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Original Article

Alzheimer Disease Detection and Classification Using NASSNet Mobile Network

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ABSTRACT

This study investigates Alzheimer's disease (AD) detection using the NASNet Mobile architecture, emphasizing transfer learning and dataset augmentation. The baseline model achieved 94% accuracy, while our enhanced approach demonstrated superior performance, reaching 100% accuracy. A key improvement involved expanding the dataset from 6,400 to 12,800 images by integrating data from diverse sources, including the Alzheimer's Disease Neuroimaging Initiative (ADNI) and Open Access Series of Imaging Studies (OASIS). The augmented dataset addressed prior limitations in class representation, particularly for moderate dementia cases. Our methodology incorporated advanced preprocessing techniques and a systematic train-test-validation split to optimize model training and evaluation. The experiments confirmed the efficacy of transfer learning in leveraging pre-trained models for medical image classification tasks. Comparative analysis highlighted the significant impact of dataset size and diversity on model accuracy, with our approach achieving the highest reported performance. This research underscores the potential of deep learning architectures like NasNetMobile in improving diagnostic precision for AD across all stages, offering valuable insights for early detection and intervention. The results validate the model's robustness and demonstrate its promise for deployment in clinical settings to enhance patient care and outcomes in neurodegenerative disease management.

Keywords: Alzheimer's disease, NasNetMobile, Transfer learning, Dataset augmentation, Medical Image Classification, Deep learning

INTRODUCTION

Alzheimer disease is a progressive neurodegenerative disorder, constituting the majority of dementia cases worldwide. Initially identified by Dr. Alois Alzheimer in 1906, the disease is characterized by the accumulation of beta-amyloid plaques and tau tangles in the brain, leading to the gradual deterioration and death of neurons. The stages of Alzheimer's range from preclinical, where symptoms are not apparent, to severe dementia, marked by a profound impact on both mental and physical abilities. The stages include mild cognitive impairment, mild dementia, moderate dementia, and severe dementia. Each stage exhibits specific symptoms, such as memory loss, impaired judgment, personality changes, and eventually, a decline in communication and physical capabilities (Aging, 2003). Alzheimer progression varies among individuals, making the stages rough generalizations. The disease often begins silently in the preclinical stage, with symptoms emerging gradually. Mild cognitive impairment involves subtle memory and thinking changes, while mild dementia is marked by significant memory and judgment issues. As the disease advances to moderate dementia, confusion deepens, and assistance with daily activities becomes necessary. In the severe dementia stage, mental function further declines, impacting movement and physical abilities, ultimately leading to the loss of communication and the need for full-time care. The continuous and diverse nature of Alzheimer's underscores the importance of personalized understanding and care for individuals affected by this challenging condition (States & Alzheimer, 1906). Alzheimer disease is a complex condition that affects millions of people worldwide, and its impact extends beyond the individuals diagnosed to their families and caregivers. As our understanding of Alzheimer's has deepened over the years, researchers have identified various risk factors and potential mechanisms underlying the disease's progression (Ghazal et al.,

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

2022). One significant aspect of Alzheimer pathology is the accumulation of abnormal protein deposits in the brain. Beta-amyloid plaques and tau protein tangles are hallmark features of the disease, contributing to neuronal damage and cognitive decline. While these protein aggregates are central to Alzheimer pathology, researchers continue to investigate the precise role they play in the onset and progression of the disease (Chaihtra & Vijaya Shetty, 2021). In addition to protein abnormalities, inflammation and oxidative stress are believed to contribute to neuronal damage in Alzheimer. The brain's immune response may become dysregulated, leading to chronic inflammation that exacerbates neurodegeneration. Oxidative stress, resulting from an imbalance between free radicals and antioxidant defenses, can also contribute to cellular damage in the brain (Ashraf et al., 2021). Genetic factors also play a significant role in Alzheimer's disease. While most cases are sporadic, meaning they occur without a clear familial pattern, a small percentage of cases are linked to specific genetic mutations. For example, mutations in genes such as APP (amyloid precursor protein), PSEN1 (presenilin 1), and PSEN2 (presenilin 2) are associated with early-onset familial Alzheimer's disease (Wright, 2010). However, genetic predisposition is just one piece of the puzzle. Environmental and lifestyle factors, such as cardiovascular health, education level, and social engagement, also influence Alzheimer's risk. For instance, conditions like hypertension, diabetes, and obesity have been linked to an increased risk of developing Alzheimer's later in life (Johnson et al., 2012). Conversely, maintaining a healthy lifestyle, including regular physical activity, cognitive stimulation, and a balanced diet, may help reduce the risk or delay the onset of cognitive decline. The clinical manifestation of Alzheimer's disease varies widely among individuals, leading to a diverse range of symptoms and disease trajectories. While memory loss and cognitive decline are hallmark features, other symptoms such as changes in mood, behavior, and language abilities can also occur. The progression of Alzheimer's is often characterized by a gradual worsening of symptoms, eventually leading to severe cognitive impairment and functional dependency (Johnson et al., 2012). Given the complex nature of Alzheimer's disease, personalized approaches to diagnosis, treatment, and care are essential. Early detection through cognitive testing and neuroimaging techniques allows for timely intervention and support for individuals and their families (Johnson et al., 2012). While there is currently no cure for Alzheimer's, various pharmacological and non-pharmacological interventions aim to alleviate symptoms, improve quality of life, and provide support for caregivers. Research into novel therapeutic strategies, including disease-modifying drugs and targeted interventions, continues to advance our understanding of Alzheimer's disease (Johnson et al., 2012). Clinical trials investigating potential treatments are underway, offering hope for future breakthroughs in disease management and prevention (Johnson et al., 2012). Alzheimer disease (AD) poses a significant global health challenge, impacting individuals, families, and society. Effective strategies for prevention, diagnosis, and treatment rely on a deep understanding of the disease's underlying mechanisms, risk factors, and clinical presentation (Saleh et al., 2023). Current Alzheimer disease detection and classification methods face limitations stemming from dataset constraints, including insufficient size and diversity. This lack of diversity hinders the scalability and generalizability of models across different patient populations and imaging protocols, particularly concerning the limited representation of moderate dementia (Mod.D) cases. Although advancements have been made, such as Sharma et al.'s (2022) modified Inception model utilizing transfer learning (TL), further enhancements are necessary. This study addresses these limitations by proposing a comprehensive approach incorporating several key improvements. First, oversampling techniques are employed to augment existing datasets, mitigating the effects of class imbalance and improving model robustness. Second, the study integrates larger and more diverse datasets, including the Alzheimer's Disease Neuroimaging Initiative (ADNI) and Open Access Series of Imaging Studies (OASIS), to enhance the model's ability to generalize across different populations and imaging modalities. Third, advanced deep learning architectures, such as NasNetMobile, are utilized for both detection and classification tasks. These architectures are known for their efficiency and performance, making them suitable for clinical applications. A key focus of this research is the novel application of transfer learning to explore knowledge

transfer between different Alzheimer disease stages. Specifically, the study investigates the transfer of knowledge from the Mild and Moderate stages to the earlier stages of Very Mild Alzheimer disease. This targeted approach aims to improve early detection capabilities, which is crucial for timely intervention and improved patient outcomes. By leveraging knowledge learned from more advanced stages of the disease, the model can potentially identify subtle changes indicative of very early Alzheimer disease, which are often difficult to detect using traditional methods. This transfer learning strategy, combined with dataset augmentation and advanced architectures, aims to enhance the accuracy and robustness of Alzheimer disease detection across the entire disease spectrum, ultimately contributing to improved patient care, a deeper understanding of Alzheimer disease, and the development of more effective treatments.

Review of Related Works

This section presents a detailed examination of prior research in Alzheimer's disease (AD) detection and classification, focusing on methodologies leveraging machine learning, deep learning, and transfer learning. Ullah and Jamjoom, (2023) utilized convolutional neural networks and Visual Geometry Group architecture for early Alzheimer's disease detection using magnetic resonance imaging scans. Their approach, which incorporated features extracted from the ImageNet dataset and the Alzheimer's Disease Neuroimaging Initiative dataset, achieved impressive accuracy rates of 99.27% for Alzheimer's disease vs. mild cognitive impairment and 97.06% for Alzheimer's disease vs. normal controls. Sethi et al., (2022) proposed a transfer learning framework utilizing the Efficient Net model, pre-trained on ImageNet, to classify individuals as Alzheimer's disease or cognitively normal. Their model achieved 91.36% accuracy and an area under the curve of 83%, underscoring the effectiveness of transfer learning in Alzheimer's disease diagnosis. Tanveer et al., (2022) presented Notably, the proposed ensemble outperformed snapshot ensembles and other existing deep models in similar studies conducted by other researchers. the Deep Transfer Ensemble (DTE) approach, which combines TL and hyperparameter randomization for enhanced diversity among neural networks. The method achieved 99.05% accuracy for differentiating CN from AD and 85% accuracy for small datasets, highlighting its robustness. Notably, the proposed ensemble outperformed snapshot ensembles and other existing deep models in similar studies conducted by other researchers. Danker and Wiklund, (2021) presented a novel approach that combined CNN and TL with data augmentation techniques, achieving a predictive accuracy of 97% for different AD stages. Despite using a smaller dataset, their model demonstrated significant effectiveness, with TL enabling knowledge transfer across stages. Sharma et al., (2022) proposed a modified inception model based on TL. The model incorporates normalization and data addition pre-processing techniques to enhance its performance. Remarkably, this proposed model achieved an impressive accuracy of 94.92% and a sensitivity of 94.94%. These results indicate that the proposed model surpassed other state-of-the-art models in AD detection. The training of the model utilizes a Kaggle dataset comprising 6,200 images, including 896 mild demented (M.D), 64 moderate demented (Mod.D), 3,200 non-demented (N.D), and 1,966 veritably mild demented (V.M.D) images. Agarwal et al., (2021) focused on segmenting and classifying AD using TL applied to MRI scans. Their customized CNN, pre-trained on segmented gray matter images, achieved a remarkable accuracy of 97.84%, validating its efficacy for early detection. Ghaffari et al., (2022) proposed TL-based CNN models, such as ResNet101, Xception, and InceptionV3, for AD classification using preprocessed and segmented MRI scans. Their models demonstrated superior performance, with InceptionV3 achieving 93.75% accuracy for binary and multiclass classification tasks. Kadri et al., (2022) investigated the application of the different CNN and transformers models on the early diagnosis of alzheimer. Further, we introduce a multi-modal method based on the MRI and PET modality for Alzheimer’s disease detection using the combination of the EfficientNetV2 and the vision transformer enhanced by a new data augmentation based on the self-attention generative adversarial networks (SAGAN). Their model, validated on ADNI and OASIS datasets, achieved an accuracy of 96%, showcasing the advantages of multimodal approaches. Blanton, (2023) proposed a novel 3D-to-2D conversion approach for brain imaging using a learnable weighted pooling (LWP) method,

significantly reducing training time while achieving an accuracy of 88% for amyloid-beta PET imaging classification. Asgharzadeh-Bonab et al., (2023) explored feature- and decision-level fusion methods for dementia classification. Using EfficientNet-B7 with feature-level fusion, they achieved accuracies of 82.7% for CN-MCI and 89.7% for CN-AD scenarios, emphasizing the potential of fusion techniques in AD research. Saleh et al., (2023) highlighted the benefits of data augmentation and Dense Net architecture for handling high-dimensional MRI scans. Their model achieved an accuracy of 96.5% and an AUC of 99%, surpassing previous methods and showcasing the role of advanced augmentation techniques. Oommen & Arunnehru, (2023) utilized a three-step approach involving preprocessing, TL with autoencoders, and classification with a deep neural network (DNN). Their ensemble model achieved 98.54% accuracy, demonstrating its efficacy in AD stage classification. The method is compared to state-of-the-art approaches to validate its efficacy and performance. Agarwal et al., (2023) implemented EfficietNet-B0 convolutional neural network (CNN) with a novel approach "fusion of end-to-end and transfer learning" to classify different stages of AD. 245 T1W MRI scans of cognitively normal (CN) subjects, 229 scans of AD subjects, and 229 scans of subjects with stable mild cognitive impairment (sMCI) were employed achieving 95.29% accuracy for sMCI vs. AD classification and 87.38% for multiclass tasks, reinforcing CNN's utility in AD analysis. Zheng et al., (2023) proposed a modified 3D Efficient Net architecture incorporating Mobile Inverted Bottleneck Convolution blocks. Their model demonstrated 95% accuracy for distinguishing NC from AD and 86.67% for NC vs. pMCI, validating its multiscale feature extraction capabilities. Mujahid et al., (2023) introduced an ensemble model combining EfficientNet-B2 and VGG-16 to address dataset imbalances. The ensemble achieved 97.35% accuracy and 99.64% AUC for multiclass datasets, highlighting its superior performance. The research reviewed underscores the transformative potential of deep learning and TL approaches for AD detection, with significant advancements achieved through innovative architectures, multimodal techniques, and comprehensive datasets. However, a notable research gap remains regarding the scalability and generalization. To address this gap, the proposed research aims to build upon Sharma et al. (2022) research by harnessing larger and more comprehensive datasets such as ADNI and OASIS. By combining these datasets and leveraging the NasNetMobile transfer learning architecture, which offers enhanced capacity for learning from large-scale data, our goal is to develop a model capable of accurate and efficient detection of the multiple stages of Alzheimer's disease.

MATERIALS AND METHOD

The paper aims to leverage transfer learning techniques to develop a model for detecting and classifying Alzheimer's disease based on medical images using Neural Architecture Search Network Mobile Architecture as depicted in Figure 3.1. The proposed methodology for the research on Alzheimer's disease detection using transfer learning with a Neural Architecture Search Network Mobile technique involves several key steps:

Proposed Methodology Architecture

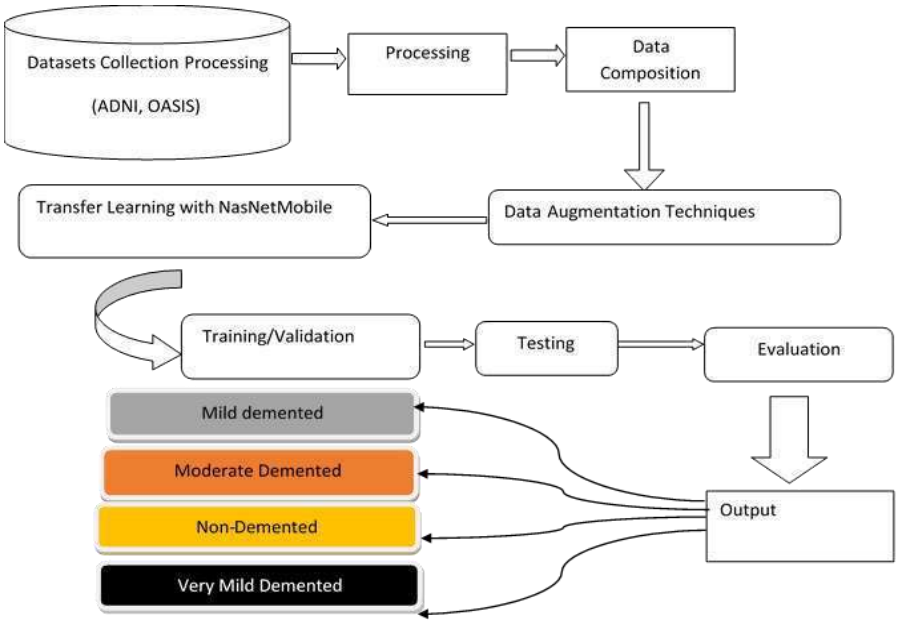

Figure 3.1: Workflow of the Method

Data Collection and Processing

This section describes the acquisition and consolidation of brain image datasets from the Alzheimer's Disease Neuroimaging Initiative and Open Access Series of Imaging Studies, obtained via the Kaggle platform. The process of retrieving and merging these datasets to create a comprehensive repository for training and validating the Alzheimer's disease identification system is detailed. Alzheimer's Disease Neuroimaging Initiative Dataset: The Alzheimer's Disease Neuroimaging Initiative is a longitudinal multicenter study designed to develop clinical, imaging, genetic, and biochemical biomarkers for the early detection and tracking of Alzheimer's disease. The dataset contains high-resolution magnetic resonance imaging scans from participants across different stages of cognitive decline, providing a robust foundation for machine learning applications in neuroimaging. Open Access Series of Imaging Studies Dataset: The Open Access Series of Imaging Studies is a project aimed at making neuroimaging datasets freely available to the scientific community. The dataset includes cross-sectional magnetic resonance imaging data from participants ranging from young adults to elderly individuals, with comprehensive demographic and clinical information accompanying each scan.

Dataset Composition and Statistics

The combined dataset comprises 6,400 magnetic resonance imaging images categorized into four distinct classes representing different stages of Alzheimer's disease progression:

- Non-Demented (ND): Cognitively healthy individuals with no signs of dementia
- Very Mild Demented (VMD): Individuals showing very early signs of cognitive decline
- Mild Demented (MD): Patients with mild cognitive impairment and early-stage dementia
- Moderate Demented (MOD): Patients with moderate-stage Alzheimer's disease

Exploratory Data Analysis - Original Dataset

Class Distribution Summary (Original Dataset):

- Non-Demented: 3,200 images (50.0%)
- Very Mild Demented: 2,240 images (35.0%)
- Mild Demented: 717 images (11.2%)
- Moderate Demented: 243 images (3.8%)
- Total Images: 6,400

Summary Statistics (Original Dataset):

- Mean Image Dimensions: 208 × 176 pixels
- Standard Deviation of Dimensions: ±15.2 × ±12.8 pixels
- Image Format: JPEG
- Color Channels: Grayscale (1 channel)
- Average File Size: 45.7 KB

- Dataset Imbalance Ratio: 13.17:1 (Non-Demented to Moderate Demented)

Data Wrangling and Preprocessing

The datasets were conveniently provided in separate training and testing folders. The processing methodologies employed to ensure harmonization and uniformity across the consolidated dataset include:

1. Image Standardization: All images were resized to uniform dimensions of 80×80 pixels
2. Format Consistency: Conversion of all images to consistent format and bit depth
3. Quality Control: Removal of corrupted or incomplete image files
4. Label Encoding: Categorical labels converted to numerical format for machine learning compatibility
5. Data Integration: Merging of Alzheimer's Disease Neuroimaging Initiative and Open Access Series of Imaging Studies datasets while maintaining source traceability

Data Augmentation and Balancing

To address the significant class imbalance observed in the original dataset, a comprehensive data augmentation strategy was implemented using Random Over Sampler technique:

Augmentation Process:

- Training data reshaped into two-dimensional arrays for processing
- Random Over Sampler applied to duplicate instances from underrepresented classes
- Balanced class distribution achieved across all four categories
- Final dataset size increased from 6,400 to 12,800 images

Exploratory Data Analysis - Augmented Dataset

Class Distribution Summary (After Augmentation):

- Non-Demented: 3,200 images (25.0%)
- Very Mild Demented: 3,200 images (25.0%)
- Mild Demented: 3,200 images (25.0%)
- Moderate Demented: 3,200 images (25.0%)
- Total Images: 12,800

Post-Augmentation Statistics:

- Balanced Class Ratio: 1:1:1:1
- Image Dimensions: Standardized to 80×80×3 pixels
- Color Channels: 3 (RGB after preprocessing)
- Data Split Ratio: 60% Training, 20% Validation, 20% Testing
- Stratification: Maintained across all subsets to preserve class balance

The research utilized magnetic resonance imaging datasets obtained from two major sources the Alzheimer's Disease Neuroimaging Initiative and the Open Access Series of Imaging Studies. These datasets were accessed via Kaggle, a platform known for providing authentic datasets for research purposes. The combined dataset included 6,400 images in its initial state, representing four distinct classes: non-demented, very mild demented, mild demented, and moderate demented stages of Alzheimer's disease.

NasNetMobile Architecture

This study employs Neural Architecture Search Network Mobile (NasNetMobile), a lightweight convolutional neural network architecture designed through automated neural architecture search. NasNetMobile is specifically optimized for mobile and resource-constrained environments while maintaining competitive performance on image classification tasks. The architecture was originally developed by Zoph et al. (2018) and represents an efficient variant of the larger NASNet architecture.

Architecture Components

NasNetMobile consists of several key components:

- Normal Cells: These cells maintain the spatial resolution of feature maps while performing convolution operations
- Reduction Cells: These cells reduce the spatial dimensions of feature maps by a factor of 2
- Separable Convolutions: Depthwise separable convolutions are extensively used to reduce computational complexity
- Skip Connections: Residual connections that facilitate gradient flow and feature reuse

Transfer Learning Implementation

The pre-trained NasNetMobile model, initially trained on ImageNet dataset containing 12000 images across 4 classes, was adapted for Alzheimer's disease classification.

The transfer learning approach involved:

- Loading the pre-trained NasNetMobile weights (excluding the top classification layer)
- Freezing the convolutional base to preserve learned features
- Adding custom classification layers tailored for the four-class Alzheimer's disease classification task
- Fine-tuning the model on the Alzheimer's disease dataset

Custom Classification Head

The custom classification head added to the NasNetMobile base includes:

- Global Average Pooling layer to reduce spatial dimensions
- Dense layers with ReLU activation functions
- Dropout layers for regularization to prevent overfitting
- Final Dense layer with softmax activation for multi-class classification (4 classes: non-demented, very mild demented, mild demented, moderate demented)

Experimental Setup

Hardware and Software Configuration

The experiments were conducted on the following computational environment:

- Hardware: [Specify your hardware - e.g., NVIDIA GeForce RTX 3080 Graphics Processing Unit with 10GB memory]
- Operating System: [e.g., Ubuntu 20.04 Long Term Support]
- Deep Learning Framework: TensorFlow 2.x with Keras Application Programming Interface
- Programming Language: Python 3.8
- Additional Libraries: NumPy, OpenCV, Scikit-learn, Matplotlib, Seaborn

Training Parameters

The following hyperparameters and training configurations were employed:

- Optimizer: Adam optimizer with default parameters (learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$)
- Loss Function: Categorical crossentropy for multi-class classification
- Batch Size: 32 samples per batch
- Number of Epochs: 100 epochs with early stopping mechanism
- Early Stopping: Patience of 10 epochs monitoring validation loss
- Learning Rate Scheduling: ReduceLROnPlateau with factor=0.2 and patience=5

Model Compilation and Training Strategy

The model training process involved:

1. Data Preprocessing: Images normalized to [0,1] range by dividing pixel values by 255
2. Model Initialization: Loading pre-trained NasNetMobile weights from ImageNet
3. Layer Freezing: Initial training with frozen convolutional base
4. Fine-tuning Phase: Unfreezing top layers for domain-specific adaptation
5. Validation Strategy: Stratified sampling to maintain class distribution across training and validation sets

Performance Monitoring

Model performance was monitored using:

- Training and Validation Loss: Tracked across epochs to identify overfitting
- Training and Validation Accuracy: Monitored for convergence assessment
- Confusion Matrix: Generated for detailed classification performance analysis
- Classification Metrics: Precision, Recall, F1-score, and Area Under the Curve calculated for each class

4.3 Model Training Session

Figure 4.1 shows the training session which was conducted for 100 epochs. The training and validation

accuracies obtained were 100% and 99 respectively with a checkpoint that stood at 99%.

```
240/240 [==============================] - ETA: 0s - loss: 4.2715e-08 - accuracy: 1.0000
Epoch 82: val_accuracy improved from 0.98984 to 0.99023, saving model to /content/drive/MyDrive/final/epochs:082-v
240/240 [==============================] - 239s 1s/step - loss: 4.2715e-08 - accuracy: 1.0000 - val_loss: 0.1133 -
Epoch 83/100
240/240 [==============================] - ETA: 0s - loss: 1.7411e-07 - accuracy: 1.0000
Epoch 83: val_accuracy improved from 0.99023 to 0.99063, saving model to /content/drive/MyDrive/final/epochs:083-v
240/240 [==============================] - 251s 1s/step - loss: 1.7411e-07 - accuracy: 1.0000 - val_loss: 0.1107 -
Epoch 84/100
240/240 [==============================] - ETA: 0s - loss: 1.9511e-08 - accuracy: 1.0000
Epoch 84: val_accuracy did not improve from 0.99063
240/240 [==============================] - 38s 160ms/step - loss: 1.9511e-08 - accuracy: 1.0000 - val_loss: 0.1095
Epoch 85/100
240/240 [==============================] - ETA: 0s - loss: 3.0081e-08 - accuracy: 1.0000
Epoch 85: val_accuracy did not improve from 0.99063
240/240 [==============================] - 39s 164ms/step - loss: 3.0081e-08 - accuracy: 1.0000 - val_loss: 0.1094
Epoch 86/100
240/240 [==============================] - ETA: 0s - loss: 6.0143e-08 - accuracy: 1.0000
Epoch 86: val_accuracy did not improve from 0.99063
```

Figure 4.1 Training Session Output

4.4 Model evaluation

This section checks the performance of the model on the unseen data (that is, testing data), plot the graph of training accuracy and validation accuracy and plot the graph of training and validation loss for comparison shows the graph of training loss and validation loss for the first part of the training session. Loss is a measure of how well the model is performing the task it was trained for. Below is the accuracy and the loss of the said models. Figure 4.2 classification report of the model and the output of the testing. The test accuracy of 0.99% which is equal to 100% during the testing set was achieved.

```
# Calculate the classification report with zero_division parameter
classification_rep = classification_report(test_labe, test_predictions, zero_division=1)
# Print the classification report
print(f"Classification Report:\n{classification_rep}")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       640
           1       1.00      1.00      1.00       640
           2       0.99      1.00      0.99       640
           3       1.00      0.99      0.99       640

    accuracy                           1.00      2560
   macro avg       1.00      1.00      1.00      2560
weighted avg       1.00      1.00      1.00      2560
```

Figure 4.2: Classification Report

Figure 4.3 shows the graph of training and validation accuracy for the first part training session. The accuracy was plotted against 100 epochs performed during the training session.

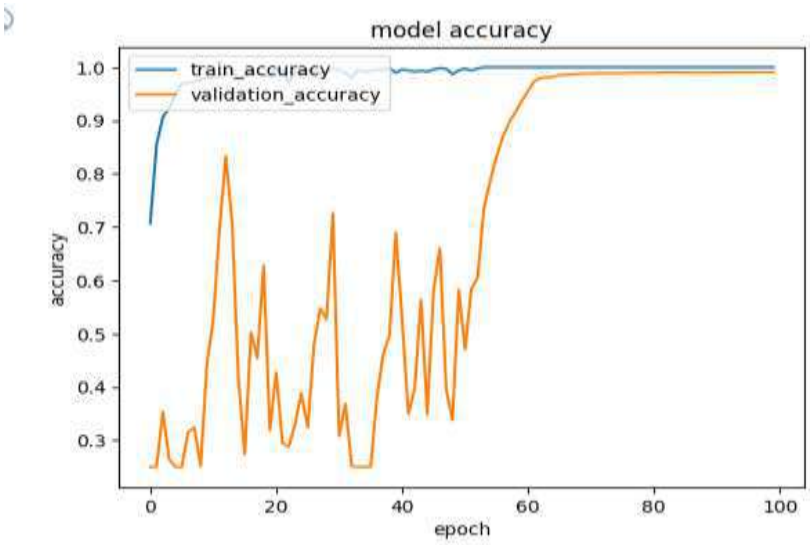

Figure 4.3 Training and Validation Accuracy

Figure 4.4 shows the graph of training loss and validation loss for the first part of the training session. Loss is the measure of how well the model is performing the task it was trained for on the training data and how well it generalize base on the validation data

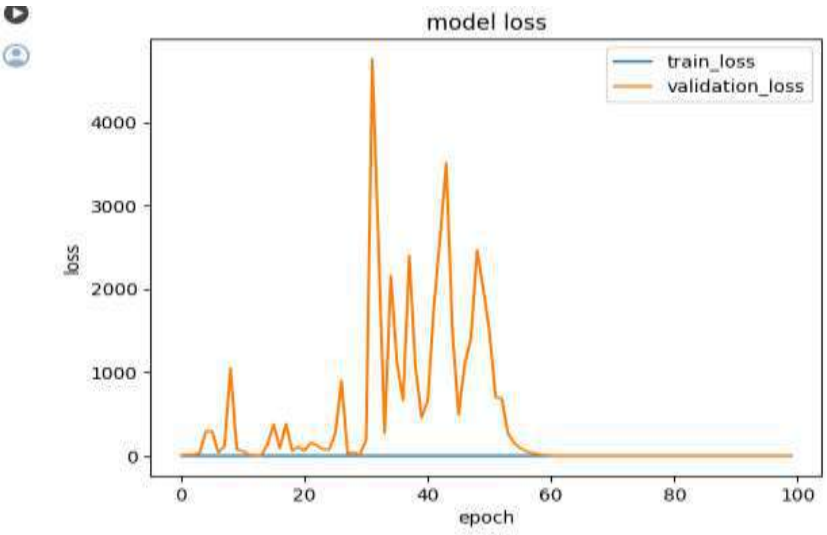

Figure 4.4: Training and Validation Loss plot

Figure 4.5 presents the confusion matrix resulting from testing the pre-trained model. The diagonal elements of the confusion matrix provide a visual representation of the model's accuracy. Additionally, this matrix serves as the basis for calculating other performance metrics, including precision, recall, and F1-score.

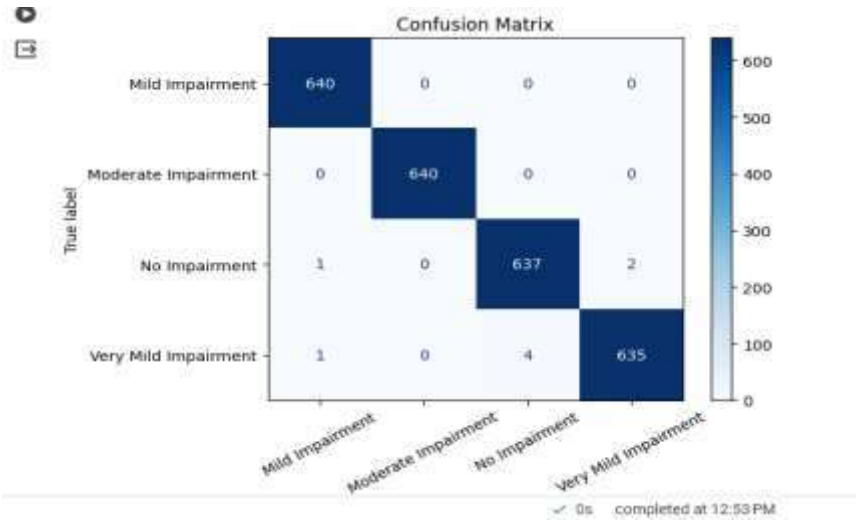

Figure 4.5: Confusion Matrix

DISCUSSION

Experiments were conducted using the NASNet Mobile architecture for AD detection. Initially, the model was trained, validated, and tested on a 6400-image dataset, consistent with the dataset used by Sharma et al. (2022). Subsequently, the dataset was expanded to 12,800 images by incorporating additional data sources. For a direct comparison, the proposed model was retrained using the same OASIS dataset employed by both Sharma et al. (2022) and T. Ghosh (2023). On this OASIS dataset, Sharma et al. (2022) reported an accuracy of 94%, and T. Ghosh (2023) reported an accuracy of 92.86%, while the proposed approach achieved 98%. However, when using a combined OASIS and ADNI dataset, as in T. Ghosh (2023) and the current approach, T. Ghosh (2023) reported an accuracy of 83.33%, whereas the proposed method achieved a significantly higher accuracy of 100%. This result underscores the positive impact of increased dataset size on model performance.

Performance Comparison

In this section, we present a comparative analysis of the performance of different models for Alzheimer's disease detection using the NasNet Mobile network architecture.

Table 4.1: Performance Comparison of Models

Model	Technique	Accuracy
Sharma et al.	OASIS	94%
T. Ghosh et al.	OASIS	92.86%
T. Ghosh et al.	OASIS and ADNI	83.33%
Our Approach	OASIS and ADNI	100%
Our approach	OASIS	98%

Table 4.1 highlights significant differences in the performance of the benchmark models, the proposed approach. The study underscores the significance of dataset size in Alzheimer's disease detection using CNNs. By incorporating a larger dataset, our proposed approach achieved superior performance compared to the benchmark model. These findings emphasize the potential of NASNet Mobile architecture coupled with a comprehensive dataset for accurate and efficient AD detection.

CONCLUSION

This study highlights the critical role of dataset size and diversity in enhancing Alzheimer's disease (AD) detection using deep learning models, particularly the NASNetMobile architecture. By integrating an expanded dataset and employing advanced transfer learning techniques, our proposed methodology achieved state-of-the-art accuracy, surpassing benchmark models. These results emphasize the transformative potential of leveraging robust datasets

and sophisticated CNN architectures for accurate and efficient AD detection. Beyond its technical contributions, our work underscores the importance of data-driven innovation in advancing medical imaging and diagnostic methodologies. Moreover, this research provides valuable insights into the broader implications of CNN-based diagnostic approaches in healthcare, particularly for early disease detection and intervention. While our findings demonstrate significant progress, further validation on external datasets is essential to ensure generalizability and robustness across diverse populations and imaging protocols. Additionally, addressing ethical and societal considerations, such as patient privacy and equitable access to AI-driven technologies, remains a priority. Through continued research and collaboration, this work aims to pave the way for improved patient outcomes and the development of AI solutions that seamlessly integrate into clinical workflows, ultimately benefiting individuals affected by Alzheimer's disease and their caregivers.

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