leading cause of dementia due to the gradual loss in memory-thinking-reasoning-behavior of individuals. According to records, 26.6 million people were affected by AD by 2006; additionally, a study predicts a concerning forecast that by 2050, 1 in 85 people will be affected [1]. So, AD is an alarming stage for society, which must be cured or controlled. Manual diagnosis of brain images is complex, prone to error, and time-consuming due to low contrast, blurred boundaries, and intricate relationships [2-3]. Till date, several automated techniques have been tested with the help of brain segment images to achieve accurate and precise diagnosis; however, it remains a challenging task [4]. Therefore, researchers are focused on prompt and effective solutions for preventing AD.

Electroencephalogram (EEG), which is a process that records brain activity from sensors attached to the scalp, is a promising tool for early diagnosis and classification of AD [5-7]. Feature selection techniques using Student's t-test (STT), Principal Component Analysis (PCA), and Partial Least Squares (PLS) have also been used for AD progression [8]. Currently, Machine Learning (ML) models provide promising results on medical data [9-11]. Researchers combined several ML methods, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest, for dementia detection [12-13]. However, the classification, incorporating ML techniques, comes up with manual feature extraction techniques.

Deep Learning (DL) models are more capable of handling large databases and learn patterns from raw data using automated feature extraction techniques. Researchers have used several pre-trained models, such as ResNet152V2, patchwise Mnet, and Transformer-Weighted Network (TW-Net), EfficientNetB3 for dementia classification [14-17]. Also expecting more efficiency during automate diagnosis, researchers have combined a few DL models like CapsNet with DenseNet-169 and enhanced DeepLabV3+ [18]. Also, another DL fusion approach includes genetic algorithm (GA) with 3-D-CNN, SVM with VGG19, and KNN with AlexNet model [19-21]. However, most authors are focused on achieving good accuracy, but there is still a gap in terms of robustness and sustainable resource allocation [20-21]. Therefore, this paper addresses those limitations, which include,

1) Early detection of dementia with minimal learnable parameters using multiclass databases.

2) Optimal resource utilization for sustainable usage.
3) Verification of robustness.
4) A mobile application has been proposed to develop the diagnostic system with a frontend, a backend, and a security system.

Therefore, Section II describes the methodology incorporated in the proposed work, including the databases used, Section III highlights the results with a brief discussion of the respective, and Section 4 concludes the study with a decision.

II. METHODOLOGY

This section describes the databases consisting of the details of MRI images, pre-processing steps, and the proposed approach, as shown in Fig.1. The outline of the pre-processing workflow includes image resizing, normalization, and class balancing, thereby ensuring uniformity and fairness in model training. The architecture of the proposed CNN model, tailored for classifying dementia stages from brain MRI images, is also described in this section, along with the training setup.

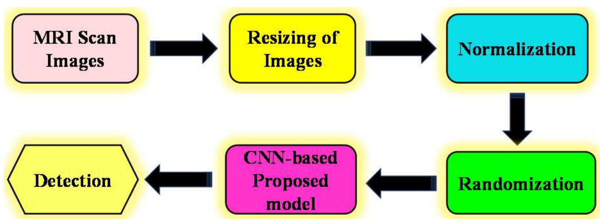


Fig. 1. Outline of the Proposed Approach

A. Database Used

This dementia diagnosis study is validated using MRI (Magnetic Resonance Imaging) scans of two online databases, Open Access Series of Imaging Studies (OASIS or OAD) and Alzheimer's Disease Neuroimaging Initiative (ADNI or ADD), which are widely utilised by researchers in the literature [22-23].

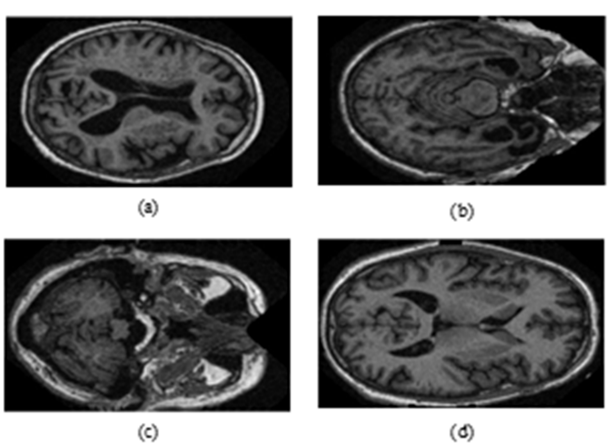
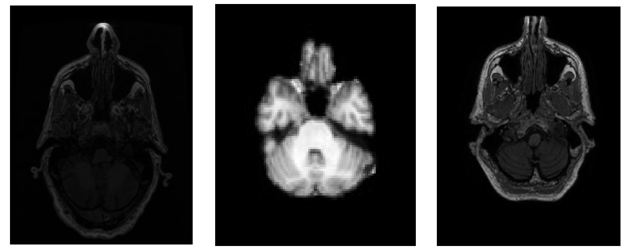


Fig. 2. OASIS database (a) VMD (b) MD (c) MoD (d) ND



(a) (b) (c)

Fig. 3. ADNI database (a) AD, (b) MCI, (c) CN

As per the OAD database, MRI scans are classified as Very-Mild Dementia (VMD), Mild Dementia (MD), Moderate Dementia (MoD), and Non-Demented (ND). The respective four classes are shown in Fig. 2. As per the ADD database, MRI scans are classified as Alzheimer's disease (AD), Mild Cognitive Impairment (MCI), and Cognitively Normal (CN). The respective three classes are shown in Fig. 3.

B. Preprocessing of the database

The initial dimensions of the images were 496X248 pixels. These are gradually reduced to find the optimal dimensions for minimum resource utilization in the form of learnable parameters. It was reduced to 248X248 pixels first, and the final dimensions are 224X224 pixels.

Normalization is the process of adjusting the value of pixel intensity to a predefined range. It enhances contrast and makes processing by other algorithms faster and easier. Normalized pixel values ($p_{normalized}$) are calculated from the original pixel value (p), which is represented in (1) with the help of the maximum pixel value (p_{max}) and minimum one (p_{min}) values with respect to the obtained.

$$x_{normalized} = \frac{p - p_{min}}{p_{max} - p_{min}} \quad (1)$$

The OAD database consists of thirteen thousand seven hundred images in the VMD class, five thousand and two images in the MD class, four hundred and eighty-eight in the MoD class, and sixty-seven thousand and two hundred images in the ND class. As the respective classes are imbalanced, the load_random_images_from_directory() function is implemented to make a balanced dataset containing three hundred and fifty sample images for each class. A manual randomization is then applied within each class to avoid selection bias due to file ordering.

C. Proposed Model

This work is aimed at automating the diagnosis of dementia with the help of a finely tuned thirteen-layer convolutional neural network (CNN), which is shown in Fig. 4. The model is completely designed to focus on optimizing learnable parameters and resources.

Our proposed model consists of five sets of convolutional layers followed by a Batch Normalization Layer. Convolution layer extracts vital features from input images using (2). The respective equation considers the input image (I), convolutional filter (K), loop variables for two-dimensional (2D) representation of an image (q,r), and kernel dimension (g). The ReLU activation function is implemented for introducing non-linearity (3), considering the activation input (t). The Batch normalization layer expedites the training through minimizing the internal covariate shift. Max-pooling layer is introduced further in the model for minimizing the spatial dimensions of the input 2-D feature map (F) using (4).

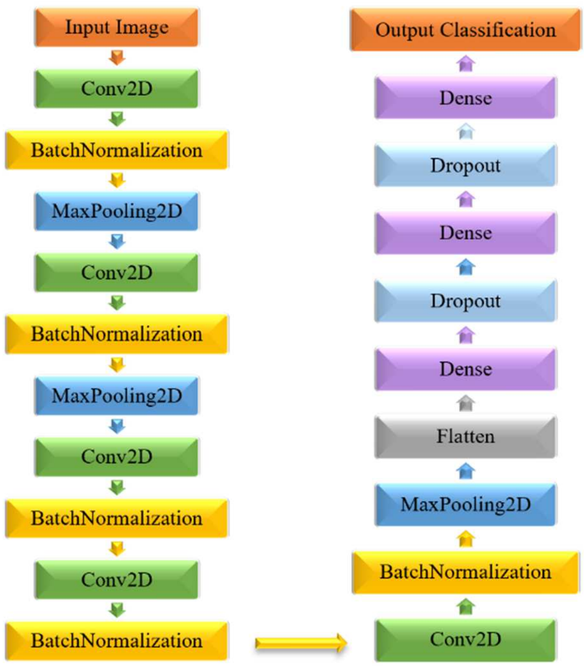


Fig. 4. Model Architechture of the Proposed Model

The output of the fifth convolution and pooling layers is fed into three consecutive dense layers, followed by two dropout layers. The output of the Dense layer is the output vector (y) computed using (5), which considers an activation function (σ), weight matrix(W), bias vector(b), flattened (1-D) feature map (m). The dropout layers help to prevent overfitting and improve generalization by turning off 50% neurons during training. Softmax function is applied after the last dense layer to produce class probabilities in dementia classification (4 classes for OASIS/OAD and 3 classes for ADNI/ADD). Class probabilities (p_i) are presented in (6) with the help of raw score (z_i) and the total number of classes (N).

$$\mathrm{I} * \mathrm{K} = \sum_{q=0}^{g-1} \sum_{r=0}^{g-1} \mathrm{I}(i,j) \cdot \mathrm{K}(i,j) \tag{2}$$

$$f(t) = \max(0, t) \tag{3}$$

$$MaxPooling(F) = max(F(i,j), F(i+1, j+1), \dots) \tag{4}$$

$$y = \sigma(\mathrm{W} \cdot m + b) \tag{5}$$

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \tag{6}$$

The proposed model utilizes the L2 regularization technique in dense layers to minimize large weights to prevent overfitting. During training, the Adam (Adaptive Moment Estimation) optimizer is used to expedite the learning capabilities from the feature patterns, aiming for good classification accuracy for the detection of Alzheimer's disease.

D. Model Training and Performance Evaluation

During the training of the model, a sparse categorical cross-entropy loss function is used. The loss is calculated using (7) to measure the dissimilarity between the true labels (y_i) and the predicted class probabilities (p_i) for multi-class dementia classification. Both datasets are segmented into a set of training and validation subsets, comprising 80% and 20% of the total images, respectively. For the OAD dataset, the train set comprises sixty-nine thousand, one hundred and forty-eight images, while the validation set encompasses seventeen thousand, two hundred and eighty-nine images. Likewise, for the ADD dataset, the training set had one thousand and three hundred fifty images, and five hundred and thirty-nine images for validation.

$$Loss = -\sum_{i=1}^{N} y_i \log(p_i) \tag{7}$$

To estimate the performance and reliability of the model, several metrics are evaluated, which include Accuracy (Acr), Precision (Prx), Recall (Rcl), are F1-Score (F1). Accuracy (Acr) is used to measure the overall correctness of the model, which is calculated by comparing the True Positive (TPI) and True Negative (TNI) of the test dataset. Precision (Prx) quantifies the exactness of the model. It expresses the total TPI samples out of all the samples that the model predicted as positive. Recall (Rcl) is a metric that indicates the completeness of the model. It measures how many TPI samples the model correctly identifies. F1-Score (F1) is the harmonic mean of precision and recall, offering a balance between the two. FPI and FNI are denoted as False Positive and False Negative, respectively. The obtained performance characteristics can be evaluated using equations (8) to (11), respectively.

$$Acr = \frac{\text{TPI} + \text{TNI}}{\text{TPI} + \text{TNI} + \text{FPI} + \text{FNI}} \tag{8}$$

$$Prx = \frac{\text{TPI}}{\text{TPI} + \text{FPI}} \tag{9}$$

$$Rcl = \frac{\text{TPI}}{\text{TPI} + \text{FNI}} \tag{10}$$

$$F1 = 2 \times \frac{Prx \times Rcl}{Prx + Rcl} \tag{11}$$

The entire experiment is simulated utilizing a Python environment with a system configuration of Random Access Memory (RAM) with 16 GB, a Processor with Intel Core i7, and an Operating System with Windows 10.

E. Mobile Application

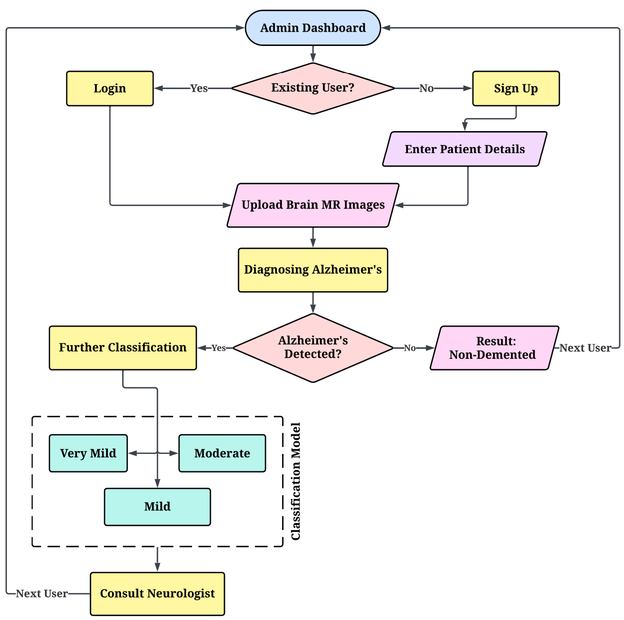


Fig. 5. Mobile Application of the Proposed Approach

An application is proposed to aid both patients and pathologists for preliminary Alzheimer's diagnosis, as shown in Fig.5. The frontend, which will contain an Admin Dashboard where users can log in/sign up and provide MRI scans for diagnosis using the underlying classification model, and get recommendations from neurologists. This part can be developed using React Native or Flutter. In the backend, the model will be stored along with all the MRI scans of each user. For storage, MongoDB may be used, and for model inference, using Flask is optimal. Security is ensured using HTTPS with TLS to adhere to HIPAA since patient data is involved. Lastly, the frontend and backend will communicate using REST API.

III. Results and Discussion

During the thorough study of dementia classification, the proposed model is compared with the existing and popular pre-trained models, which are shown in the respective subfigures of Figs. 6 and 7, respectively.

The proposed model shows 92% and 68% accuracy on OASIS and ADNI, respectively. Similarly, the computational time was observed to be 53 minutes and 62 minutes, respectively. It is observed from Fig. 7(a) that DenseNet and EfficientNetB3 performed better than other pretrained models. Therefore, DenseNet and EfficientNetB3 are compared with the proposed model for the ADNI database only, which is shown in Fig. 7(b). Although, ADNI database contains a smaller number of images, it outperforms other existing conventional models with respect to accuracy and computational time. This CNN-based model reports a total of 58 million learnable parameters. Table I reports the model performance metrics of dementia classification for each class using both databases.

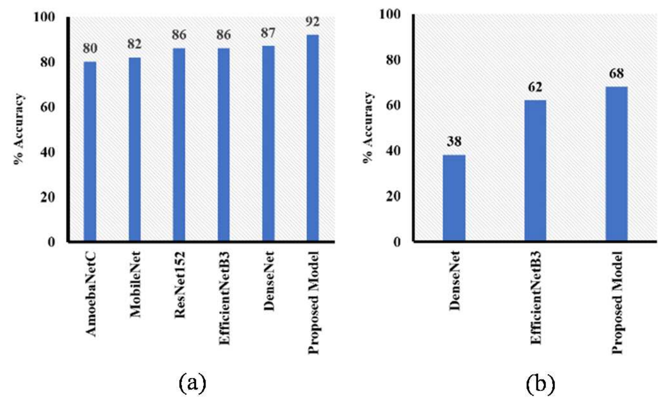


Fig. 6. Reported % Accuracy (a) OASIS (b) ADNI

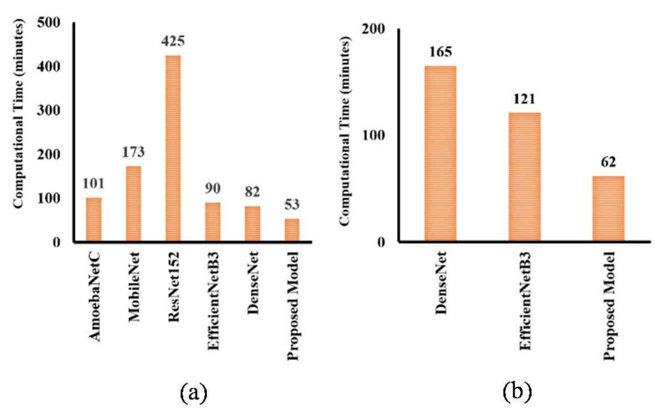


Fig. 7. Reported Computational Time (a) OASIS (b) ADNI

TABLE I. PERFORMANCE MATRIX ON OASIS AND ADNI

	Class	Performance Metrics		
		Precision	***Recall***	***F1-Score***
OASIS	VMD	0.88	0.91	0.89
	MD	0.93	0.99	0.96
	MoD	0.98	1.00	0.99
	ND	0.93	0.84	0.88
ADNI	AD	0.70	0.92	0.79
	MCI	0.58	0.76	0.65
	CN	1.00	0.37	0.54

IV. CONCLUSION

This study initiates a CNN-based, finely tuned model for the accurate and early diagnosis of dementia using two open-source databases, OASIS and ADNI. The proposed CNN-based model reports 92% classification accuracy with a computation time of 53 minutes and 68% with a processing time of 62 minutes for the OASIS and ADNI databases, respectively, using a CPU. Training the model on both datasets ensures robustness. The model is also optimized with respect to learnable parameters to reduce the usage of resources with high classification accuracy. It has been proposed that developing a mobile application would be optimal since it can be used by patients/doctors/pathologists/neurologists from anywhere in the world conveniently. This transports our Alzheimer's classification model to people in need. Therefore, this approach may enlighten the real-world medical research as it reports the highest accuracy with minimum computational need compared to conventional deep learning models.

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DECLARATION ON GENERATIVE AI

The authors(s) have not employed any Generative AI tools during the preparation of this article.

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