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A Multi-Class Classification Framework with SMOTE based data Augmentation Technique for Alzheimer's disease Progression

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***Abstract* - The detection of Alzheimer's disease is a critical task in medical diagnostics due to its rapid progression and profound impact on cognitive function. Deep learning (DL) offers unprecedented capabilities in analyzing medical imaging data, particularly in neuroimaging like MRI scans. However, class imbalances within the dataset persist, making it difficult to discern intricate patterns indicative of Alzheimer's pathology. This project aims to overcome this challenge by integrating advanced DL techniques with data augmentation methodologies, specifically SMOTE. This strategic integration aims to overcome the limitations of class imbalances within the initial MRI dataset, enhancing the precision and reliability of the classification model. This interdisciplinary exploration aims to redefine Alzheimer's detection capabilities, enhancing diagnoses and offering the potential for broader applications in understanding and managing complex neurodegenerative disorders.**

Keywords— Classification, preprocessing, Data augmentation, Alzheimers, Magnetic resonance imaging, MRI, Computed tomography(CT), SMOTE, ResNet50, ResNet152, EfficientNetB2, CNN.

I. INTRODUCTION

Embarking upon an exploration within the expansive realm of medical diagnostics, the primary objective at hand involves the early and precise identification of Alzheimer's disease a severe neurological condition characterized by a progressive deterioration of cognitive functions. To confront this formidable challenge, there arises a necessity for the implementation of innovative methodologies aimed at unraveling the intricate signs associated with Alzheimer's. This is where Deep learning (DL) assumes a pivotal role, serving as a sophisticated tool with the ability to analyze brain images, particularly those derived from advanced imaging techniques like magnetic resonance imaging (MRI). The main focus is on the techniques used for preparing and enhancing the Alzheimer's dataset. The discussion revolves around the utilization of data augmentation to address overfitting issues and enhance the accuracy of the model. In this dataset there are 6400 MRI images that have been categorized into four groups; Mild Demented, Moderate Demented, Non Demented and Very Mild Demented [1]. Despite notable progress in the application of DL for detecting subtle indicators of Alzheimer's, a persistent challenge lingers within the dataset itself. The current project takes on the responsibility of addressing this challenge by deploying advanced DL methodologies and creative approaches to augment the dataset [2]. Notably, the emphasis is on methodologies such as Synthetic Minority Over-sampling Technique (SMOTE), strategically applied to rectify the issue of insufficient examples for certain patterns in the initial MRI images[3]. The ultimate objective is to significantly enhance the accuracy and reliability of the subsequent classification model. Through the meticulous integration of DL, brain scans, and supplementary data, the research aspires to transcend the mere identification of Alzheimer's. The vision encompasses contributing to improved and more precise diagnoses, potentially extending our understanding and management not only of Alzheimer's but also of various other intricate brain disorders. This undertaking resembles a pioneering exploration, charting new territories in the methodologies employed for the detection and comprehension of Alzheimer's and diverse other intricate brain-related issues[4]. Data augmentation, Synthetic Minority Over-sampling Technique (SMOTE), constitute essential techniques in Deep learning, addressing challenges related to imbalanced datasets and enhancing model generalization. Data augmentation involves artificially expanding a dataset through transformations like rotation and scaling, providing models with a more diverse training set and reducing the risk of overfitting. SMOTE tackles imbalanced datasets by oversampling the minority class with synthetic instances, fostering a more balanced representation and aiding model training in scenarios where one class is underrepresented. These techniques collectively contribute to building more robust Deep learning models, particularly beneficial in applications such as image classification, medical diagnosis, or fraud detection.

Dementia is a term used to describe a decline, in capacity that significantly disrupts daily life [5]. One of the leading causes of dementia is Alzheimer's disease, which is a neurological disorder marked by the gradual deterioration of cognitive abilities, as memory, reasoning, and everyday tasks. To classify the progression of Alzheimer's disease experts often categorize it into stages based on the severity of symptoms. Here are some used terms to describe the stages of dementia associated with Alzheimer's disease:[6]

A. Non-Demented:

These are individuals who do not experience any decline, in their abilities. They have memory and cognitive functioning.

B. Very Mild Dementia (or Early Stage):

At this stage individuals might face a decrease in abilities, which can be considered a normal part of aging. They may occasionally forget names or misplace objects. Can still manage to live

C. Mild Dementia (or Mild Cognitive Impairment. MCI):

People with dementia show noticeable cognitive decline that surpasses what is expected during normal aging. Symptoms may include memory loss, difficulty finding words, challenges in planning and organizing tasks and decreased ability to perform activities. However they can still handle day to day activities with some effort or time.

D. Moderate Dementia:

Moderate dementia is characterized by a decline in abilities. Individuals may struggle with tasks such as managing finances recalling history and organizing thoughts. Memory loss becomes more prominent at this stage. They may require assistance, with their activities.

Below given are some MRI dementia images from the dataset

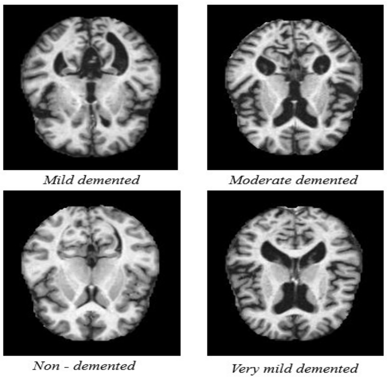

Fig. 1. Types of dementia mentioned in the dataset

II. LITERATURE SURVEY

Utilizing a 1D Convolutional Neural Network (1D CNN) we aim to classify Alzheimers disease and explore data augmentation methods. These techniques will include a modified version of Generative Adversarial Networks (GANs). The performance of models is compared in this study. The accuracy of Convolutional Neural Network (CNN) Vision Transformer (ViT) and Convolutional aided Transformer (CaiT) models is evaluated. Among them the DeepViT model achieved the accuracy with a score of 90.2%.[7]. The use of learning models, like InceptionV3, DenseNet121, Xception and ResNet101 to classify Alzheimers disease. These models are well known for their performance in image classification tasks and computational efficiency. The researchers also incorporate networks (CNNs) and transfer learning techniques to enhance the classification process. Transfer learning helps by initializing network layers with trained weights from the same model architecture but, on a different dataset. This approach addresses the challenge posed by limited labeled data.[8]

Convolutional neural networks (CNNs) have become a tool, in detecting Alzheimers disease (AD) by predicting brain age. By analyzing MRI scans CNNs can effectively extract features. Indirectly identify AD patients who may experience accelerated brain aging. This approach offers benefits, including complexity resilience, to noise and interpretability. Despite these advantages there are still obstacles to overcome regarding data availability, model generalizability and clinical validation. Ongoing research is dedicated to addressing these challenges and further improving the effectiveness of CNNs in diagnosing AD and facilitating intervention.[9]. It covers an understanding of the challenges involved in estimating accuracy when comparing machine learning algorithms with a focus, on active learning techniques. This compilation offers an overview of approaches to address class imbalance, in machine learning drawing from influential research and studies tailored to specific applications.[10].

To create a method that's both affordable and non intrusive, for detecting Alzheimers disease at a stage the researchers gathered data from a group of individuals. This group included both people and those diagnosed with Alzheimers disease. Using machine learning techniques they analyzed the radar data to identify patterns associated with the disease. The findings of this study demonstrate the potential of utilizing radar data and machine learning to detect and monitor Alzheimers disease in its early stages. Such advancements could greatly impact the development of tools and interventions.[11].

Using learned transformations to augment data, for medical image segmentation employing dimension reduction techniques, for text clustering and utilizing PCA embedded forest and enhanced random forest classifiers.[12]. Using a combination of brain imaging techniques and deep learning methods researchers have developed an approach to detect Alzheimers disease at an early stage. The algorithm proposed in their study has shown promise by achieving levels of accuracy, sensitivity, specificity and AUC ROC. This breakthrough has the potential to significantly enhance accuracy and improve patient outcomes.[13].

The RNN model underwent training using a comprising of DTI scans from individuals, with MCI well as healthy controls. Subsequently the model was employed to forecast AD conversion in a set of MCI patients. The findings indicated that the RNN model demonstrated an accuracy rate of 82% in predicting AD conversion. These results imply that the RNN model holds potential as a tool, for diagnosis of AD[14].

The structure of CNN describing its components such, as layers pooling layers, connected layers, dropout layers and activation functions. It also emphasizes the advantages of transfer learning, which enables the utilization of a trained model to yield impressive outcomes even when working with limited training data[15].

Due, to the amount of data a repeated 10 fold cross validation approach was utilized. The evaluation metrics employed included accuracy, precision, recall and the F1 score, for the AD class. The findings indicated that the suggested method exhibited encouraging results in identifying Alzheimers disease through speech analysis.[16]. A study that used the Inception V3 transfer learning model to identify the level of risk, for Alzheimers disease. The study applied techniques such, as pooling, flattening, batch normalization pairwise dense layers and dropout to analyze the data and extract important features.[17].

The detection of white matter degeneration, in Alzheimers disease using machine learning is a process. It involves classifying multicenter DTI data and addressing the class imbalance problem through a data augmentation based framework. The goal is to enhance the performance of the detection model for identifying stages of Alzheimers. This study holds significance as it tackles an issue in Alzheimers disease detection and sheds light on the effectiveness of machine learning and data augmentation techniques, in improving accuracy and reliability of detection models.[18].

A new approach has been proposed for detecting Alzheimers disease (AD) using a perceptron (MLP) model and maximal information coefficient (MIC) coefficients. The study makes use of the OASIS dataset, which contains data. Various variables such, as Group (indicating AD diagnosis) Visit, MR Delay, EDUC, SES, MMSE, CDR, eTIV, nWBV and ASF are analyzed. The methodology involves preprocessing the dataset to address class imbalance through the SMOTE technique and incorporating MIC coefficients. Upon examination the study concludes that MIC coefficients can be used as a measure to identify stages of AD. This suggests their potential, in facilitating interventions. Ultimately improving outcomes.[19]. A model called a network (CNN) has been developed to identify dementia, from MRI scans. The CNN model achieved results with a training accuracy of 98.64% testing accuracy of 96% and an F1 score of 98.64%. The study compared the CNN model to models like VGG16, VGG19 and InceptionResNet. It was found that the proposed CNN model outperformed all the others with an accuracy level that was 11% higher, than InceptionResNet and a testing F1 score of 98.64%[20].

A modified version of the resolution adversarial network (SRGAN) has been developed to improve Alzheimers MRI data. The research focuses on creating a data augmentation pipeline that can generate reasonable variations of structural brain MRI sequences. The proposed model uses a SRGAN architecture to enhance the quality of MRI images and generate data, for training a classification model. According to the study this model performs better than models in terms of accuracy, precision, recall and F1 score. The proposed model achieved an accuracy rate of 98.64%, precision rate of 98.64%, recall rate of 98.64% and F1 score of 98.64%. The research also discusses evaluation metrics like accuracy, precision, recall and F1 score used to assess the performance of the proposed model. For feature extraction VGG 19 is utilized in the proposed model along, with transfer learning for training the model. Pixel shuffle upscaling for image enhancement [21].

III. PROPOSED METHODOLGY

The dataset consists of different types of diseases of Alzheimer's like Mild Demented, Moderate Demented, Non Demented, and very mild Demented. the data is very imbalanced data with percentages of 14,1,50,35 respectively. After SMOTE(Over Sampling) Technique the classification of individuals is changed to 25 % respectively.

When there is an unequal distribution of classes or categories in a dataset—that is, when some classes contain notably fewer occurrences than others—it is referred to as data imbalance. Machine learning models may perform worse as a result of this imbalance, especially when it comes to classification tasks where the models may become biased in favor of the majority class and find it difficult to anticipate examples from the minority class. In many real-world applications, such as fraud detection, medical diagnosis, or rare event prediction, when the incidence of some outcomes is rare relative to others, imbalanced datasets are a typical occurrence. For machine learning models to be fair and robust and to perform well across all classes, it is imperative that data imbalances be addressed. It's usual practice to use methods like oversampling, undersampling, or SMOTE algorithms to mitigate the challenges posed by imbalanced datasets.

SMOTE: A machine learning technique called SMOTE, or Synthetic Minority Over-sampling Technique, was created to solve the issue of class imbalance in datasets. SMOTE creates synthetic instances of the minority class by generating synthetic samples along the line segments linking existing instances of the minority class. This technique is especially useful in situations when the majority class outnumbers the minority class. SMOTE improves machine learning model performance by balancing class distribution by the introduction of synthetic instances. This is especially important for tasks like classification, where biased models might result from unbalanced data.

A hybrid sampling technique is performed on the dataset. The dataset is highly imbalanced, hybrid sampling techniques is performed so that, some synthetic samples are generated in low data classes, some duplicate data is removed and some of the data is integrated into existing data in high data containing class. Below is the representation of class distribution before sampling.

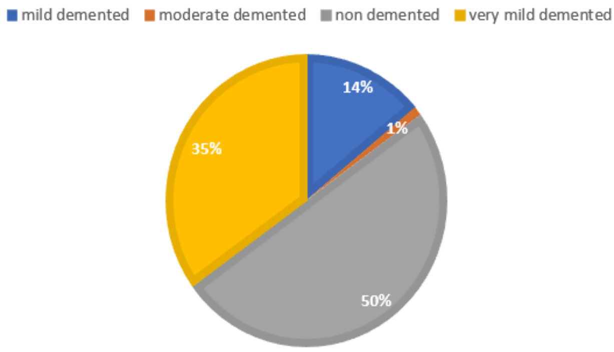

Fig. 2**:** Class distribution before oversampling

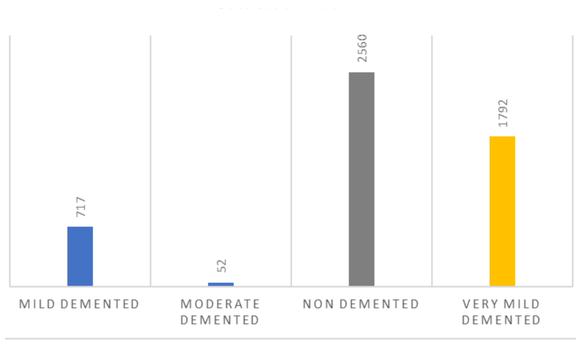

Fig. 3**:** Class count before oversampling

The process of classifying images starts with issue definition and the labeling of a dataset, which is subsequently divided into training, validation, and test sets. For this objective, an appropriate neural network architecture—usually a Convolutional Neural Network (CNN),RESNET-50,RESNET152,efficientnet. The validation set is used to adjust hyperparameters after the model has been trained on the training set. On the test set, the model's performance is assessed using measures like accuracy, precision, and recall. The model is used to forecast fresh photos after being optimized for efficiency. In a production setting, ongoing observation and possible model updates are carried out to guarantee flexibility in response to modifications in the input distribution or the requirement for fresh data for retraining. The goal of this iterative procedure is to create a precise and robust image classification model for the specified problem.

CNN- A subclass of deep neural networks called convolutional neural networks (CNNs) is used to process and analyze visual input, especially pictures. CNNs use a special architecture consisting of fully linked, pooling, and convolutional layers. In order to help the network acquire hierarchical representations, the convolutional layers employ filters or kernels to find patterns and features within local receptive fields of the input data. Pooling layers provide computing efficiency and translation invariance by reducing spatial dimensions. High-level characteristics are included for classification or regression tasks in the fully linked layers. CNNs have shown remarkable performance in image-related tasks, including object identification, image segmentation, and picture classification. They are also effective tools for a variety of computer vision applications due to their capacity to autonomously learn pertinent characteristics.

RESNET-50 ResNet-50, also known as Residual Network with 50 layers, is an architecture of deep convolutional neural networks that rose to fame due to its effectiveness in image categorization applications. Microsoft Research introduced ResNet-50, a residual learning framework that lessens the difficulties associated with training very deep networks. It makes use of residual blocks, which enable the network to bypass one or more layers during training in order to overcome the vanishing gradient issue and create much deeper models. In particular, ResNet-50 has 50 levels and a stack of ever more complicated residual blocks. It is a popular option for a variety of computer vision applications due to its pre-trained weights, which are frequently utilized in transfer learning and offer a reliable and effective architecture for extracting hierarchical features from images.

RESNET152- A member of the ResNet family, ResNet-152 is a deep convolutional neural network architecture that was created to tackle the difficulties associated with training very deep neural networks. ResNet-152, created by Microsoft Research, expands on the original ResNet concept by adding 152 levels, providing even more capability for identifying complex hierarchical patterns in picture data. It uses residual blocks, which mitigate the vanishing gradient problem and make it easier to train deep models by allowing one or more layers to be bypassed by shortcut connections. ResNet-152 is very good at tasks like object identification, feature extraction, and picture classification because of its deeper architecture, which improves its representation learning capabilities. In order to enable the model to adapt to new tasks with minimal labeled data, transfer learning frequently makes use of the model's pre-trained weights. With its outstanding depth and performance, ResNet-152 stands as a powerful tool in the field of computer vision for tasks requiring nuanced feature extraction and understanding of complex visual patterns.

Efficient net: A series of neural network topologies called EfficientNet was created to provide cutting edge results while maximizing efficiency in terms of processing power and model size. Google introduced EfficientNet, which uses a compound scaling technique to optimize these dimensions for improved accuracy and efficiency trade-offs. It does this by methodically balancing network depth, breadth, and resolution. The model architecture is built on a baseline network that is gradually scaled up; the scaling coefficients are established using a methodical procedure. EfficientNet has outperformed bigger models while using fewer parameters and processing resources. It has shown superior in a variety of computer vision applications, including object identification and picture categorization. Because of its adaptability and efficiency, EfficientNet is a well-liked option for real-world applications where resource limits and accuracy are important factors

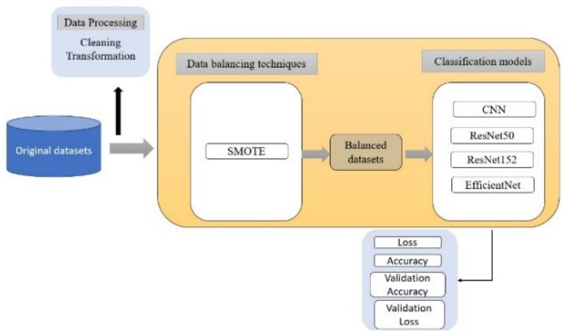

Fig. 4. Flow chart

In the Alzheimer's detection project, a structured methodology was followed, adhering to established standards. The process was initiated with the acquisition of the original image dataset, comprising samples of Alzheimer's and non-Alzheimer's cases. To address potential class imbalance and enhance model robustness, data augmentation was performed using TensorFlow's ImageDataGenerator. This augmentation process introduced diversity into the dataset, mitigating the risk of overfitting during subsequent classifier training.

Furthermore, the dataset was partitioned into training and testing subsets to facilitate rigorous model assessment. To counteract potential imbalances in the augmented dataset, Synthetic Minority Over-sampling Technique (SMOTE) method were considered. These techniques generated synthetic instances of the minority class, thereby augmenting the dataset further. This was particularly relevant in the context of Alzheimer's detection where the prevalence of positive cases might be limited.

The next stage involved the selection and implementation of Deep learning classifiers, such as CNN (Convolution Neural Networks), ResNet50, ResNet152, EfficientNetB2. These classifiers were chosen for their efficacy in image classification tasks and their ability to discern complex patterns within the data.

The classifiers were then trained on the augmented training dataset, leveraging the diversified samples created through data augmentation. Subsequently, the performance of these classifiers was rigorously evaluated using the reserved testing data. This comprehensive evaluation not only provided insights into the classifiers' accuracy but also served to validate the effectiveness of the data augmentation strategy in enhancing model generalization.

The integration of SMOTE technique addressed potential class imbalances in the dataset, reinforcing the robustness of subsequent Deep learning classifiers. ResNet50, ResNet152, EfficientNetB2 chosen for their suitability in image classification, underwent training on the augmented dataset and were evaluated in the context of Alzheimer's detection. This approach ensured a systematic and well-documented process in the pursuit of accurate and reliable Alzheimer's detection models.

IV. EXPERIMENTAL RESULTS

Results provide a comparative analysis of the performance of the 4 models that are considered. Those are CNN, Resnet50, Resnet152, EfficientNetB2. First using the SMOTE technique, the classes are oversampled without any loss. Below is the pie chart and bar chart being the representations of the data after oversampling. The representations of data before oversampling are mentioned in proposed methodology section.

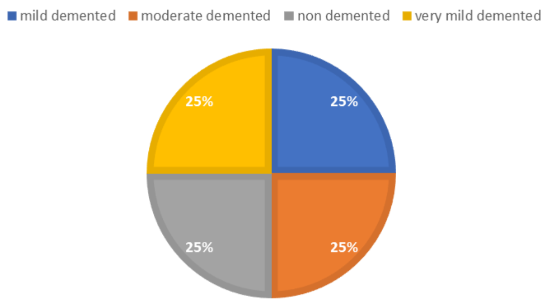

Fig 5: class distribution after Oversampling

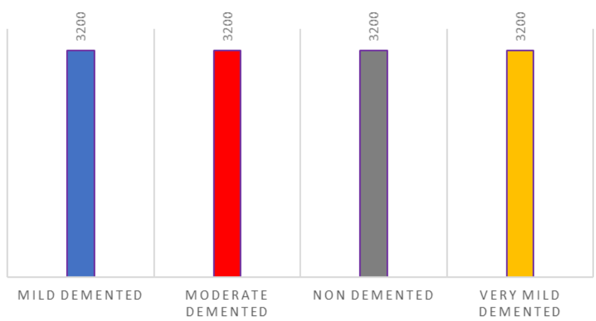

Fig 6: class count after oversampling

The below given table shows the difference of test accuracy and test loss before and after over-sampling using SMOTE

Table 1. Model accuracies and loss comparison

	Metrics before oversampling		Metrics after oversampling	
Models/Metrics	val_accuracy	val_loss	val_accuracy	val_loss
CNN	0.487881154	17.06028	0.25	1.3863
Resnet50	0.588741183	8.854034	0.9292	0.5671
Resnet152	0.00938233	1307.781	0.25	2144.8398
EfficientNetB2	0.526192367	0.983554	0.9854	0.0651

Among all the metrics EfficientNetB2 has performed better with better accuracy and loss. Even Resnet50 performed better after the EfficientNetB2 Model. the models CNN and ResNet152 have a huge validation loss and even accuracies are fluctuating. A detailed representation of their accuracies and losses is given below. The worst models are compared together in fig6 and the best models are compared in fig7.

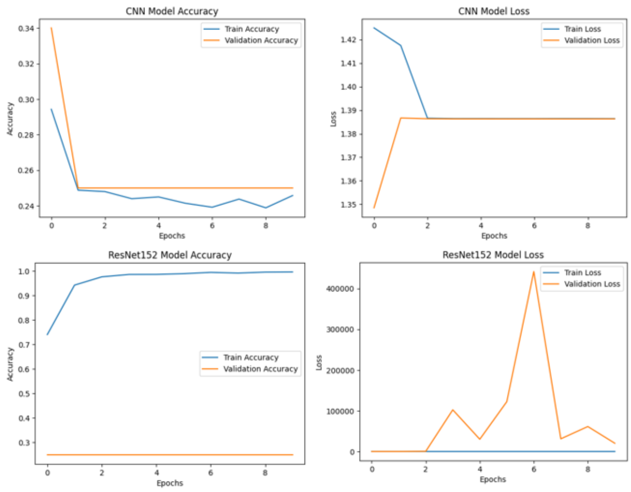

Fig 7: Comparison of worst-performed models

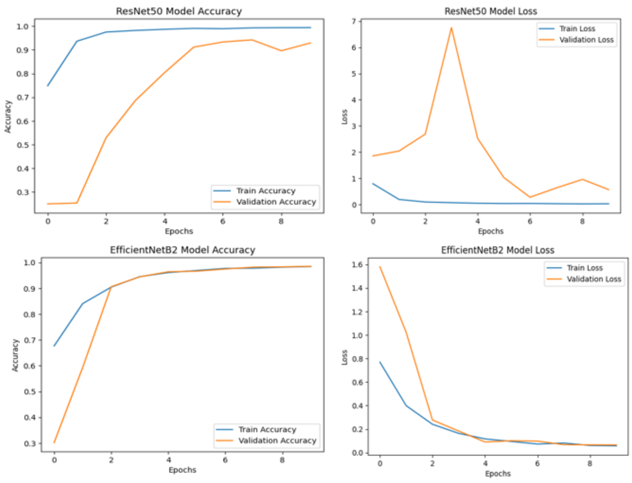

Fig 8: Comparison of best-performed models

EfficientNetB2 ended up having 0.0579 training loss and 0.9847 training accuracy, 0.0651 as val_loss and 0.9854 val_accuracy. ResNet50 ended up having a 0.0258 training loss and 0.9941 training accuracy, 0.5671 as val_loss, and 0.9292 as val_accuracy. So with this, it is concluded that EfficientNetB2 is performing better than ResNet50, but even ResNet50 is not that bad. Below are the confusion matrices of ResNet50 and EfficientNetB2.

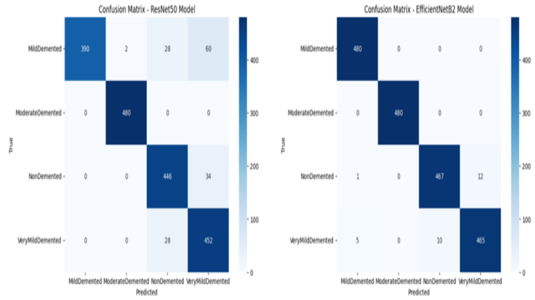

Fig 9: Confusion matrices of best-performed models

V. CONCLUSION

In conclusion, the utilization of deep learning algorithms, particularly Convolutional Neural Networks (CNNs) employing ResNet-50, ResNet-152, and EfficientNet architectures, has demonstrated promising outcomes in the detection of Alzheimer's disease. The evaluation of these models on a dataset with a specific class distribution has shed light on their respective performances. The dataset consists of a diverse range of classes, ensuring a comprehensive evaluation of the model's capabilities. Among the tested architectures, EfficientNetB2 emerged as a standout performer, showcasing exceptional accuracy in Alzheimer's detection. This observation suggests that, for the given dataset, a relatively shallower architecture is well-suited, striking a balance between model complexity and computational efficiency. However, it's essential to note that while EfficientNetB2 excelled, ResNet-152, CNN, and ResNet50 despite their deeper architectures, displayed varying degrees of success.

In summary, the selection of the most appropriate algorithm for Alzheimer's detection hinges on a thorough understanding of the dataset's class distribution, computational resources, and task-specific requirements. Continued research, experimentation, and validation with diverse datasets are imperative to fortify the reliability and generalizability of deep learning models in the crucial task of Alzheimer's disease detection.

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