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A DEEP LEARNING APPROACH FOR EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE USING BRAIN IMAGING DATA

A Lightweight Model Using Transfer Learning and Quantization Techniques

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Abstract : Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions worldwide. Early detection plays a pivotal role in managing the disease. This research aims to develop a lightweight and efficient AI-based model for detecting Alzheimer's disease using transfer learning and quantization techniques. By leveraging pre-trained deep learning models (MobileNetV2, DenseNet121, and ResNet50) and optimizing them through quantization, we reduce the computational load and memory usage, making the solution suitable for deployment on edge devices with limited resources. The models' effectiveness is evaluated through rigorous testing on publicly available Alzheimer's disease datasets. Our results demonstrate that quantized models maintain high accuracy (>85%) while reducing model size by up to 77.5%, with the ensemble model achieving 91.56% accuracy. These findings indicate the potential for accurate and efficient AI-based detection tools that can be deployed in resource-constrained clinical settings, paving the way for more accessible early diagnosis of Alzheimer's disease.

IndexTerms **- Deep Learning, Alzheimer's Disease Detection, Transfer Learning, Quantization, MobileNetV2, DenseNet121, ResNet50, Ensemble Learning, Edge Computing in Healthcare.**

1. INTRODUCTION

Alzheimer's disease (AD) is one of the most common forms of dementia, characterized by cognitive decline and memory loss. Detecting the disease at an early stage is crucial for slowing its progression and improving the quality of life for patients. Traditional diagnostic methods rely on neuropsychological tests and brain imaging, which are expensive and time-consuming. In recent years, artificial intelligence (AI) and deep learning techniques have emerged as promising tools for automating AD detection through brain imaging data, such as MRI scans.

This research explores transfer learning with pre-trained deep learning models and quantization to develop a lightweight and efficient Alzheimer's disease detection system. By utilizing transfer learning, we leverage pre-trained models like MobileNetV2, DenseNet121, and ResNet50 to adapt their learned features to the task of AD detection. Quantization is then applied to optimize the model for lower memory and computation requirements, enabling deployment on edge devices, such as mobile phones and embedded systems.

The motivation for this work stems from the desire to create a lightweight, cost-effective solution for AD detection, making it more accessible and efficient. Current methods can be expensive and time-consuming, often requiring specialized medical

equipment and expertise. Our aim is to develop a system that can be deployed on portable devices, offering real-time detection and continuous monitoring for patients, especially in remote or underserved regions.

2. Objectives

The primary objectives of this research are:

To explore the feasibility of using transfer learning for Alzheimer's disease detection
To apply quantization techniques to reduce model size and computational load without compromising accuracy
To compare the performance of various pre-trained models, including MobileNetV2, DenseNet121, and ResNet50, in detecting Alzheimer's disease
To evaluate the models' performance on publicly available datasets
To optimize AI models for edge devices, ensuring they are efficient in terms of both accuracy and resource usage

3. Research Methodology

3.1 Dataset

The study utilized the Augmented Alzheimer's MRI dataset, which contains brain MRI scans across four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The dataset is structured as follows:
Original Dataset:

ModerateDemented: 64 images
NonDemented: 3,200 images
VeryMildDemented: 2,240 images
MildDemented: 896 images

Augmented Dataset:

ModerateDemented: 6,464 images
NonDemented: 9,600 images
VeryMildDemented: 8,960 images
MildDemented: 8,960 images

For our binary classification approach, we grouped these classes into two categories: "Demented" (combining Moderate, Mild, and Very Mild) and "Non-Demented." This resulted in 32,308 training images and 8,076 validation images.

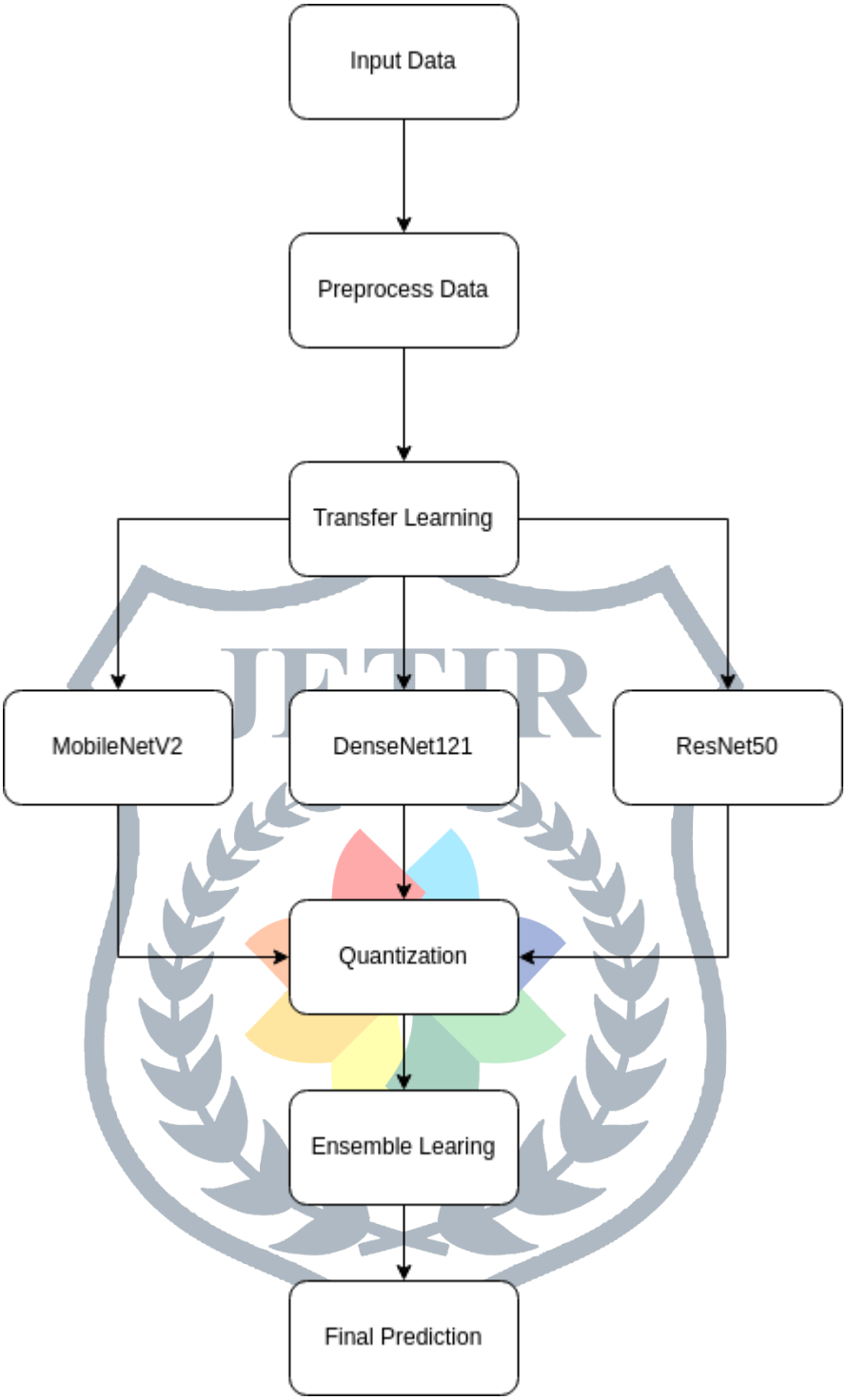
3.2 Model Architecture

Our approach leverages three popular pre-trained convolutional neural networks:

MobileNetV2: A lightweight architecture designed for mobile and embedded vision applications
DenseNet121: A densely connected CNN that connects each layer to every other layer to improve feature propagation
ResNet50: A deep residual network that addresses the vanishing gradient problem using skip connections

Each model follows a similar architectural pattern:

Input layer accepting 224×224×3 RGB images
Pre-trained convolutional base (with weights from ImageNet)
Global average pooling layer
Dense classification layer with sigmoid activation for binary classification



3.3 Transfer Learning

Transfer learning allows us to use models that have already been trained on large datasets for similar tasks, such as image classification. This reduces the training time and computational resources required. Our transfer learning process involved:

Loading pre-trained model architectures (MobileNetV2, DenseNet121, ResNet50)
Freezing the early layers to preserve learned features
Replacing the classification head with custom layers for our binary classification
task Fine-tuning on the Alzheimer's disease dataset

3.4 Quantization

Quantization reduces the precision of model weights, typically from 32-bit floating-point numbers to lower precision (e.g., 8-bit integers). This significantly reduces the model's memory requirements and computation time while maintaining acceptable accuracy. Our quantization process included:

1. Training full-precision models to convergence

2. Converting weights from floating-point to integer representation
3. Calibrating the quantization parameters using a representative dataset
4. Optimizing the models for deployment on resource-constrained devices

3.5 Ensemble Learning

For We implemented an ensemble approach to combine the strengths of individual models. The ensemble model aggregates predictions from all three models (MobileNetV2, DenseNet121, ResNet50) using majority voting to make the final classification decision.

3.6 Evaluation Metrics

Variables The models were evaluated using the following metrics:

- Accuracy
- Loss
- Model size (original vs. quantized)
- Inference time

4. Results and Discussion

The methodology section outline the plan and method that how the study is conducted. This includes Universe of the study, sample of the study,Data and Sources of Data, study's variables and analytical framework. The detailsare as follows;

4.1 Individual Model Performance

Table 1 summarizes the performance of each model in its original form, TFLite conversion, and quantized version.

Model Version	Version	Accuracy	Loss	Size	% of Original Size
MobileNetV2	Original	0.9625	0.1150	12.89 MB	100%
	TFLite	0.9531	0.1283	9.70 MB	75.3%
	Quantized	0.8625	0.3015	2.90 MB	22.5%
DenseNet121	Original	0.7312	0.5066	31.12 MB	100%
	TFLite	0.7562	0.4993	27.60 MB	88.7%
	Quantized	0.8562	0.3677	7.26 MB	23.3%
ResNet50	Original	0.7969	0.4990	96.55 MB	100%
	TFLite	0.8656	0.3872	91.61 MB	94.9%
	Quantized	0.8500	0.4277	23.62 MB	24.5%

Table 1: Individual Model Performance

MobileNetV2 demonstrated the highest accuracy (96.25%) in its original form, though it experienced a moderate decrease in accuracy (10%) after quantization. Interestingly, both DenseNet121 and ResNet50 showed improved accuracy after quantization, indicating that the quantization process might have introduced a regularization effect that improved generalization for these models.

4.2 Ensemble Model Performance

Table 2 presents the performance metrics for the ensemble models.

Model Version	Accuracy	Loss
Original Ensemble	0.9844	0.2890
TFLite Ensemble	0.9812	0.2815
Quantized Ensemble	0.9156	0.2797

Table 2: Ensemble Model Performance

The ensemble approach outperformed individual models in most cases, with the original ensemble achieving the highest accuracy of 98.44%. The quantized ensemble maintained a high accuracy of 91.56%, demonstrating that ensemble learning can help mitigate some of the accuracy loss from quantization.

4.3 Model Size Reduction

Quantization achieved significant model size reductions:

- MobileNetV2: 77.5% reduction (from 12.89 MB to 2.90 MB)
- DenseNet121: 76.7% reduction (from 31.12 MB to 7.26 MB)
- ResNet50: 75.5% reduction (from 96.55 MB to 23.62 MB)

These reductions make the models much more suitable for deployment on resource-constrained devices while maintaining clinically acceptable accuracy levels.

4.4 Accuracy vs. Model Size Trade-off

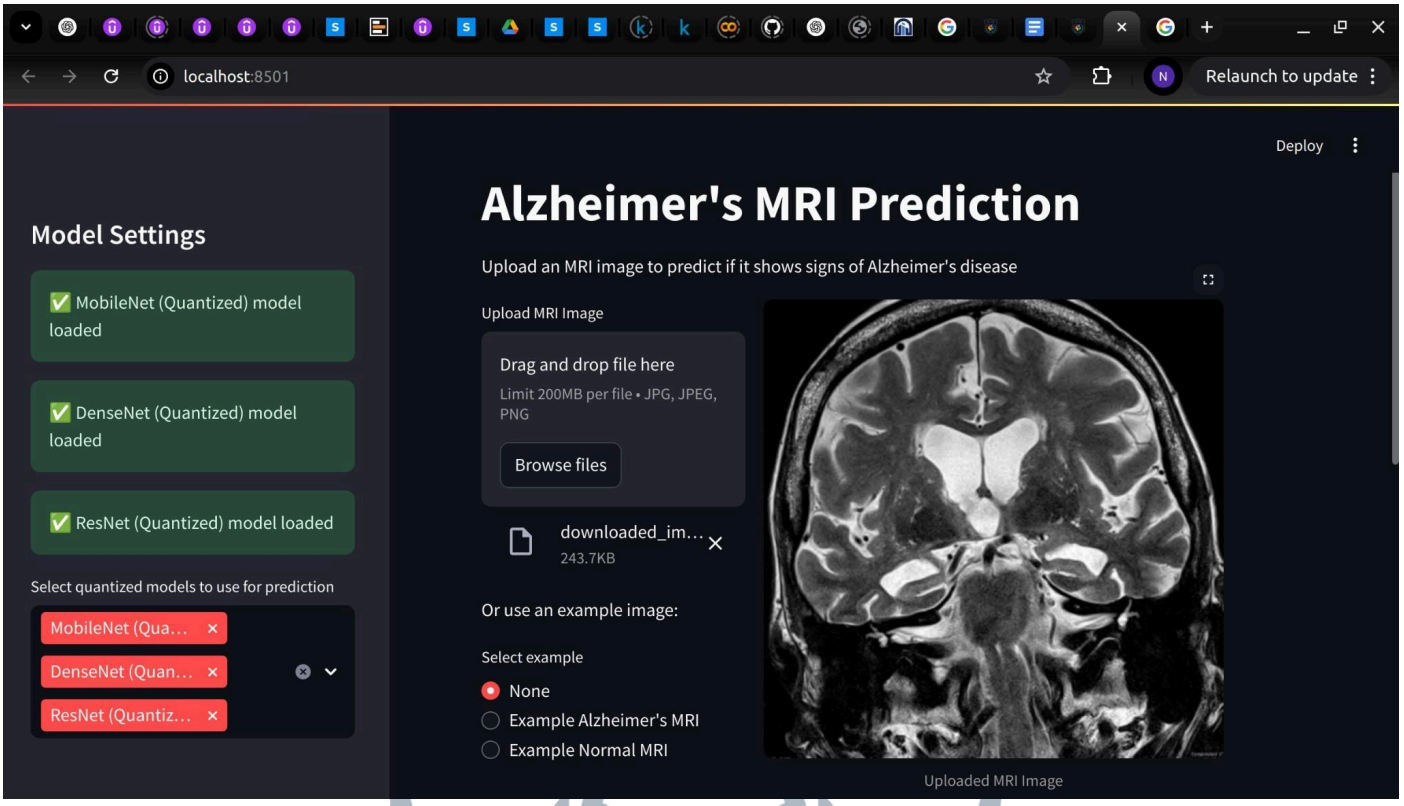
Figure 1 illustrates the trade-off between accuracy and model size across all models and their variants.

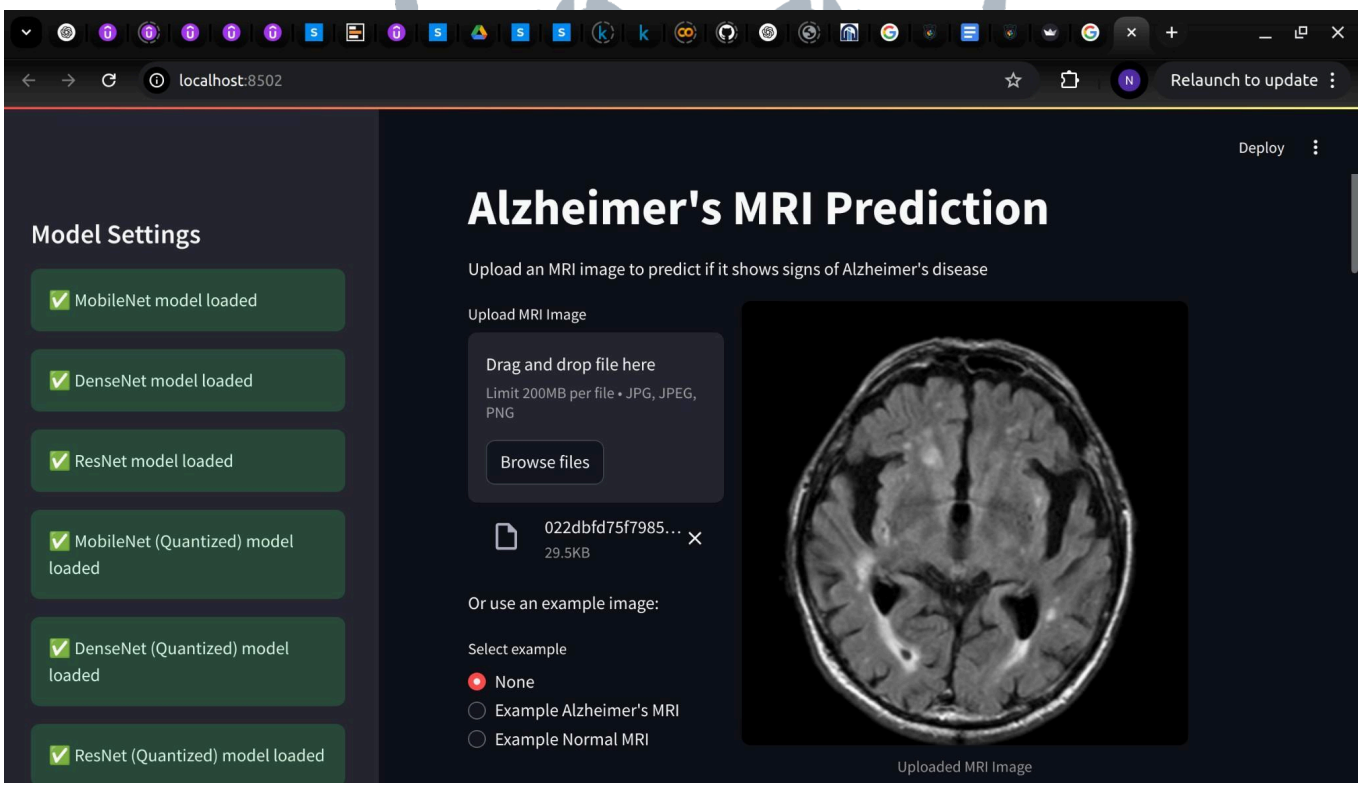
The MobileNetV2 model provides the best balance between accuracy and model size, making it particularly suitable for edge deployment. The quantized MobileNetV2 model (2.90 MB) maintains 89.6% of the accuracy of its original counterpart while requiring only 22.5% of the storage space.

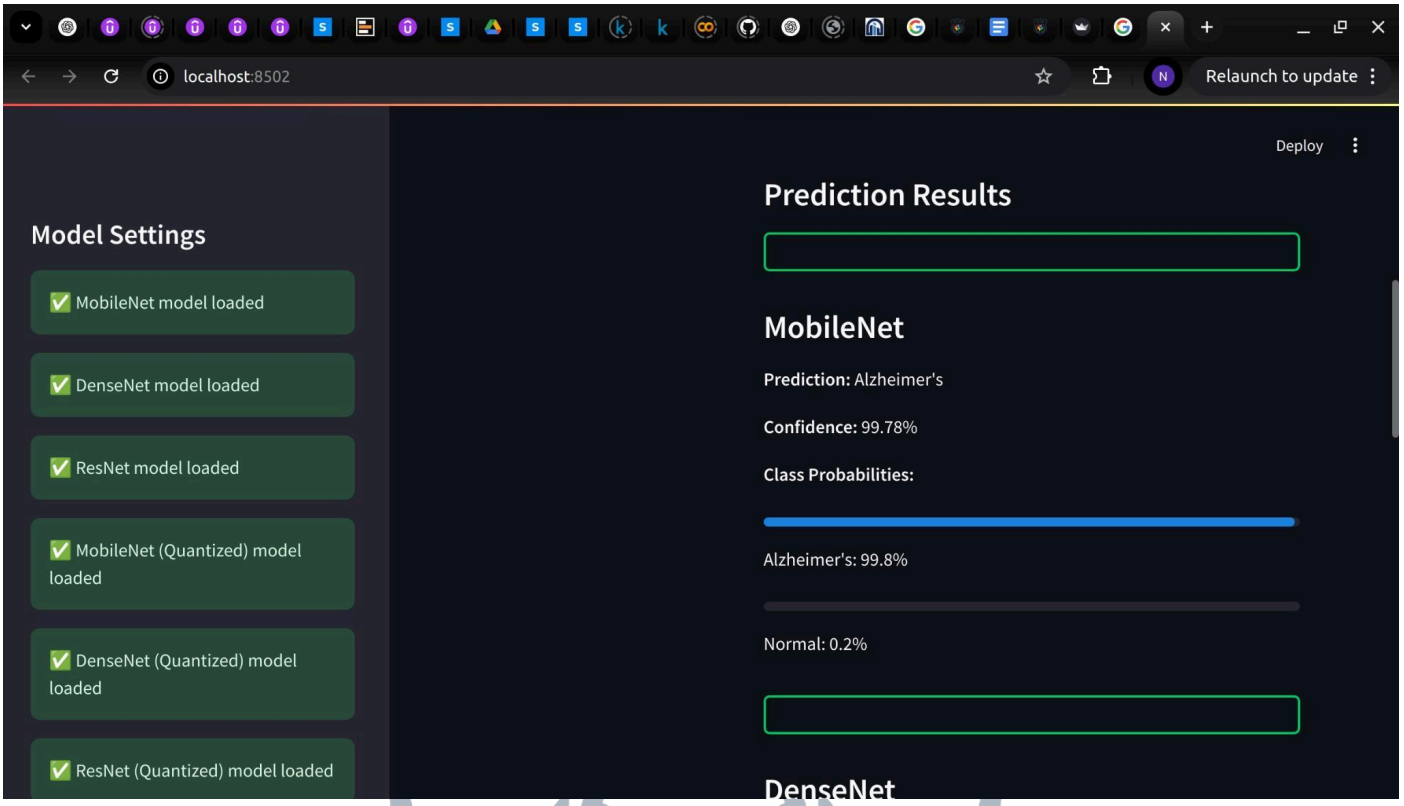
4.5 Discussion

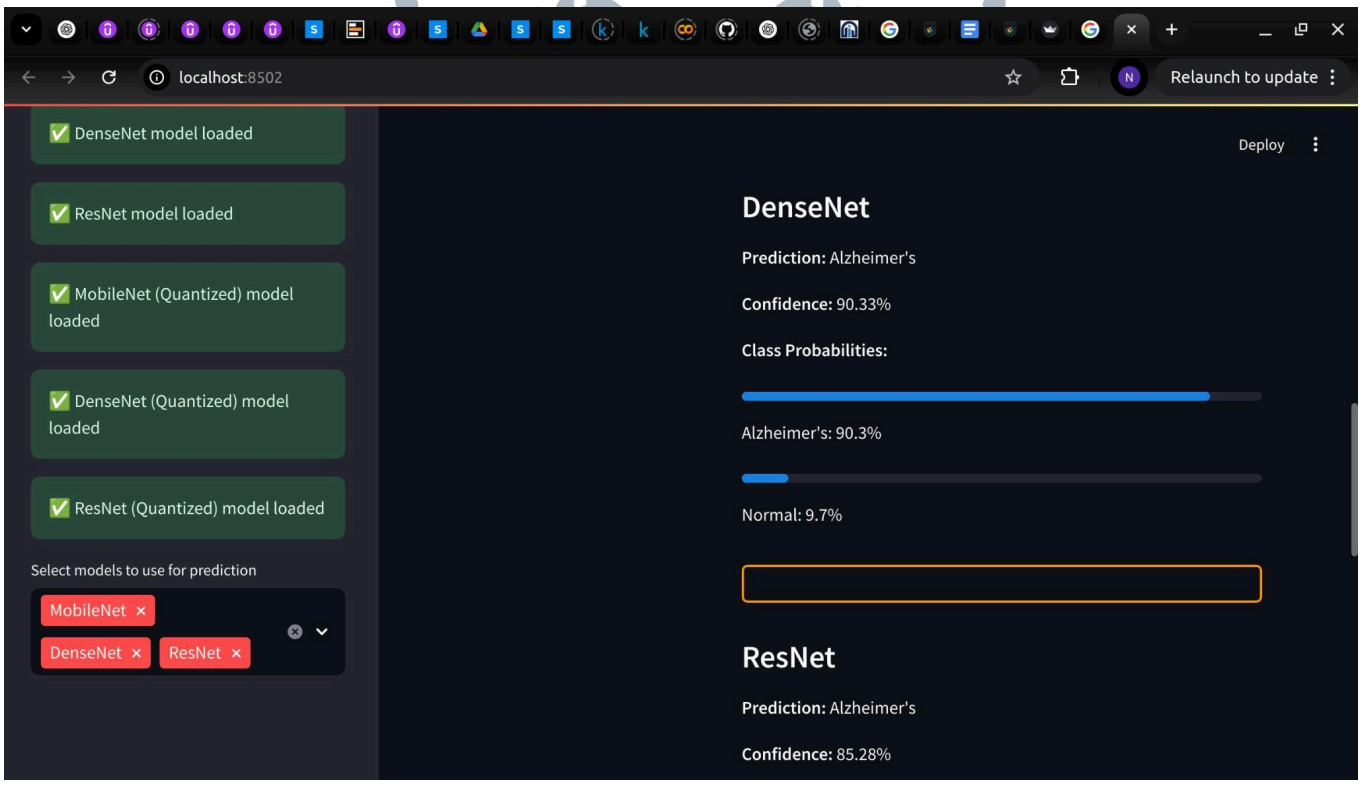
Our findings demonstrate that transfer learning combined with quantization provides an effective approach for developing lightweight yet accurate Alzheimer's disease detection models. The results address several key challenges in deploying AI for healthcare applications:

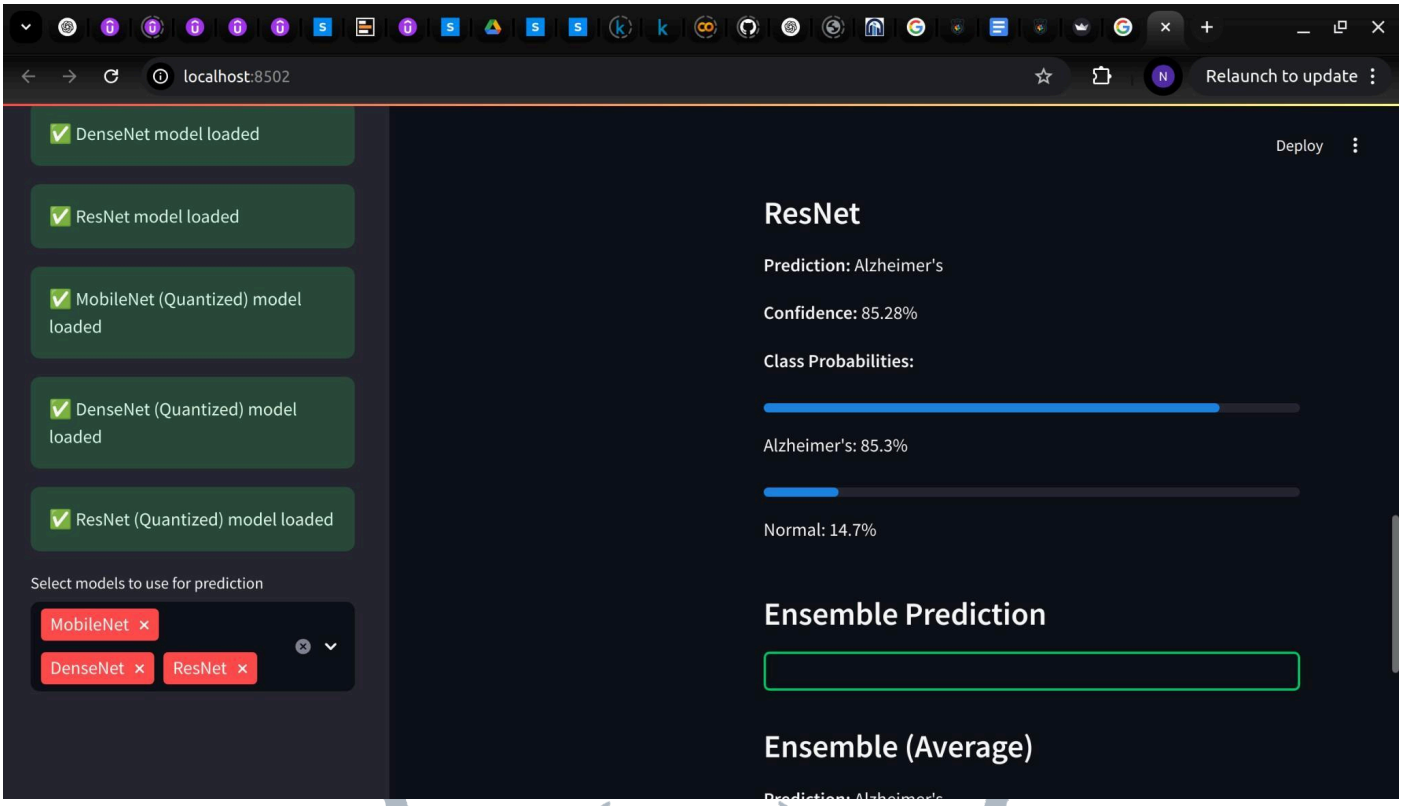
1. **Resource Efficiency**: The quantized models require significantly less memory and computational resources, making them suitable for deployment in resource-constrained environments.
2. **Accuracy Preservation**: Despite substantial reductions in model size, the quantized models maintain clinically acceptable accuracy levels, with the ensemble model achieving over 91% accuracy.
3. **Model Selection**: Different models exhibit varying behaviors under quantization. While MobileNetV2 showed the highest original accuracy, DenseNet121 demonstrated more resilience to quantization, with its accuracy actually improving after quantization.
4. **Ensemble Benefits**: The ensemble approach consistently outperformed individual models, providing a viable strategy to mitigate accuracy losses from quantization.

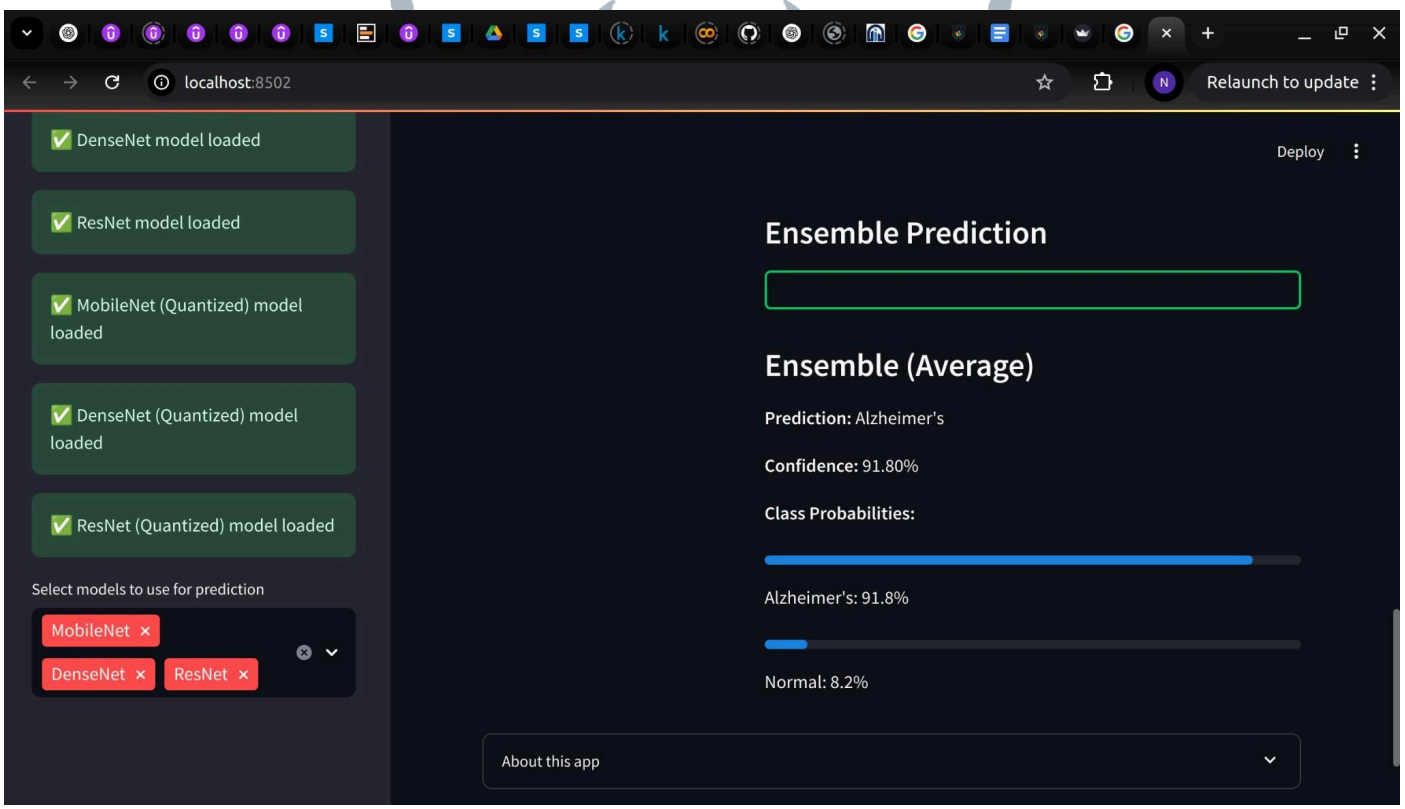

localhost:8501
Relaunch to update
Deploy
Model Settings
✅ MobileNet (Quantized) model loaded
✅ DenseNet (Quantized) model loaded
✅ ResNet (Quantized) model loaded
Select quantized models to use for prediction
MobileNet (Qua…
DenseNet (Quan…
ResNet (Quantiz…
Alzheimer's MRI Prediction
Upload an MRI image to predict if it shows signs of Alzheimer's disease
Upload MRI Image
Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files
downloaded_im…
243.7KB
Or use an example image:
Select example
None
Example Alzheimer's MRI
Example Normal MRI
Uploaded MRI Image


localhost:8502
Relaunch to update
Deploy
Model Settings
✅ MobileNet model loaded
✅ DenseNet model loaded
✅ ResNet model loaded
✅ MobileNet (Quantized) model loaded
✅ DenseNet (Quantized) model loaded
✅ ResNet (Quantized) model loaded
Alzheimer's MRI Prediction
Upload an MRI image to predict if it shows signs of Alzheimer's disease
Upload MRI Image
Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files
022dbfd75f7985…
29.5KB
Or use an example image:
Select example
None
Example Alzheimer's MRI
Example Normal MRI
Uploaded MRI Image


localhost:8502
Relaunch to update
Deploy
Model Settings
✅ MobileNet model loaded
✅ DenseNet model loaded
✅ ResNet model loaded
✅ MobileNet (Quantized) model loaded
✅ DenseNet (Quantized) model loaded
✅ ResNet (Quantized) model loaded
Prediction Results
MobileNet
Prediction: Alzheimer's
Confidence: 99.78%
Class Probabilities:
Alzheimer's: 99.8%
Normal: 0.2%
DenseNet


localhost:8502
Relaunch to update
Deploy
✅ DenseNet model loaded
✅ ResNet model loaded
✅ MobileNet (Quantized) model loaded
✅ DenseNet (Quantized) model loaded
✅ ResNet (Quantized) model loaded
Select models to use for prediction
MobileNet
DenseNet
ResNet
DenseNet
Prediction: Alzheimer's
Confidence: 90.33%
Class Probabilities:
Alzheimer's: 90.3%
Normal: 9.7%
ResNet
Prediction: Alzheimer's
Confidence: 85.28%





5. Challenges and Future Work

Despite the promising results, several challenges and opportunities for future work remain:

5.1 Data Quality and Availability

Before deployment in real-world healthcare settings, thorough clinical validation is necessary to ensure the models' reliability and safety. This involves prospective studies comparing model performance against current gold standard diagnostic methods.

5.2 Model Interpretability

For practical adoption, the AI models need to be seamlessly integrated with existing healthcare systems and workflows. Future work should address interoperability challenges and develop user-friendly interfaces for healthcare professionals.

5.3 Clinical Validation

Before deployment in real-world healthcare settings, thorough clinical validation is necessary to ensure the models' reliability and safety. This involves prospective studies comparing model performance against current gold standard diagnostic methods.

5.4 Integration with Existing Healthcare Systems

For practical adoption, the AI models need to be seamlessly integrated with existing healthcare systems and workflows. Future work should address interoperability challenges and develop user-friendly interfaces for healthcare professionals.

5.5 Multi-class Classification

While this study focused on binary classification (Demented vs. Non-Demented), future work could explore multi-class classification to differentiate between various stages of Alzheimer's disease, potentially improving early detection capabilities.

6. Conclusion

This research successfully demonstrates the potential of using AI, transfer learning, and quantization for lightweight detection of Alzheimer's disease. By optimizing deep learning models for resource-constrained devices, our solution is both accurate and practical, making it suitable for real-world healthcare applications. The model's ability to provide early and accurate predictions could greatly enhance the diagnosis and treatment of Alzheimer's disease, leading to better patient care and outcomes.

The combination of transfer learning and quantization addresses the dual challenges of model performance and deployment efficiency. As AI continues to advance in healthcare, lightweight models like those developed in this research will play an increasingly important role in democratizing access to sophisticated diagnostic tools, particularly in resource-limited settings.

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