Disease Prediction using Deep Learning Technique

Project report submitted in partial fulfillment
of the requirements for the degree of

Bachelor of Technology

by

Kshitiz Bairathi - 22ucc055 (CCE)
Kanishk Garg - 22ucs100 (CSE)
Rakshit Munot - 22ucc084 (CCE)

Under Guidance of
Dr. Munoj Kumar (Department of CCE)

LNMIIT
The LNM Institute of
Information Technology

The LNM Institute of Information Technology, Jaipur

April 2025

The LNM Institute of Information Technology
Jaipur, India

CERTIFICATE

This is to certify that the project entitled "Disease Prediction using Deep Learning Technique" , submitted by Kshitiz Bairathi (22ucc055), Kanishk Garg (22ucs100) and Rakshit Munot (22ucc084) in partial fulfillment of the requirement of degree in Bachelor of Technology (B. Tech), is a bonafide record of work carried out by them at the Department of Electronics and Communication Engineering , The LNM Institute of Information Technology, Jaipur, (Rajasthan) India, during the academic session 2016-2017 under my supervision and guidance and the same has not been submitted elsewhere for award of any other degree. In my/our opinion, this thesis is of standard required for the award of the degree of Bachelor of Technology (B. Tech).

Date

Adviser: Dr. Manoj Kumar

Dedicated to My Family and Friends

Acknowledgments

We would like to acknowledge the following individuals for their invaluable contributions to the project ”Disease Prediction Using Deep Learning Technique ”Our supervisor, Dr. Manoj Kumar, and “Dr. Rahul Sharma for providing guidance and support throughout the project.

We would also like to acknowledge the use of various online resources that helped us to complete this research. These resources proved to be invaluable in helping us to understand complex concepts and techniques, and we are grateful for the opportunity to learn from them.

Finally, we would like to thank our friends and family for their encouragement and support during the research process. Their belief in us and our work helped to keep us motivated and on track, and we are deeply grateful for their unwavering support. We are deeply indebted to all of these individuals and organizations for their contributions to this research project. Without their help, this project would not have been possible.

Abstract

This research work carries the theme of developing, evaluating, and implementing a Convolutional Neural Network (CNN) model for the target application area of early detecting a patient's possibility of having dementia or, in precise terms, Alzheimer's Disease, through deep learning techniques. To this end, brain scans from magnetic resonance imaging (MRI) are scrutinized for morphological modifications related to early stages of the disease. We use CNNs for feature extraction and supplement with a graph-based classification method using Graph neural networks (GNNs) to further the cause of improvement in precision/accuracy of predictions. The experiments were based on a multiclass Alzheimer's MRI dataset which included more than 44000 images. The stand-alone built and pre-trained models like VGG16, ResNet50, DenseNet121, MobileNetV2 were evaluated. The results show that the combined capabilities of CNNs and GNNs enrich disease prediction performance thereby making the diagnosis process scalable, low-cost, and accurate in health care.

Contents

Chapter *1*

Introduction

1.1 The Area of Work

Our work focuses on building a deep learning system to identify different stages of dementia from brain MRI scans. We first develop a CNN model that automatically extracts important features from the images. After that, we create a similarity graph between the images and use Graph Neural Networks (GNNs) for final predictions. The study includes both designing models from scratch and using well-known pretrained architectures like VGG16, ResNet50, DenseNet121, and MobileNetV2. Overall, the goal is to speed up Alzheimer's diagnosis, make it more accurate, and create a solution that can easily scale to serve more people.

1.2 Problem Addressed

Traditional image classification predominantly relies on Convolutional Neural Networks (CNNs) as a method of learning how to classify images, and they do so by learning the features from the images and mapping them to the corresponding labels. On the other hand, these CNNs are not meant to capture the relation or similarity between different images. We believe that such structural relationships can

improve the quality of classification. Our approach involves two steps:

- **Feature Extraction** – The first step involves retrieving high-level features from the images by using a CNN.
- **Graph-Based classification** – At this point, we build a graph for images as nodes connected through K-Nearest Neighbors (KNN)-derived edges based on feature similarities among them. Further processing of the graph using the Graph Neural Network (GNN) finally leads to classification.

With the adjacency matrix in GNNs, which gives us information about how similar images are to each other, Classification accuracy is expected to soar higher than what can be achieved from CNNs alone.

1.3 Existing System

CNN-Based Image Classification: Traditional models like VGG16, ResNet50, and DenseNet121 are used to classify MRI images. These models focus on extracting features from individual images and predicting the disease stage independently. While they achieve good performance, they ignore the structural relationships between images.

Chapter *2*

Litrature Survey

To establish a good foundation for this work, we queried many existing articles on deep learning in medical imaging, predominantly centered on detecting dementia and Alzheimer's disease. These articles address several approaches varying from CNN-based feature extraction, transfer learning using pre trained models, and graph-based methods, all highlighting better classification performance. The concepts borrowed from these papers provide foundations for the proposed system and guide us towards the right models and datasets. Here's a summary of what we found:

Detecting Alzheimer's Disease Using Deep Learning [3]

- **Methodology** – Custom deep CNN inspired by Inception-v4, with data augmentation and hyper-parameter tuning.
- **Strengths** – Optimized CNN for small dataset. No hand-made features are required. Uses transfer learning.
- **Limitation** – No comparison with other deep learning models.

Transfer Learning in MRI Image Classification [4]

- **Methodology** – Images partitioned to extract hippocampus ROI; then classified using CNN and Transfer Learning (AlexNet).
- **Strengths** – ROI extraction enhances relevant features. Transfer Learning boosts performance.
- **Limitation** – Small dataset. Class classification only (AD vs. normal).

Alzheimer's Disease Detection using CNN and Transfer Learning [1]

- **Methodology** – GAN to augment minority classes; CNN for feature extraction; Transfer Learning for hyperparameter tuning.

- **Strengths** – Solves data imbalance with GAN. Uses full datasets with cross-validation. Achieves high accuracy and generalizability.
- **Limitation** – No external dataset used for validation. Limited clinical feature integration.

A fine-tuned CNN model for accurate Alzheimer's Disease Classification [2]

- **Methodology** – Used AlexNet, GoogleNet, MobileNetV2 with solvers (ADAM, SGDM, RMSprop); evaluated with Grad-CAM.
- **Strengths** – Transfer learning. reduces training cost. Effective with small datasets. Explainability with Grad-CAM.
- **Limitation** – Generalizability to other datasets untested. Requires fine-tuning for new data.

Chapter *3*

Proposed Work

we're aiming to improve how dementia is detected using MRI brain scans by combining the strengths of two powerful deep learning approaches — CNNs and Graph Neural Networks (GNNs). Traditionally, CNNs have been great at extracting features from images, but they don't really understand how different images relate to one another. That's where our idea comes in.

We plan to first use a CNN model to extract high-level features from MRI images, capturing details like texture, shape, and structure. Then, instead of making predictions directly, we'll build a graph where each image is a node, and edges connect images that are similar to each other (using a K-Nearest Neighbors approach). This graph will then be processed by a GNN, which is better at capturing relationships between images, to make the final classification.

The hope is that by combining both these methods, our system can detect patterns of dementia more accurately — especially in those difficult, early-to-spot cases. It's about moving beyond treating images in isolation and starting to understand them in context with one another.

In short, it's a fresh approach to dementia detection that leverages the strengths of modern AI techniques, and we're excited to see how much of a difference it can make.

Chapter *4*

Simulation and Results

We tried out two different strategies. First, we built a CNN model from scratch with varying numbers of convolutional layers — starting from 7 layers and going all the way up to 13. This helped us see how the depth of the network affects its ability to pick up on patterns in MRI scans. Alongside that, we also tested several pre-trained models like DenseNet-121, VGG16, ResNet50, and MobileNetV2. These models come with pre-learned knowledge from massive image datasets, and we fine-tuned them for our dementia classification task.

To evaluate how well these models performed, we used AUC-ROC curves and confusion matrices. These tools allowed us to visualise how accurately each model was classifying different stages of dementia — from non-demented to moderate dementia.

What we found was that the deeper CNN models and fine-tuned pre-trained networks consistently outperformed simpler models. Pre-trained models like DenseNet-121 and ResNet50, in particular, showed promising results, achieving higher accuracy and better consistency across different classes. This reinforces how powerful transfer learning can be in medical imaging tasks.

In short, our results showed that deep learning models — especially when fine-tuned and carefully designed — can make a real difference in diagnosing dementia early and reliably.

4.1 Experimental results and Graphs

Model	Accuracy(%)	Precision	F1-Score	Specificity
7-Convolution Layers	93.30	0.9336	0.9342	0.9775
8-Convolution Layers	88.48	0.9421	0.8715	0.9613
9-Convolution Layers	96.50	0.9656	0.9660	0.9882
10-Convolution Layers	96.63	0.9670	0.9673	0.9887
11-Convolution Layers	96.33	0.9642	0.9664	0.9876
12-Convolution Layers	96.61	0.9675	0.9673	0.9885
13-Convolution Layers	96.50	0.9663	0.9663	0.9881
VGG16	95.16	0.9532	0.9533	0.9836
ResNet50	92.80	0.9307	0.9305	0.9757
MobileNetV2	96.34	0.9645	0.9646	0.9877
Densenet-121	98.01	0.9807	0.9809	0.9933

Chapter *5*

Conclusions and Future Work

5.1 Scope of further work

- The next step is to implement the Graph Neural Network (GNN) model alongside the CNN we already built. Right now, we're using CNNs for feature extraction — but soon, we'll construct a graph where each image acts as a node, and similar images are connected based on feature similarity.
- Once this graph is ready, we'll pass it through a GNN for classification. This will help the model not just look at individual MRI images but also understand the relationships between similar images, which can improve accuracy — especially for those borderline or confusing cases.
- After successfully integrating the GNN model, we plan to compare its performance with our existing CNN-only models. Metrics like accuracy, AUC-ROC, and confusion matrices will be evaluated to see if this new combination genuinely offers a boost in performance.
- If the results are promising, the final step will be to optimize the system for real-world deployment. This means reducing model size, increasing processing speed, and maybe even building a lightweight version suitable for use in clinics or on mobile devices in remote areas.
- This structured plan will allow us to gradually enhance our current model and move toward a smarter, relationship-aware AI system for early and reliable dementia detection.

5.2 Conclusion

We Conclude that :-

- If we are considering both cost and performance , the model from scratch with 10-convolution layers is best (96.63% accuracy).
- For pretrained model, DenseNet-121 is best (98.01% accuracy).

Bibliography

[1] K. T. Chui, B. B. Gupta, W. Alhalabi, and F. S. Alzahrani. An mri scans-based alzheimer's disease detection via convolutional neural network and transfer learning. *Diagnostics*, 12(7), 2022.

[2] M. Z. Hussain, T. Shahzad, S. Mehmood, K. Akram, M. A. Khan, M. U. Tariq, and A. Ahmed. A fine-tuned convolutional neural network model for accurate alzheimer's disease classification. *Scientific Reports*, 15(1):11616, 2025.

[3] J. Islam and Y. Zhang. A novel deep learning based multi-class classification method for alzheimer's disease detection using brain mri data. pages 213–222, 2017.

[4] M. Zaabi, N. Smaoui, H. Derbel, and W. Hariri. Alzheimer's disease detection using convolutional neural networks and transfer learning based methods. pages 939–943, 2020.