AlziFusionNet: Alzheimer's disease detection Using transfer learning-based hybrid Deep learning model.

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KEYWORDS

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ABSTRACT

Neurological ailments such as Alzheimer's Disease (AD) drastically affect brain function and cognitive capacity. With the growing incidence of AD, early and accurate diagnosis is essential for effective treatment and patient management. There is no cure for this disease and a lot of care by caregivers is required. As the disease progresses, it also hampers the family relationship as there is not much awareness among people. Early detection of this disease will help in slow progression along with various therapies, and psychological and cognitive tests. Alzheimer's detection at an early stage may change the life of the patient, as early detection of the disease with the help of drugs and therapy can slow the progression of the disease. There are various stages of this neurological problem. MRI Magnetic Resonance Imaging and CT Computed Tomography scan can be utilized to study multiple stages. A data set from Kaggel consists of 6400 MRI images and is divided into four classes. Image normalization technique is applied along with the data pipeline to optimize the performance. various parameter settings are done to get the highest accuracy. AlziFusionNet is proposed to distinguish Alzheimer affected brain and normal brain from MRI. it is based on a transfer learning-based combination, applying global average pooling and batchnormalization, will lessen the overfitting and the model is computationally efficient. AlziFusionNet demonstrated encouraging results and remarkable performance. It proves it is a benchmarking technique. This AlziFusionNet achieved a testing accuracy of 99.87% and a training accuracy of 99.90% with precision, recall, and F1 score between 1.00 and 0.98. The model is highly optimized and demonstrates strong generalization performance, even for classes with limited data.

INTRODUCTION

Alzheimer's is a gradually increasing condition that causes nerve cells in the brain to degenerate. Whose most significant symptoms include dementia [1] with cognitive deterioration and memory weakening that significantly affect the day to day of life for millions of patients and their families. These conditions place an immense burden on families and caregivers [2] and society at large while also putting the health and safety of those affected in danger. We can conduct neuropsychological tests with neuroimaging data [3] for the detection at early stage. This work is motivated to deal with brain disease as one of the urgent global health challenges [4]. Alzheimer's is a progressive and incurable condition of the brain. It progresses gradually after being diagnosed, causing the death of memory cells [5] and reducing an individual's cognitive abilities. This neurological disorder causes neuron dysfunction or death. After a diagnosis of Alzheimer's disease, the average life span is usually few years [6]. Since an early diagnosis is an absolute requirement for effective management of the disease, early interventions, and conventional methods usually fail to provide this through timely and accurate assessments. Advances in the field of medical imaging especially MRI have opened many new avenues for enhancing accuracy in diagnostics through visualization of brain structure and function. There are various hybrid deep learning algorithms used to detect Alzheimer's at a very early stage. We are looking to design and test an appropriate image classification model for classifying accurate instances of Alzheimer's based on MRI images. Deep learning a subfield of artificial intelligence, has changed the landscape of medical imaging by enabling the automatic extraction of complex patterns from large datasets. Hybrid models are promising candidates for overcoming the challenges involved in the detection of Alzheimer's. Such models depend on the strengths of the several algorithms used, making them more predictive and robust.

OBJECTIVES

To Develop Strong Models: Propose the implementation and execution of a deep learning-based model. It must recognize Alzheimer's disease with enough accuracy among the varied forms of source data such as medical imagery, like MRI and PET scans.
Test Performance of various architectures: To check how deep architectures differ in being accurate and able to point out the beginning and more advanced stages of Alzheimer's disease. For Data Integration to explore multimodal data integration, such as genetic, cognitive, and imaging data, that can improve the detection capability of deep learning models.
To identify the most important features contributing to model predictions and improve interpretability toward understanding the underlying mechanisms behind Alzheimer's disease. A comparison of the performance between hybrid deep learning approaches and other diagnostic methods,
Clinical Application: Implication and feasibility of using such models in clinical practice to improve early diagnosis and To understand the gaps in the ongoing research and propose future research that may further enhance the detection based on deep learning techniques.

IMPACT OF THE WORK

New diagnostics

Deep learning models, especially hybrid models of multiple Deep learning techniques, provide new opportunities for the early detection of Alzheimer's. Early and accurate diagnosis is important in the management of AD and might slow its progression. New diagnostic tools or improvements on existing ones could be the inspiration from the review of hybrid deep learning models; they would be efficient, accurate, and accessible for clinicians.

These would include different hybrid deep learning models with best features from various different algorithms to be able to address problems when studying Alzheimer's disease, that is, use a CNN algorithm for image data as MRI or PET scans; RNNs for the data being time-series as from cognitive test scores, decision trees on structured data, among other examples. The review can indicate challenges in healthcare applications such as overfitting, imbalance in data, and interpretation.

Precision Medicine

It will probably discuss how hybrid deep learning models can aid personalized medicine through tailoring the diagnosis and treatment of the patient according to his individual data. These models would help identify patient subgroups that might respond differently to treatments, thus enhancing the chances of a better outcome in a patient and minimizing unnecessary interventions. This would be a very important step toward precision medicine in AD care.

Clinical Adoption

The review of hybrid deep learning models can fill the gap between theoretical research and clinical application. If the paper arouses healthcare providers to make use of AI-based diagnostic tools, this may open a pathway for earlier intervention and better resource management in the clinical setting.
Promotion of Further Research It can motivate further research in both academia and industry, considering gaps in current methodologies and challenges in detection. Finding promising areas for future exploration. Researchers may be motivated to develop new hybrid models or enhance already developed, which would contribute to the growth of knowledge in this field.

Collaborations and Interdisciplinary Progress

Researching Alzheimer's disease is highly interdisciplinary: neurology and psychiatry will always be included, along with computer science and data science. Publication of such a paper promoting collaborations in the fields by bringing novel approaches to not only AD diagnosis but its understanding itself will be able to generate wide-ranging applications.

Research Directions

Although the paper is focused on Alzheimer's, the methodologies that were discussed, especially the hybrid deep learning models, can be applied in more diverse neurodegenerative diseases or medical conditions where diagnostic challenges are similar. This will add to more generalized healthcare AI and deep learning applications.

Public Awareness and Education

This lastly opens doors for public awareness because the reviews can reach not just healthcare professionals or even policymakers but the general public of what deep learning can deliver towards healthcare. This would help explain some of the AI technologies and instead promote them towards more real-world use cases in healthcare.

LITERATURE REVIEW

Here, we briefly describe the various benchmarked models

Generative Adversarial Networks and Deep Convolutional Neural Networks [7]

SinhaRoy, R et al. developed a hybrid model of GAN and DCNN using data set ADNI that achieved an accuracy of 99.7%. To overcome the class imbalance problem GAN is applied. Including GANs with DCNNs may improve the interpretation of MRI images significantly for Alzheimer's disease. GANs can generate highly realistic synthetic MRI images that can expand limited datasets to train DCNNs and enhance generalization. Pré-trained GANs can enhance the feature extraction capabilities of DCNNs, which is very effective in detecting anomalies related to Alzheimer's disease.

ResNet-18 and Support Vector Machines (SVM) [8]

Abunadi, I.et al and colleagues developed a model of hybrid ResNet-18 and SVM which attained an accuracy of 97.9%, and a model of hybrid AlexNet and SVM which achieved an accuracy of 98.5% using a data set as “Alzheimer’s Dataset (4 Class of Images). The data argumentation method is applied to overcome the problem of class imbalance. ResNet-18 and AlexNet can extract features from complex datasets, while SVM can classify these features effectively, creating a powerful hybrid approach for tasks like Alzheimer's detection in MRI images.

Inception V3 and Resnet50 [9]

Vashishtha, A .et al applied a SMOTE method to overcome class imbalance problem. Combination of Inception V3 and Resnet50 achieved a accuracy of 99%.the data set used is “Alzheimer’s Dataset (4 Class of Images).

Inception V3 to find features from the MRI images. This block will capture detailed spatial features through its diverse convolutional paths.

ResNet50 Uses residual connections to enable training deeper networks, hence improves feature learning as gradients are backpropagated appropriately.

Combining the feature maps from both networks. This can be done by flattening the outputs and concatenating them into a single feature vector. The output layer applies a SoftMax activation function to output class probabilities for the Alzheimer's detection task.

Inception and ResNetV2 [10]

Suganthe, R. C.et al proposed a classification model based on a combination of Inception and ResNet V2 architecture. That model achieved 79.12% accuracy. Used the dataset “Alzheimer’s Dataset (4 Class of Images).

Inception will capture of multi-scale features in images, using modularity. It will capture detailed spatial features. ResNet50 uses residual connections to enable training deeper networks and combine the feature maps from both networks, improving feature learning to produce class probabilities for the Alzheimer’s detection task.

Resnet18 and Densenet121 [11]

Odusami.M.et al proposed hybrid model of Resnet18 and Densenet121 with data set of ADNI They used a concatenation of feature technique. It achieved an accuracy of 99.64%.ResNet18 extracts compact 512-dimensional features and adds a fully connected (FC) layer with 512 neurons. In the same way, DenseNet121 extracts discriminative features, followed by an FC layer that takes 1024 inputs and outputs 512 values. Then, outputs from these FC layers are concatenated and forwarded to final FC layers. Experimental results show that this feature concatenation approach offers multi-scale information from input images, which is good for Alzheimer's disease (AD) categorization.

Ensemble of VGG16 and EfficientNet [12]

Class	No of images
MildDemented	896
ModerateDemented	64
NonDemented	3200
VeryMildDemented	2240
Total	6400

Mujahid, M.et al and his colleagues used Adaptive synthetic (ADASYN) oversampling technology used to deal imbalanced classes in datasets. A combination of VGG16 and EfficientNet achieves an accuracy of 97.35%. Outputs of both models were concatenated by applying the "concatenate" function, followed by the addition of a dropout layer to prevent overfitting. The flatten layer transformed the features, concatenated by the model to a suitable format of the fully connected layers. Four batch normalization layers were added to the model to speed up the training, and three dense layers with activation functions were added for better performance. Batch normalization stabilized the model and made it learn faster.

DEMENT Model [13]

Murugan, S.et al developed a DEMNET model . They also applied a SMOTE method for handling class imbalance problems. Used the dataset "Alzheimer's Dataset (4 Class of Images). This achieved an accuracy of 95.43%.

In this architecture, extracting discriminative features in images to highlight different stages of dementia is considered. The proposed model, DEMNET, consists of four DEMNET blocks. Finally, in order to avoid problems with the dynamic range of input values, batch normalizati on was added after every convolutional layer. Batch normalization serves as a regularization technique within the DEMNET block, thus reducing overfitting.

CNN + LSTM Hybrid [14]

Bhoite, A. .et al used the combination of CNN and LSTM.This model achieved an accuracy of 89.5%. ADNI dataset is used for this study. The MRI scans are scanned to extract spatial features by use of CNNs, and LSTMs are used to identify temporal patterns in sequential data. The combination of these models improves the accuracy, sensitivity, and specificityof diagnosis, with a great potential to be a useful for early detection of Alzheimer's disease.

ADD-Net [15]

M. M. S. Fareed et al., proposed ADD-Net with SMOTETOMEK method to handle data-set imbalance problems. Achieved an accuracy of f 96.70%. Used the dataset "Alzheimer's Dataset (4 Class of Images).

The proposed solution introduces a novel deep CNN for detecting AD with relatively few parameters, ideal for training on smaller datasets. The ADD-Net is developed from scratch to accurately classify the stages of AD while reducing the number of parameters and computational costs. Each block of the network has been named the ADD block and is constructed specifically to classify AD in its early stages across all relevant classes.

MATERIALS AND METHODS

Data-In this research paper dataset from kaggel is used. The dataset holds total 6400 Images categorized into four classes representing three stages of Alzheimer's disease and the fourth "no dementia" class. AD MRI data set ("Alzheimer's Dataset (4 Class of Images) & Kaggle" [16]

Table1-Dataset distribution

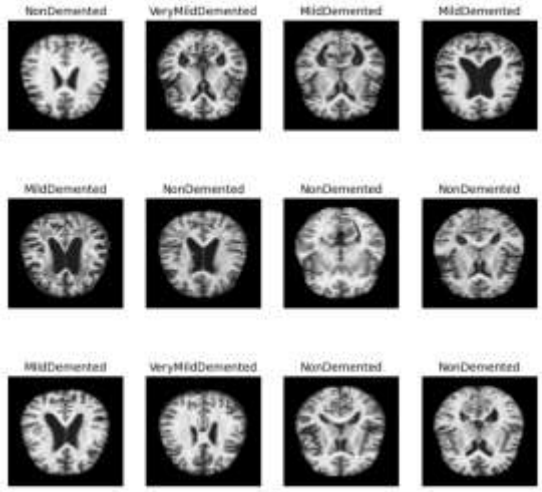

Fig 1 sample images from dataset

For this model to run colab with
A100 GPU is used. The dataset is imbalanced but still model is still performing well with a golbalaveragepooling2D technique.
A dataset is divided into 80:10:10 ratios for training testing and validation. Image normalization technique is applied to give MRI images. The normalization process scales the pixel values of images to the range [0, 1] by dividing the pixel values by 255. Model can converge efficiently and improve generalization. It also reduced the overfitting problem.
After normalization, auto auto-tuning is applied. The use of AUTOTUNE in TensorFlow's data pipeline helps optimize performance by automatically tuning the number of parallel calls and prefetching based on available CPU resources.
The cache method allows the data set to be cached in memory and it speeds up subsequent epochs by avoiding reloading data
The Prefetch method enables asynchronous data loading, it allows the data pipeline to fetch the next batch of data while the
model is processing the current batch, this also helps in maximizing training throughput.

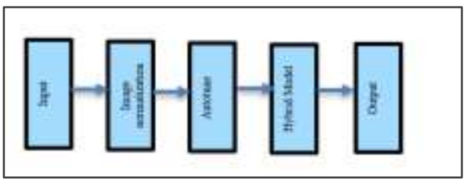

Fig 2: Data flow

PROPOSED MODEL

In this proposed model integrates InceptionV3(48 layers) and ResNet152V2(152 layers) . Both are pretrained imagenet models.InceptionV3 balances the speed and accuracy. Also, useful when there is limited memory and processing power, It is best suitable for real-time applications. ResNet152V2 uses residual connection without degradation of the performance of a model. Input images of size 256X256 are given separately to Inception V3 and ResNetV2.

Freezing layers: Freezing initial layers of the base model preserve fundamental features it would have learned from ImageNet, such as edges, textures, and simple shapes, which are helpful on a very broad range of image classification tasks.

If these layers are frozen, the model does not relearn the low-level features, instead saving much time in the process and gaining more capability to generalize to new data.

Unfreezing layers:

On the flip side, unfreezing the final 40 layers lets the deeper layers of the model adapt to specific patterns in your dataset. These later layers usually capture more complex, high-level features (like object parts or specific shapes) that are unique to your task. It is fine-tuning these layers that helps the model specialize in your problem and thus improves performance and accuracy.

Essentially, this approach finds an easy balance between reusing features pre-trained on ImageNet by freezing the early layers while adapting the model to your dataset by unfreezing the deeper layers, allowing the model to do learn task-specific tuning.

This is a relatively common and effective transfer learning strategy, especially in instances involving limited data or the need to adapt a general model into one intended for a new, specialized task. Globalaveragepooling2D and batch normalization is applied to both outputs.

GlobalAveragePooling2D:

GlobalAveragePooling2D reduces overfitting because it does not require the fully connected layers after pooling. These simplifications help avoid overfitting, with this being particularly critical for deep models. This layer can process images of arbitrary sizes efficiently, as the output of the pooling layer is always a fixed-size vector corresponding to the number of channels regardless of the spatial dimensions of the input image.

In addition, it simplifies the model architecture by modifying the need to learn subtle spatial relationships between features, It will improve the efficiency and accuracy.

Batch Normalization:

Batch Normalization normalizes the activations, calculating the mean and variance across the batch and adjusting them using learned parameters.

That stabilizes training in preventing inside covariate shift, helping it to converge quicker, flow better, and train efficiently. It also helps in regularization and prevents overfitting, improving generalization.

Concatenation:

The outputs of ResNet152V2 and InceptionV3 branches are concatenated. Model can get features from both models, potentially capturing complementary information.

Fully Connected Layers:

A dense layer of 1024 units and activation function of ReLU is used to process the concatenated features. Dropout layer (0.4) is applied to reduce overfitting. BatchNormalization is applied after the dense layer to stabilize training further.

Output Layer:

A SoftMax output layer with 4 units is used for classification, making the model suitable for a multi-class classification problem (i.e., the model outputs probabilities for 4 classes).

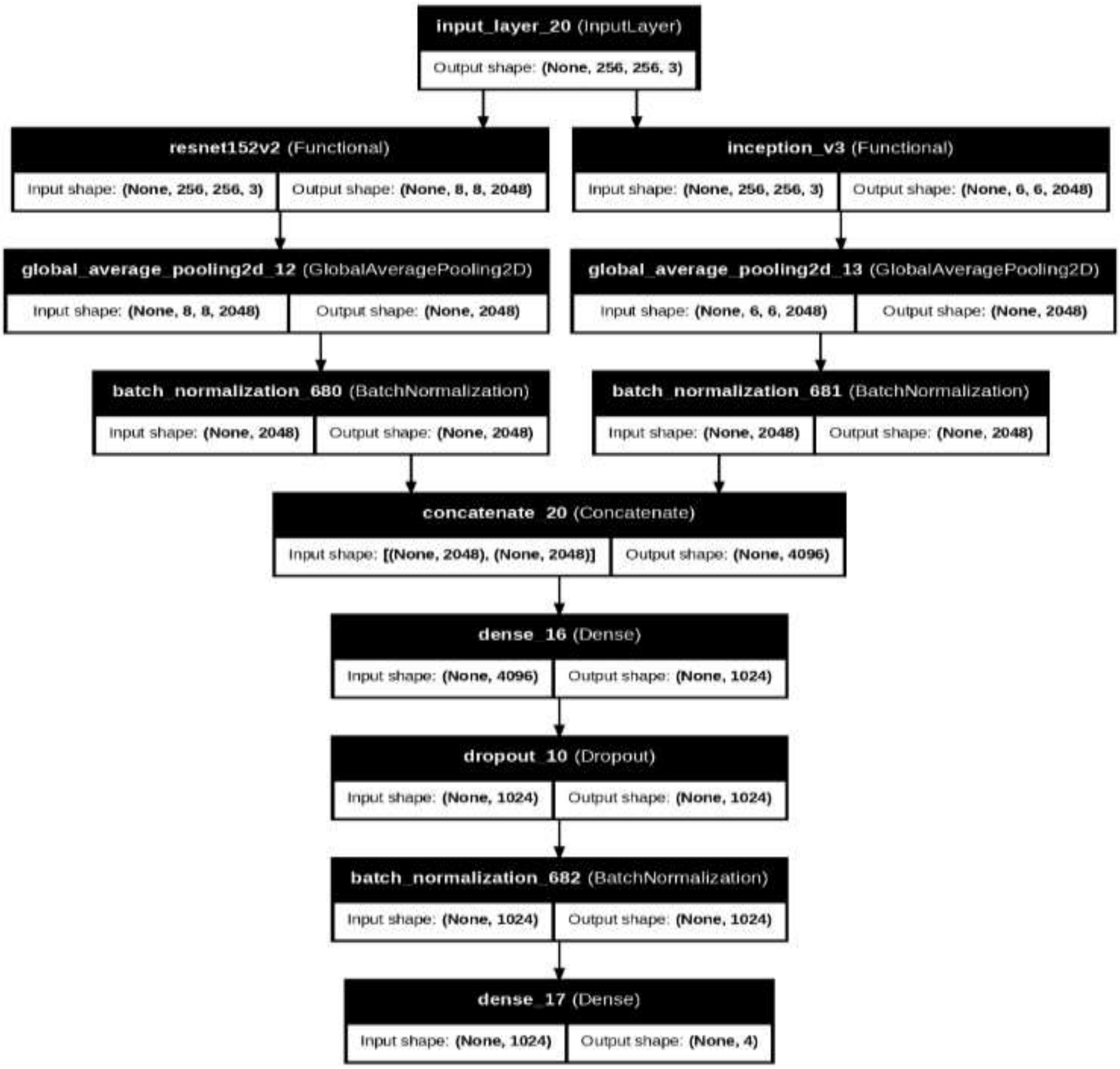

Fig 3: Hybrid model architecture

Parameter name	**Parameter**
Input shape	256X256
Batch Size	32
Call back	ReduceLRonPlateau
Minimum learning rate of	1e-6
Hidden layer activation	ReLU
Epochs	20
Learning rate	0.01
Optimizer	adam
Output layer activation	SoftMax
Dropout	0.4
loss	'sparse_categorical_crossentropy'

Table 2: Parameters list

ARCHITECTURE

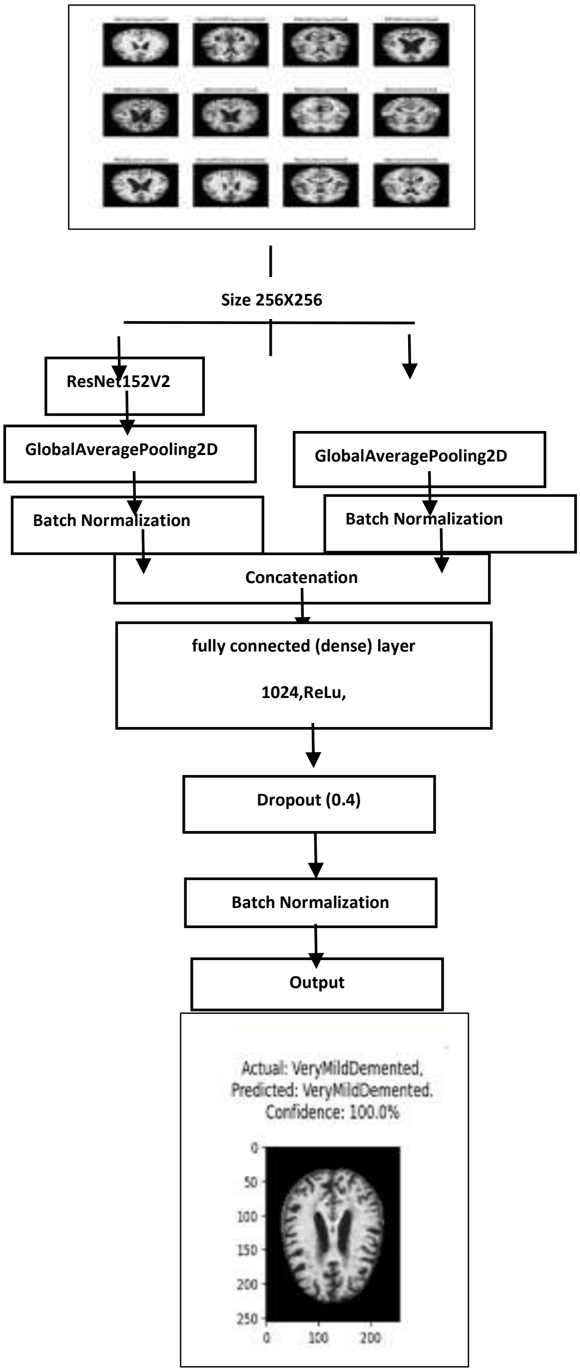

Fig 4: Block diagram of AlziFusionNet Model

RESULTS AND DISCUSSION

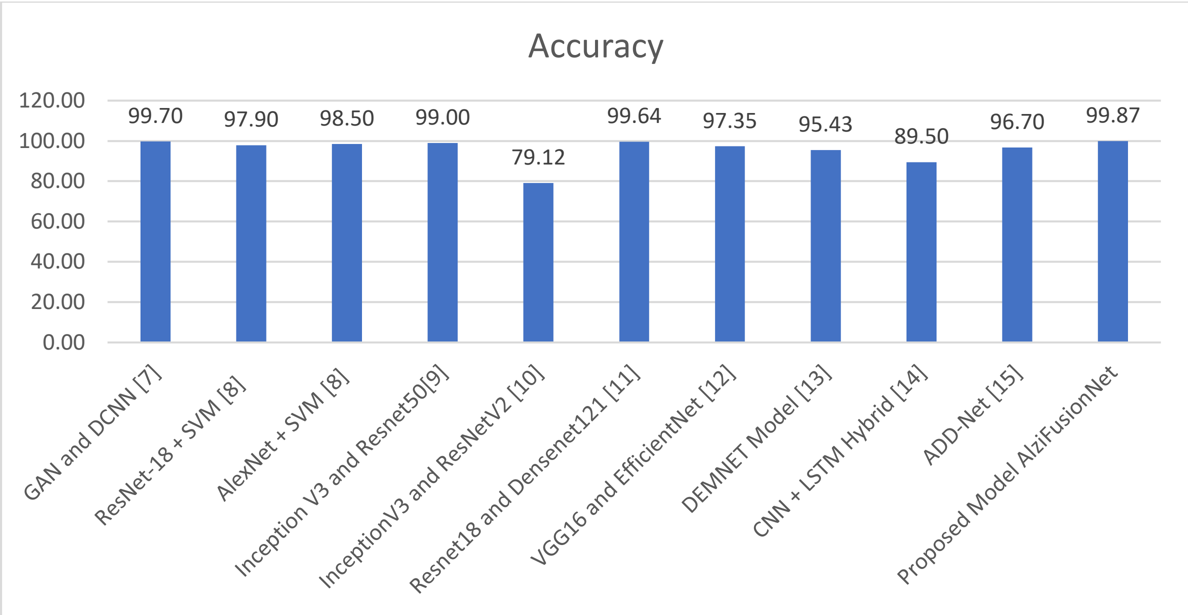

Fig 4: Accuracy Comparison chart

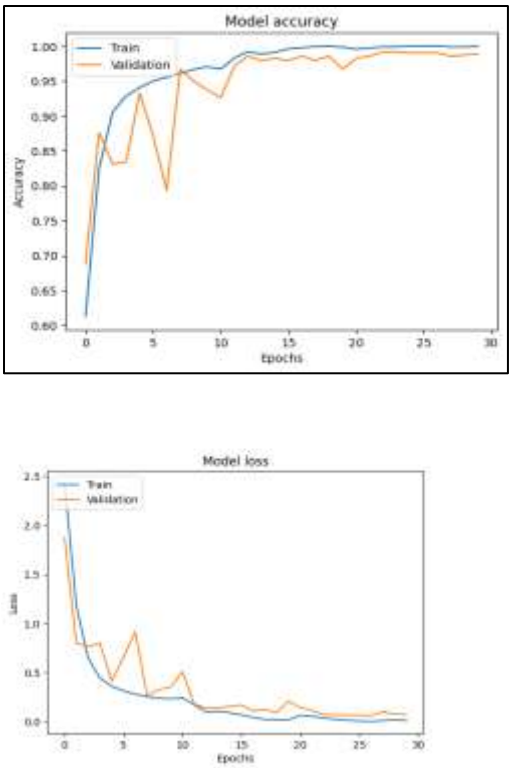

Fig 5: Model accuracy comparison chart

Table 3: Hybrid Model list

Model	Accuracy
GAN and DCNN [7]	99.7%
ResNet-18 + SVM [8]	97.9%
AlexNet + SVM [8]	98.5%
Inception V3 and Resnet50[9]	99%
InceptionV3 and ResNetV2 [10]	79.12 %
Resnet18 and Densenet121 [11]	99.64%
VGG16 and EfficientNet [12]	97.35%
DEMNET Model [13]	95.43%
CNN + LSTM Hybrid [14]	89.5
ADD-Net [15]	96.70%
Proposed Model AlziFusionNet	**99.87%**

Table 4: Performance measures of

Class	Precision	Recall	F1-Score
MildDemented	0.99	1	0.99
ModerateDemented	1	1	1
NonDemented	1	1	1
VeryMildDemented	1	1	1

Fig 6: Model loss comparison chart

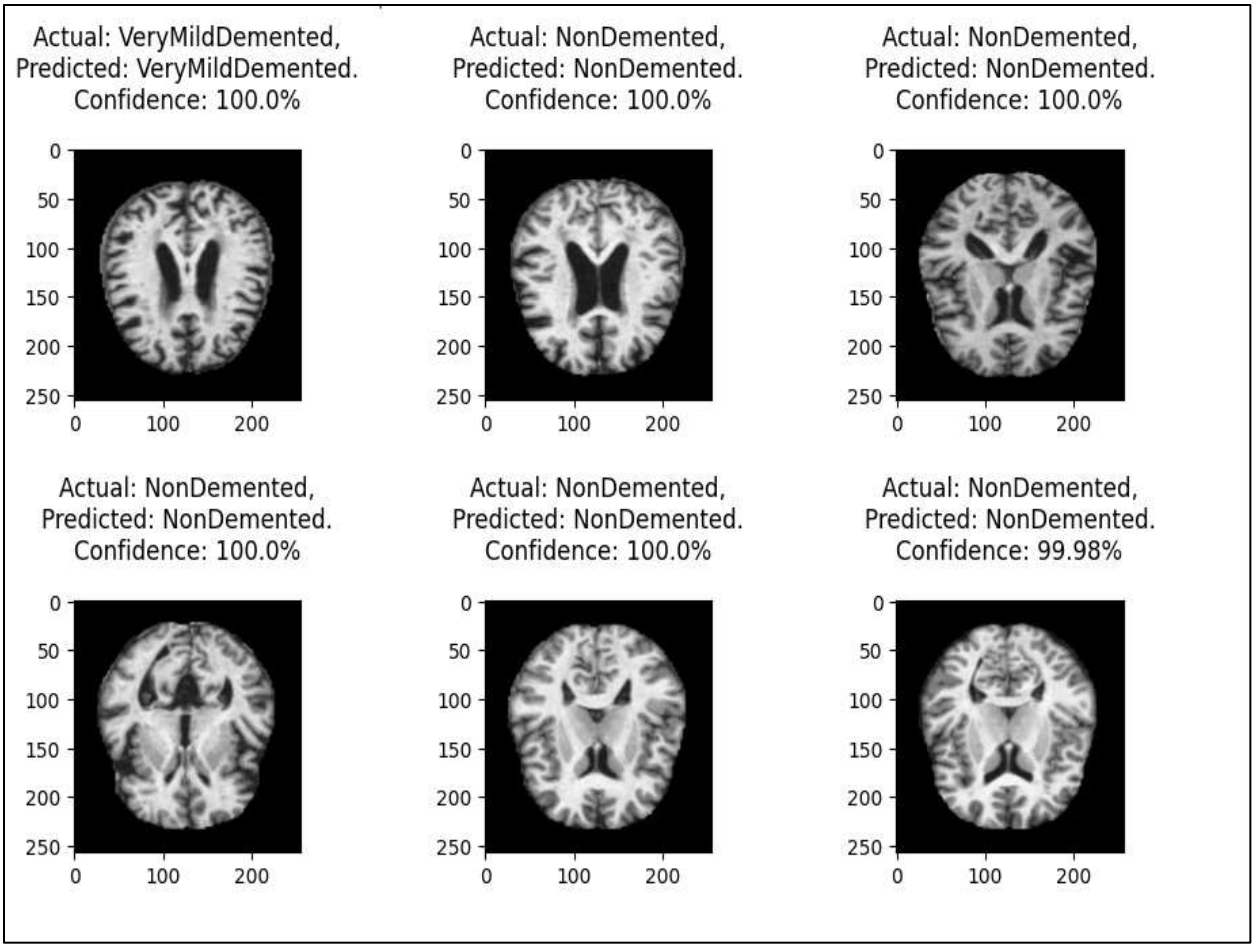

Fig 7: Model output sample images

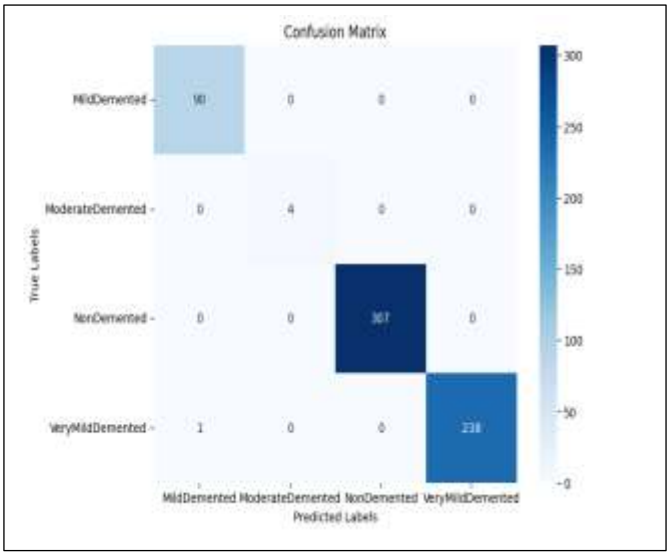

Fig 7: Confusion Matrix

CONCLUSION

In the proposed model the combination of a ResNet152V2 and Inception V3 is used. Output from both models is concatenated which helps to capture the details of the image. The model shows the highest accuracy of ~~99.76%~~ without applying any image argumentation technique to balance the dataset. If an image is rotated or flipped it may lead to wrong image classification. Any changes in images during the synthetic process to increase the count of images may lead to wrong predictions. The model performs exceptionally well, is highly accurate, and is reliable in its predictions. It achieves 99% to 100% precision, recall, and F1-score for all classes, which means the error is almost negligible. The model can very strongly generalize this information since it correctly classifies all stages with minimal misclassification; therefore, it is a good tool for this task. In the study, this AlzifusionNet model can be tested on different datasets and we may obtain better results.

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