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Efficient Model based on Deep Learning for the Classification of Dementia

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Abstract— Alzheimer's disease to severe dementia are all forms of dementia, which are neurodegenerative disorders that affect brain memory. The most prevalent type of dementia that impairs thinking and memory is Alzheimer's disease. Network width, depth, and resolution are scaled uniformly by Efficient Net using a set of compound coefficients. This study uses callback functions to diagnose four types of dementia in order to slow down the learning process and increase accuracy. Additionally, contrast CNN and the Inception V3 model with the EfficientNet deep learning model. Using EfficienNetB2, classification accuracy is approximately 99.3%.

Keywords- Alzheimer’s Diseases (AD), Mild Demented (MiD), Moderate Demented (MoD), Non Demented (NmD),Very Mild Demented(VmD)

I. INTRODUCTION

A neurodegenerative and chronic brain condition called dementia gradually destroys brain cells, impairs memory and reasoning, and finally speeds up the loss of motor skills [1]. The World Alzheimer's Association (WAA) estimates that 50 million individuals worldwide are badly affected by Alzheimer's disease (AD), and the number of new cases is growing quickly. Around 60 million people could be impacted by severe Alzheimer's disease (AD) in the next 50 to 60 years. It is crucial to make an early diagnosis of dementia, which is made easier by contrasting the symptoms experienced by patients with those typically associated with the disease. There are conventional techniques that are used to diagnose dementia, depending on the medical histories of the patients [2, 3]. However, these techniques require high-calibre medical specialists, whose availability is limited. In addition to being available, the aforementioned techniques have a higher risk of human error. By removing the need for experts in the early detection of serious illnesses like dementia, the application of artificial intelligence (AI) has revolutionised the healthcare system. Based on specific characteristics, such as examination of voice, language, motions of the body, and brain imaging, dementia can be diagnosed with the aid of AI [4–7]. However, due to the lack of a standard data set, which is vital in order to compare the aforementioned AI-enabled approaches, Luz et al. [8] organised a forum, viz., Alzheimer’s Dementia Recognition through Spontaneous Speech (ADReSS), where different groups can work together to set up the benchmark of the data set, facilitate the comparisons of AI-enabled features, and eventually yield results with improved accuracy. Syed et al. [9] employed the ADReSS data set and created a multimodal approach that permits early identification of Dementia with better efficacy.

Alzheimer Diseases have following stages:

- **Very Mild Demented (VmD):** This is the earliest stage of dementia, during which the patient begins to forget familiar names and everyday activities.
- **Mild Dementia (MiD)**: Patients lose their ability to concentrate and work at this level.
- **Moderate Dementia (MoD):** During the MoD stage, the patient begins to forget significant past events, makes it difficult to leave the house alone, and loses empathy.
- **NMD (non-dementia):** Patients who do not have dementia

Many research papers employ the Efficient Net model for the accurate categorization and early identification of AD. In [10], Zheng et al. employed 3D Efficient Net to classify AD based on structural magnetic resonance imaging. The accuracy of the

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suggested model for structural magnetic resonance imaging was calculated to be 95.0% for NC versus AD, 86.67% for NC versus pMCI, and 83.33% for sMCI versus pMCI. The pre-processed MRI scans used in this work demanded additional computation and complexity for the classification. In their [11] work, Pranata et al. used Optimizer analysis and synthesis to create an effective-net architecture model for classifying Alzheimer's disease based on magnetic resonance imaging (MRI). For AD classification, Nadam optimisation has achieved the greatest accuracy value of 97% with a loss of 0.1104. In [12], Nawaz et al. categorise MRI pictures into three groups: AD, moderate cognitive impairment, and normal control, achieving a classification accuracy of 99.89% even with imbalanced classes.Fig.1-4 shows various classes of Dementia.

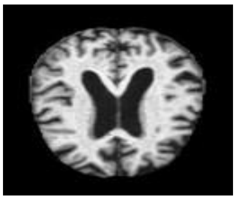

Fig1:Mild Demented

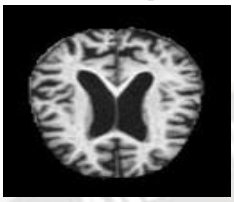

Fig2:Moderate Demented

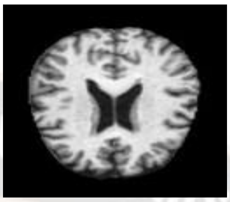

Fig3:Non Demented

Fig4:Very Mild Demented

A. **Research Objectives**

Utilise adaptive median filtering to preprocess an MRI dementia image. 2. Callback functions such as TensorBoard, ModelCheckpoint, and ReduceLROnPlateau are used for classification. 3. EfficientNet B2 classification of dementia MRI images.

B. Dataset Description

Four different pre-processed MRI dementia picture types are included in the dataset: Mild Dementia (MiD), Moderate Dementia (MoD), Non-Demented (NmD), and Very Mild Dementia (VmD), which are all defined in Table 1 and made available by various public repositories and illustrated in Fig 2. The dataset's images are 176 * 208 in size.

Table1:Description of Datasets

SNO	Class	Number of Images
1	Mild Demented	896
2	Moderate Demented	64
3	Non Demented	3200
4	Very Mild Demented	2240

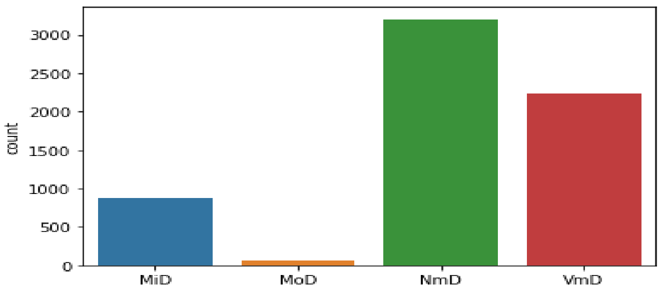

Fig2:Number of Datasets

II. PROPOSED WORK

There are two main processes in this MRI image categorization work. (1) Adaptive Median Filtering was used to preprocess the MRI image; (2) EfficientNetB2 was trained and used to classify the preprocessed picture; and (3) efficient callback functions were used. The Adaptive Median Filter (AMF) compares each pixel value in the MR picture to its surrounding neighbour pixels, as illustrated in Fig. 3, and treats them as noise. AMF filters the MRI image using two layers. The adaptive median filter's algorithm operates on the rectangular region Sxy. Zmin,Zmax A minimum, maximum, medium, and grey level value in Sxy is represented by Zmed, Zxy at coordinates (x, y). Smax is the largest size of Sxy that is permitted.

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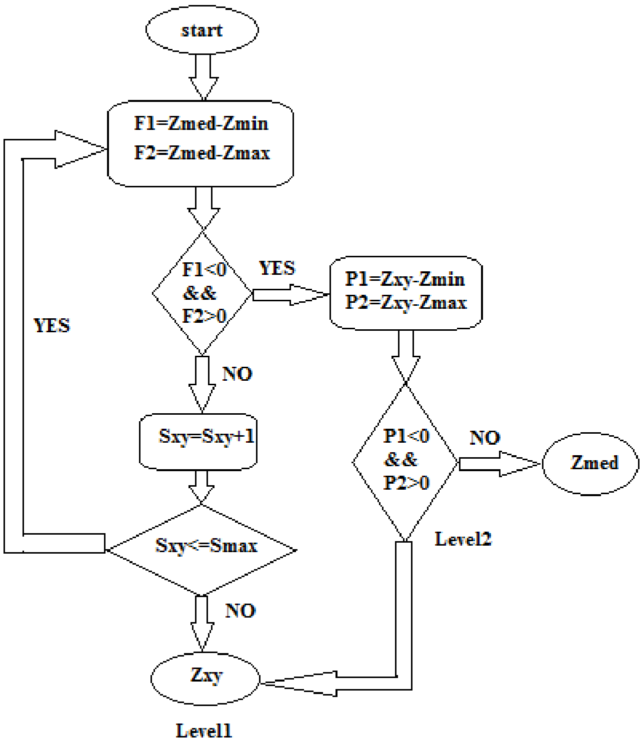

Fig3:Adaptive Median Filtering

Level 1:

F1 = Z_{med} - Z_{min} **(1)**

F2 = Z_{med} - Z_{max} **(2)**

If : F1 > 0 AND F2 < 0 **(3)**

Else: Increment the window size.

If : Ww (Size of window) <=Smax **(4)**

Repeat Level 1.

Else: Output Z_{xy}.

Level 2:

P1= Z_{xy} – Z_{min} **(5)**

P2 = Z_{xy} – Z_{max} **(6)**

If: P1 > 0 AND P2 < 0 output Z_{xy} **(7)**

Else: Output Z_{med}.

The single-value output of the filter at coordinates (x,y) replaces the corrupted pixel MR images with Sxy. This is the feature value of the preprocessed picture transfer to the EfficientNetB2 model employing three callback functions as:(1) ReduceLROnPlateau (RLRP): Improve performance by reducing learning rates (2) TensorBoard (TB): Callback for Visualisation and Representation (3) ModelCheckpoint (MCp): Callback to save the Keras model or model weights at some frequency. Depth Scaling, width scaling, and Resolution Scaling are the inheritance properties of EfficientNet B2. The Algorithm model for MRI image categorization follows the following sequence:

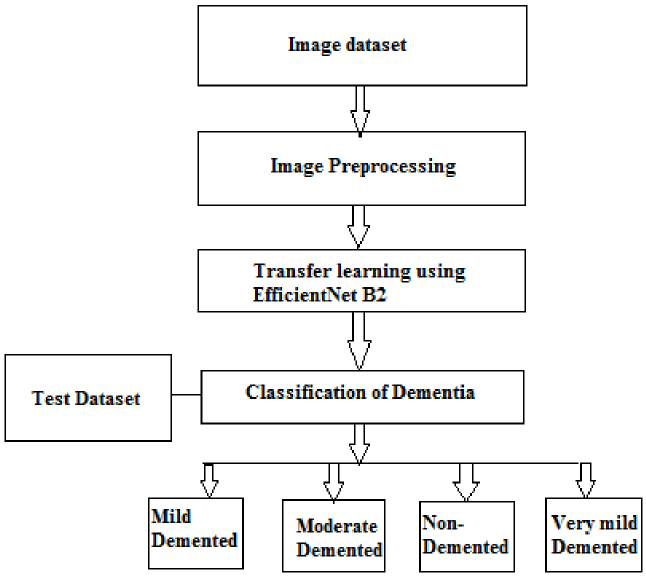

Fig4:Proposed work

Although the network resolutions, width, and depth are improved by this classification model's scaling of dimensions, the accuracy advantage lessens as EfficientNet models get larger. The effectiveness of this model employing EfficientNetB2 in terms of training and validation losses is displayed in Fig. 4. In comparison to the inception V3 model given in Figures 6 and 7, as well as the sequential model presented in Figures 8 and 9, MSE decreases as indicated in Figure 5 for the Training and Validation of Data, and Accuracy improves. In the suggested work, CNN, a multilayered perceptron (MLP) consisting of an input layer, ten hidden layers, and a single output layer, is used. While the output is handled by FC-Layers, S-Layers are used for subsampling, and C-Layers are used for convolution.

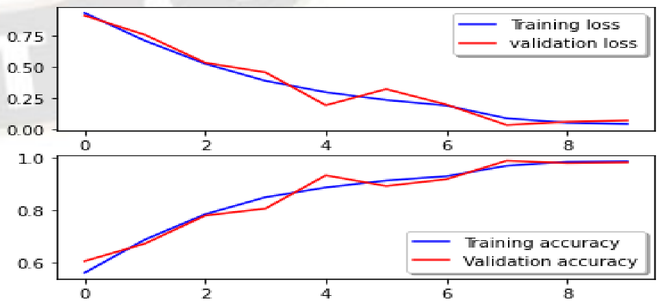

Fig5:Training and Validation loss and accuracy

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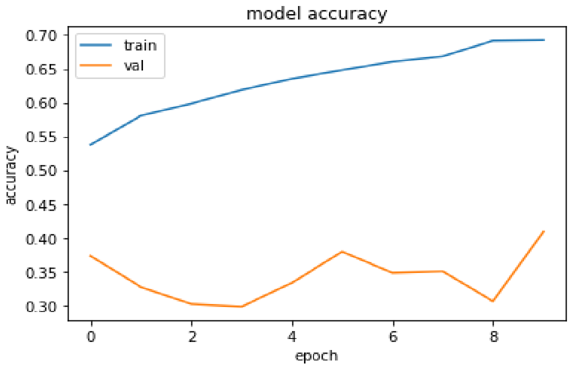

Fig6: Accuracy using Inception V3 model

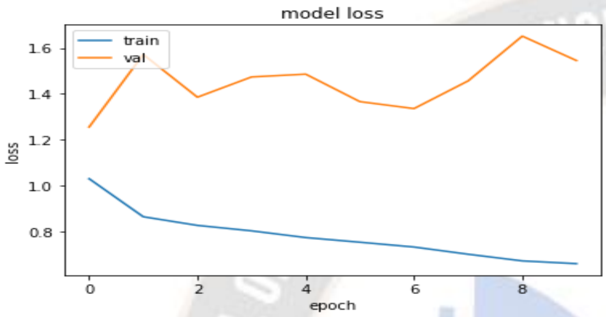

Fig7: Training and Validation loss using Inception V3 model

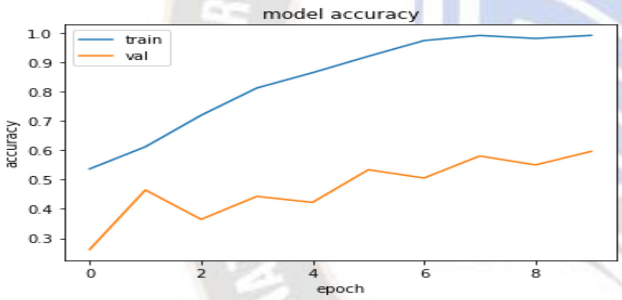

Fig8:Model Accuracy using Sequential model

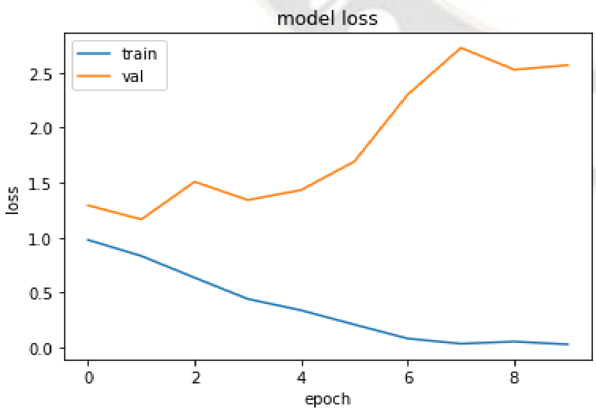

Fig9:Training and Validation loss using Sequential model

III. PERFORMANCE ANALYSIS IN TERMS OF ACCURACY

Accuracy defines the correctness of the specific MRI image class out of four classes. It is the ratio of True values to Total values shown in Equation 8.

$$\text{Accuracy} = \frac{\text{TN+TP}}{(\text{TN+TP+FN+FP})} \tag{8}$$

where TP stands for "True Positive," TN for "True Negative," FP for "False Positive," and FN for "False Negative." The proposed approach is contrasted with various deep learning methods in Table 2. It is obvious that using EfficientNetB2 results in the maximum accuracy with the fewest losses. Figure 10 shows comparative graph using deep learning with Random Forest, Supervised Vector Machine (SVM),K-Nearest Neighbour, Decision tree classifier.

Table2.Comparison with other technique

SNO	Deep Learning Technique	No of Epoch	Accuracy	Loss	Validation Accuracy
1	CNN Model [12]	10	99.06	2.56	59
2	Inception Model with adam optimizer [13]	10	94.92	1.5452	41
3	**EfficientNet B2(Proposed)**	**15**	**99.32**	**0.026**	**98**
4	Deep Learning+Random Forest[14]	10	88	0.02	88
5	Deep Learning+KNN[15]	10	78	0.03	76
6	Deep Learning+Decision Tree[16]	10	79	0.02	78
7	Deep Learning+SVM[17]	10	92	1.24	91

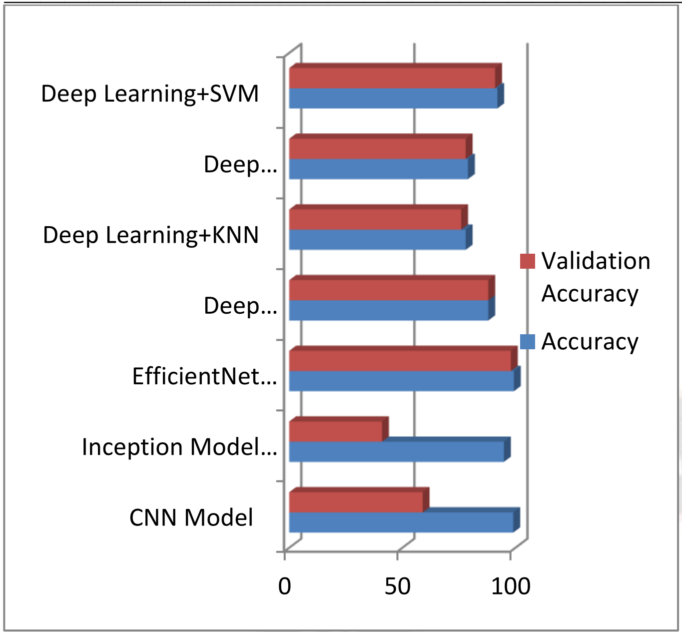

Fig10:Comparison with other Deep learning techniques

IV. CONCLUSION AND FUTURE WORK

The Validation accuracy for dementia classification based on the EfficientNet model is increased to around 98.91% using Adaptive Median Filtering, which is based on the precise pixel value of the image. This simple study analysed MRI images to find the earliest indications of Alzheimer's disease and categorised them using various categorization methods. The suggested approach outperforms the competing Deep Learning model for the categorization of dementia, according to validation accuracy.

V. DECLARATIONS

A. Ethical Approval

Not Applicable

B. Competing interests

Not Applicable

C. Author's contributions

All Authors equally contributed in manuscript.

D. Funding

Not Applicable

E. Availability of data and materials

The dataset has an image size of 176 *208 provided by various online public repositories.

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