Disease Prediction Using Deep Learning Technique

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INTRODUCTION

What is Dementia ?

Dementia is a condition that affects a person's brain and makes it hard for them to remember things, think clearly, make decisions, or even talk properly.

How To Detect it ?

To detect this disease we use **Neuroimaging Techniques**

Shrinkage (Atrophy) of Brain Areas

Certain parts of the brain shrink in dementia, especially:

- **Hippocampus** (important for memory)
- **Cerebral cortex** (important for thinking and decision-making)
- This shrinkage shows up clearly on an MRI or CT scan.

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Changes in Brain Structure

MRI shows more detailed images and can detect:

- Loss of brain tissue
- Damage in white matter
- Enlargement of brain spaces (ventricles)

What is MRI ?

- **MRI** stands for **Magnetic Resonance Imaging**.

- It's a **safe and painless** test that uses **strong magnets and radio waves** to take detailed pictures of the inside of your body — especially your brain, spine, and soft tissues.
- Imagine a **camera that can see inside your body** without surgery.

How it Works:

- You lie down inside a big machine (like a tunnel).
- The machine uses **magnetic fields** and **radio signals**.
- A computer turns the signals into **clear images of organs** (like the brain).
- No harmful radiation is used (unlike X-rays or CT scans).

Uses of MRI

- Detects **tumors, stroke, bleeding**
- Diagnoses **dementia** (like Alzheimer's)
- Checks for **brain injury**
- Finds **joint problems**
- Detects **heart defects or damage**

What is Deep Learning ?

Deep Learning is a type of **machine learning** that uses structures called **neural networks** to learn patterns from data—especially large and complex datasets.

Why Deep Learning Works Well with Big & Complex Data ?

1. **Automatic Feature Extraction :-**

Traditional ML require manual feature engineering but DL automatically extract all the important features.

2. **Multiple Layers → Capture Complex Patterns :-**

1st layer -> Edges
2nd layer ->Shapes
3rd layer -> Small objects (like eye).
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Final layer -> Full object (like face).

3. **High Accuracy :-**

For complex tasks (like image recognition, language translation), deep learning usually **beats traditional ML models** in accuracy.

4. Versatile :-

Works on a variety of data types: **images, audio, text, videos, etc.**

What is Neural Network ?

A **Neural Network** is a computer system designed to **mimic the way the human brain works,** In simple way a Neural Network is a series of connected **nodes (neurons)** arranged in **layers**, which process data and learn to make predictions or classifications.

Input Layer :-

Takes in the raw data (e.g., pixel values of an image, numbers, text).

Hidden Layers

These are the core of the network.

Each layer finds patterns and features from the previous layer's output.

The deeper the network, the more complex patterns it can learn.

Output Layer

Gives the final result (e.g., cat or dog, yes or no, number prediction).

What is CNN (Convolutional Neural Network) ?

CNN stands for **Convolutional Neural Network** – a special type of neural network **mainly used for image data** (though it can be used for other things too like audio or video).

Why is it special?

Regular neural networks treat all data equally (like a flat list), but **CNN's understand the structure of images** (height, width, depth).

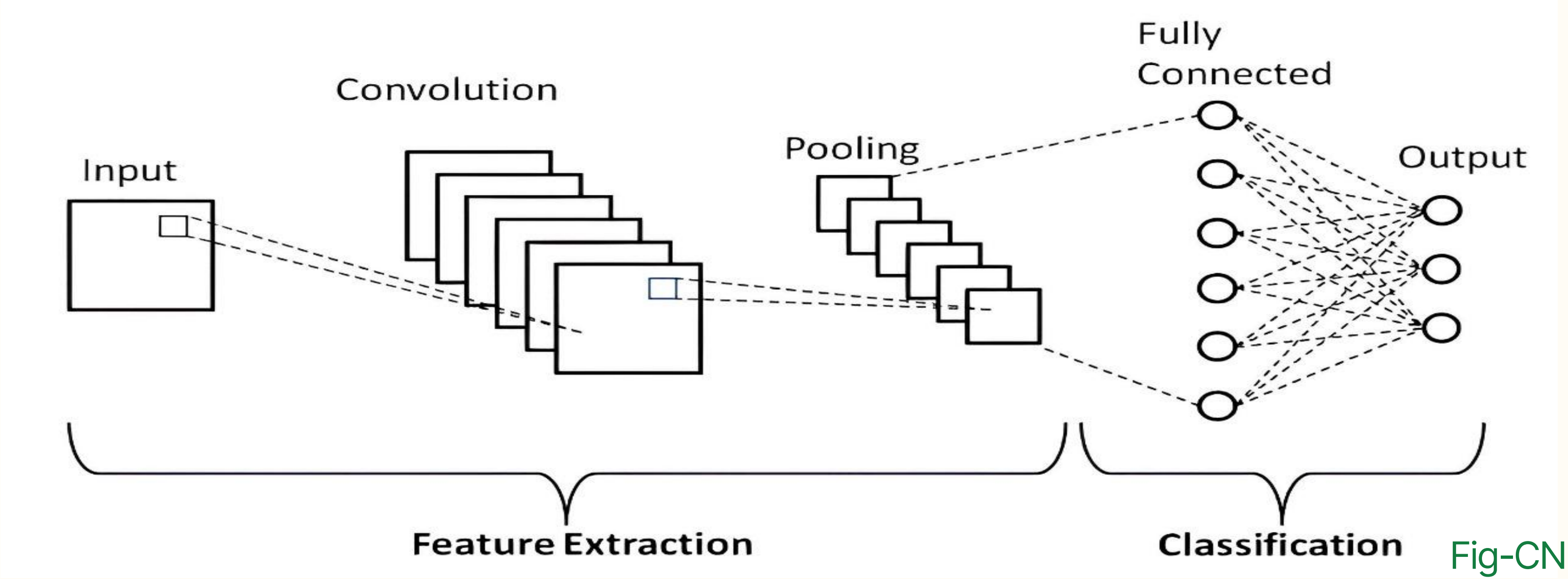


Fig-CNN-1

Structure of a CNN :-

Input Layer :-

- Takes an image (e.g., 28x28 pixels, 3 color channels for RGB).

Convolutional Layers :-

- Applies **filters** (small grids) to detect features like edges, textures, etc.
- Think of this like sliding a magnifying glass over the image to detect important spots.

Activation Function :-

- Adds non-linearity to help the network learn complex patterns.

Pooling Layer (usually Max Pooling) :-

- Shrinks the image size by picking the most important info (reduces computation and overfitting).

Fully Connected (Dense) Layers :-

- Final layers that flatten the data and make decisions (e.g., "This is a cat").

Output Layer :-

- Gives the final prediction (like class 0–9 for digit recognition).

How CNN techniques are benifitial for detecting disease :-

1. Automation of Diagnosis :-

- CNNs can analyze medical images (like MRI, CT scans) automatically.
- Reduces need for multiple specialists, lowering diagnostic costs.

2. Faster Diagnosis :-

- CNNs give results in seconds or minutes.
- Cuts down on hospital stays and follow-up appointments.

3. Scalability :-

- Once trained, CNN models can analyze thousands of scans cheaply.

Example : Dementia Detection

A CNN model trained on MRI scans can :-

- Predict risk of Alzheimer's early.
- Flag abnormalities automatically.
- Help rural clinics provide specialist-level screening.

Impact: A CNN-based diagnosis tool could be built into a ₹1000–₹2000 scan package, compared to ₹5000+ specialist reviews or city hospital costs.

Problem Statement

- Traditional image classification tasks rely heavily on Convolutional Neural Networks (CNNs), which learn to classify images based on extracted features and corresponding labels. However, CNNs lack an explicit mechanism to model the relationships or similarities between different images.

- We hypothesize that incorporating structural relationships between images can enhance classification performance. Our approach involves two stages:

  1. **Feature Extraction** – Use a CNN to extract high-level features from images.

  2. **Graph-Based Classification** – Construct a graph where each node represents an image, and edges are formed using K-Nearest Neighbors (KNN) based on feature similarity. This graph is then fed into a Graph Neural Network (GNN) for classification.

- By leveraging the adjacency matrix in GNNs, which encodes pairwise similarities between image features, we aim to improve classification accuracy beyond what CNN's alone can achieve.

Why we use Deep Learning instead of traditional Machine Learning ?

Accuracy :-

In **Deep Learning (DL)** models, increasing the size of the dataset typically leads to a **continuous improvement in accuracy**. This is because deep learning models have high capacity and can learn complex patterns more effectively when more data is available.

On the other hand, in **Traditional Machine Learning (ML)** models, the accuracy **increases up to a certain point** with more data, but then **plateaus**.

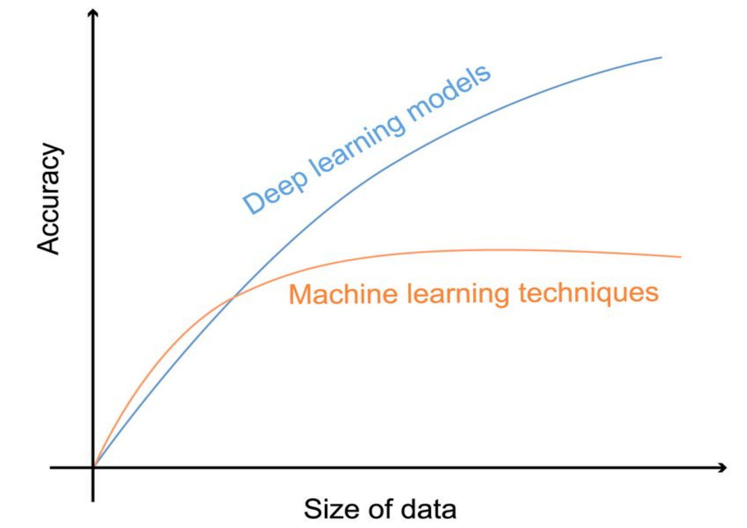


Fig-1

Feature Engineering :-

We don’t need feature engineering to extract features , Deep Learning models automatically extract features from the image .

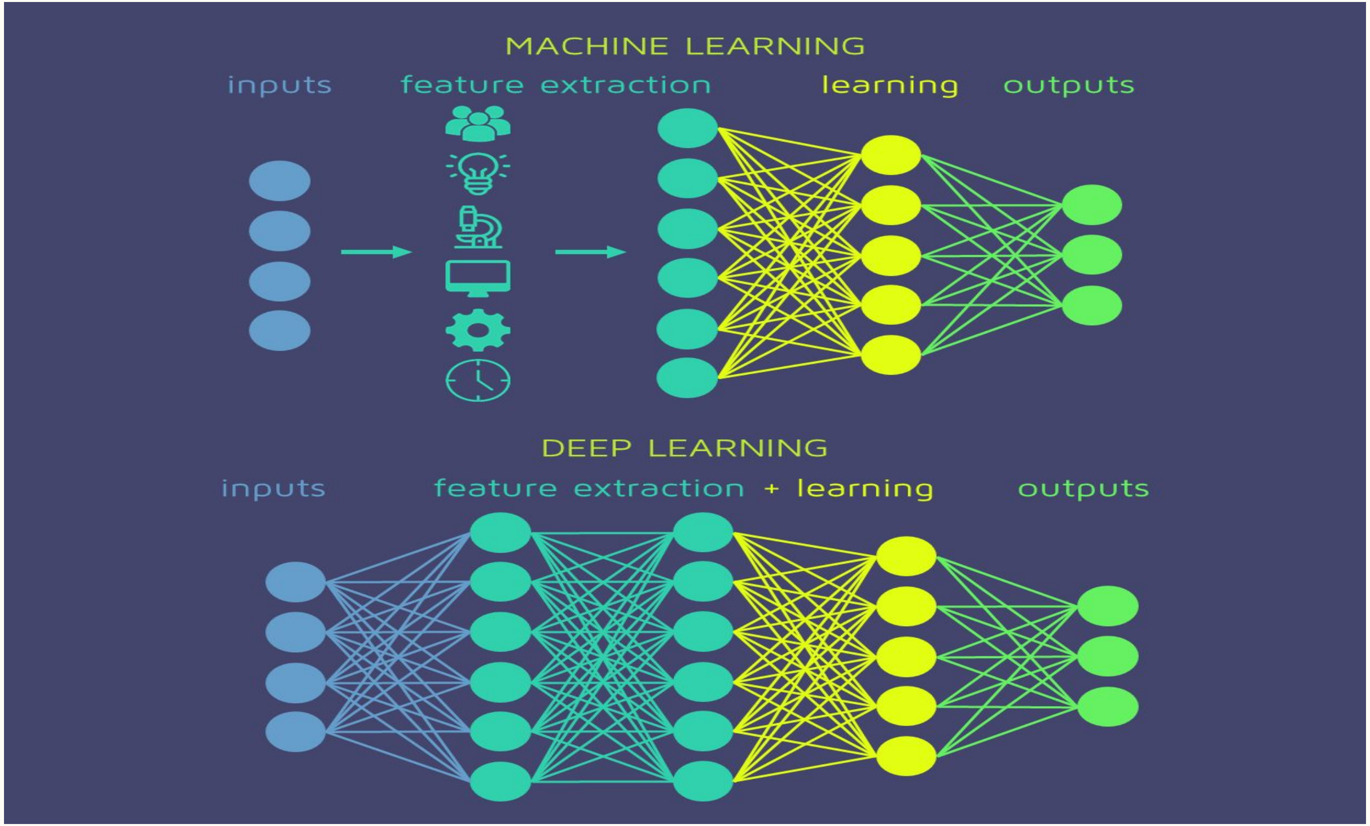


Fig-2

LITERATURE REVIEW

RESEARCH PAPER -1

S. No.	Authors	Year	Objective	Methodology	Key Findings	Strengths / Limitations
1	1. Jyoti Islam 2. Yanqing Zhang	2017	Propose a deep CNN model (based on Inception-v4) for multi-class classification of Alzheimer's stages.	Custom deep CNN inspired by Inception-v4, with data augmentation and hyperparameter tuning.	Achieved 73.75% accuracy on OASIS dataset; faster model needing no handcrafted features.	***<u>Strengths</u>:*** - Optimized CNN for small dataset. - No handcrafted features required. - Uses transfer learning. ***<u>Limitations</u>***: - No comparison with other deep learning models.

RESEARCH PAPER -2

S. No.	Authors	Year	Objective	Methodology	Key Findings	Strengths / Limitations
2	1.Marwa Zaabi 2. Nadia Smaoui 3. Houda Derbel 4. Walid Hariri	2020	To detect Alzheimer's Disease using CNN and Transfer Learning with ROI-based feature extraction.	Images partitioned to extract hippocampus ROI; then classified using CNN and Transfer Learning (AlexNet).	CNN accuracy: 88.10%, Transfer Learning (AlexNet) accuracy: 92.86%, outperforming other deep models.	***<u>Strengths</u>:*** -ROI extraction enhances relevant features. -Transfer Learning boosts performance. ***<u>Limitations</u>:*** -Small dataset. -Class classification only (AD vs. normal).

RESEARCH PAPER -3

S. No.	Authors	Year	Objective	Methodology	Key Findings	Strengths / Limitations
3	1. Wadee Al halabi 2.Kwok TaiCH 3. Brij B. Gupta 4. Fatma Salih Alzahrani	2022	Propose GAN-CNN-TL model for improved multi-class AD detection using MRI.	GAN to augment minority classes; CNN for feature extraction; Transfer Learning for hyperparameter tuning.	Accuracy: 96.9% (OASIS-1), 96.1% (OASIS-2), 97.5% (OASIS-3); model outperformed previous approaches.	***<u>Strengths</u>:*** – Solves data imbalance with GAN. – Uses full datasets with cross-validation. – Achieves high accuracy and generalizability. ***<u>Limitations</u>:*** – No external dataset used for validation. – Limited clinical feature integration.

RESEARCH PAPER -4

S. No.	Authors	Year	Objective	Methodology	Key Findings	Strengths / Limitations
4	1.Muhammad Zahid Hussain 2. Tariq Shahzad 3.Shahid Mehmood 4. Kainat Akram.	2025	Develop a fine-tuned CNN model using transfer learning to classify Alzheimer's disease stages.	Used AlexNet, GoogleNet, MobileNetV2 with solvers (ADAM, SGDM, RMSprop); evaluated with Grad-CAM.	Best model (AlexNet + ADAM) achieved 99.4% accuracy on Kaggle and 98.2% on OASIS; effective early-stage detection.	***<u>Strengths</u>:*** -Transfer learning. reduces training cost. -Effective with small datasets. -Explainability with Grad-CAM. ***<u>Limitations:</u>*** -Generalizability to other datasets untested. -Requires fine-tuning for new data.

Dataset

- The **Alzheimer's Disease Multiclass Dataset** is a comprehensive collection of MRI slices images aimed at supporting research and development in medical imaging and artificial intelligence.

- It contains approximately **44,000 MRI images**, providing a large and diverse sample size for robust machine learning model training and evaluation.

- The images are **categorized into four distinct classes** based on the **severity of Alzheimer's Disease**, allowing for multiclass classification tasks:

  1. **NonDemented:** Contains 12,800 MRI images of subjects with no signs of dementia.

  2. **VeryMildDemented:** Contains 11,200 MRI images of subjects with very mild symptoms of dementia.

  3. **MildDemented:** Contains 10,000 MRI images of subjects with mild dementia.

  4. **ModerateDemented:** Contains 10,000 MRI images of subjects with moderate dementia.

- Each class represents a different stage in the progression of Alzheimer's disease, enabling the development of models that can detect early to advanced stages

- The dataset is suitable for training a variety of **machine learning and deep learning models**, especially Convolutional Neural Networks (CNNs), for tasks such as:

    1. **Disease classification**
    2. **Progression prediction**
    3. **Feature extraction**

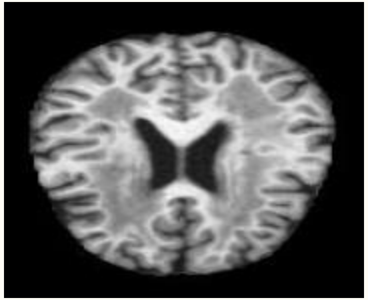
- It supports research in areas like **neurology, computer vision, medical diagnostics**, and **AI in healthcare**.

- The clean and well-labeled nature of the dataset makes it ideal for both **supervised learning** and **transfer learning** approaches.

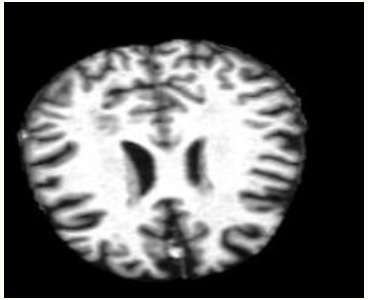
- This dataset serves as a valuable resource for developing tools that can assist in the **early diagnosis** and **monitoring of Alzheimer's Disease**, potentially improving patient outcomes through timely intervention.

Source Link of Dataset

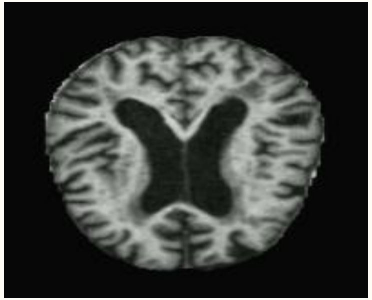
Image Details :-



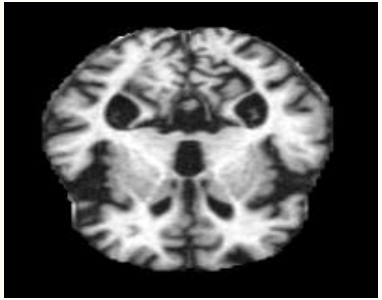
Non-Demented



Very-Mild Demented



Mild-Demented



Moderate Demented

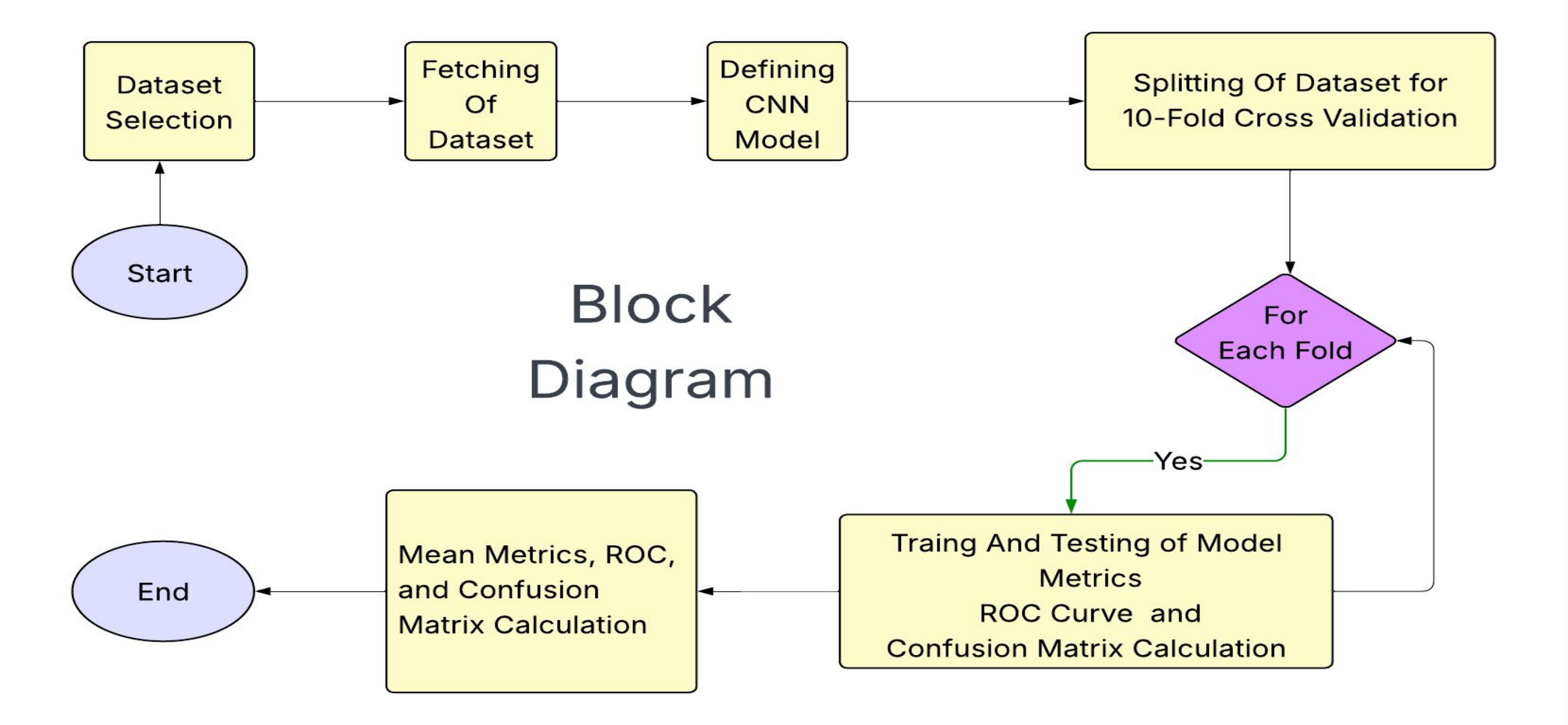
- **Format:** JPEG.
- **Resolution:** 180 x 180 pixels.
- **Mode:** RGB.

Preprocessing Status :-

- Skull-stripped: Yes
- Centered brain structure: Yes
- Background: Clean black, no external artifacts

Note :- All above images are taken from dataset itself.

MODEL ARCHITECTURE

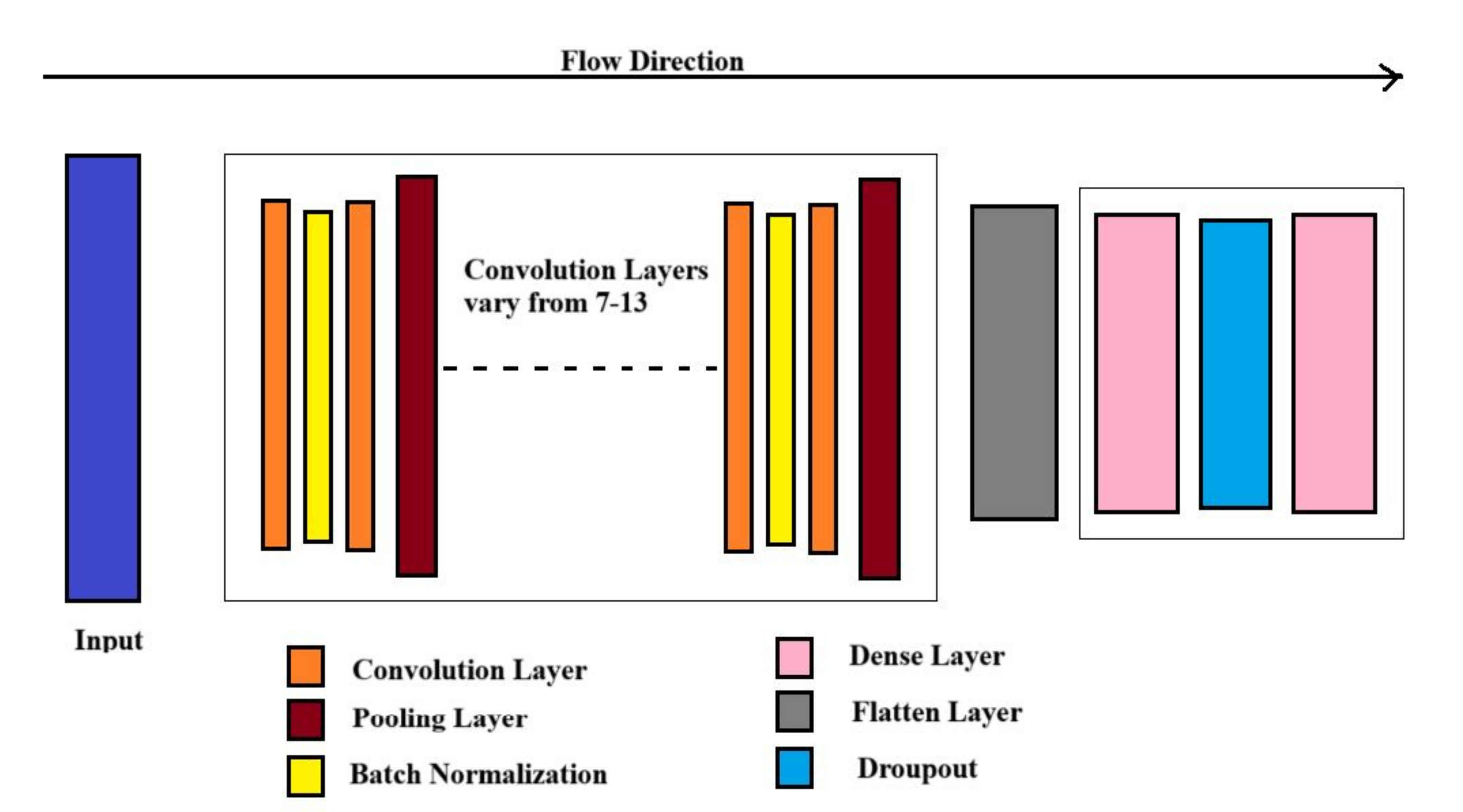


Software Used →Lucid.app

Source Link → https://www.lucidchart.com/pages

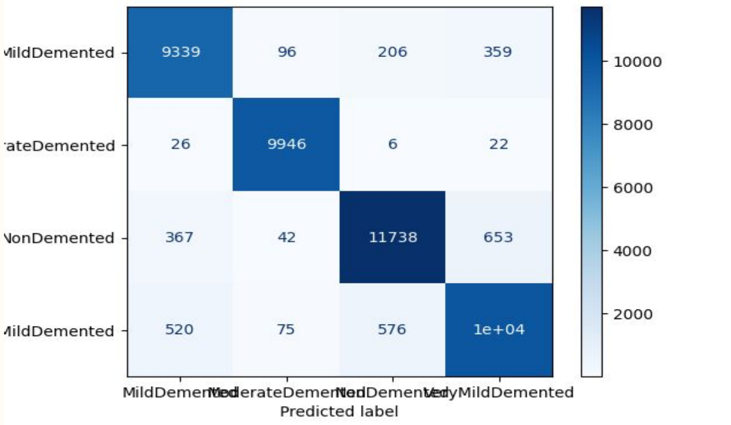
EXPERIMENTAL WORK

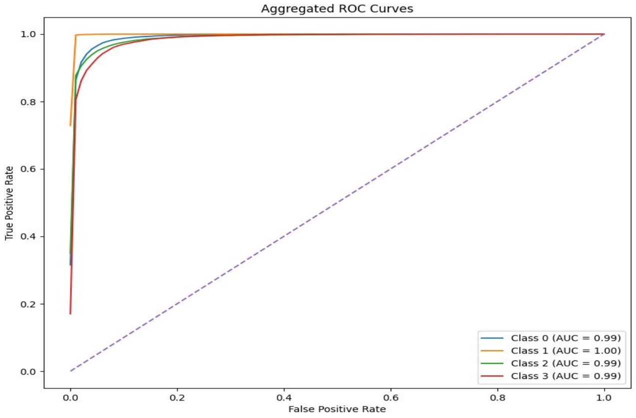
Model From Scratch



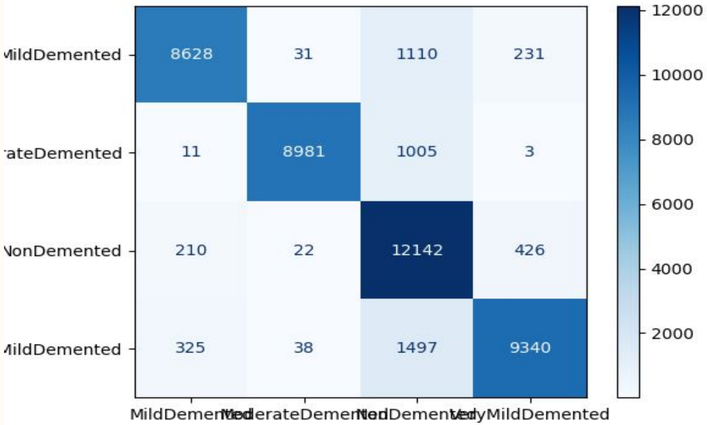
Model	Accuracy	Precision	F1-Score	Specificity
7-Convolutional Layers	93.30%	0.9336	0.9342	0.9775
8-Convolutional Layers	88.84%	0.9421	0.8715	0.9613
9-Convolutional Layers	96.50%	0.9656	0.9660	0.9882
10-Convolutional Layers	96.63%	0.9670	0.9673	0.9887
11-Convolutional Layers	96.33%	0.9642	0.9644	0.9876
12-Convolutional Layers	96.61%	0.9675	0.9673	0.9885
13-Convolutional Layers	96.50%	0.9663	0.9663	0.9881

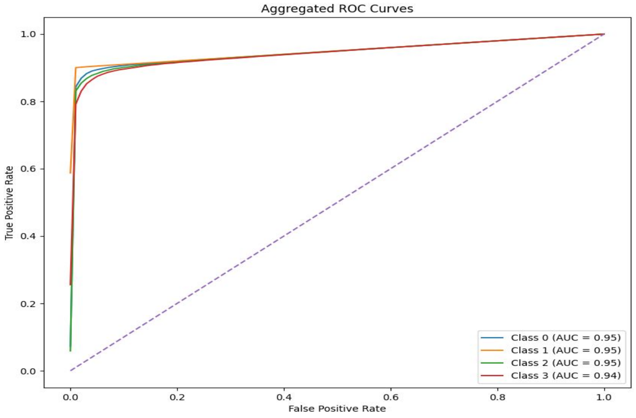
AUC , ROC curves & Confusion Matrix



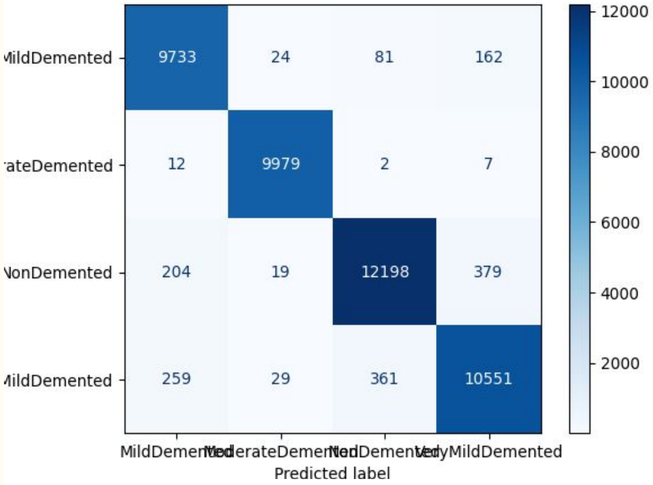


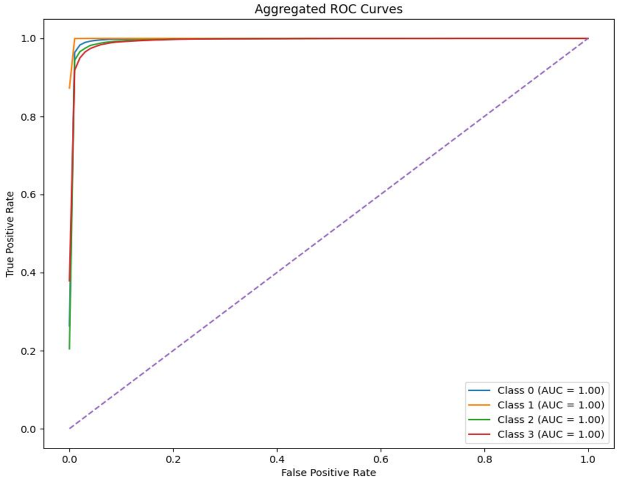
7-Conv Layers



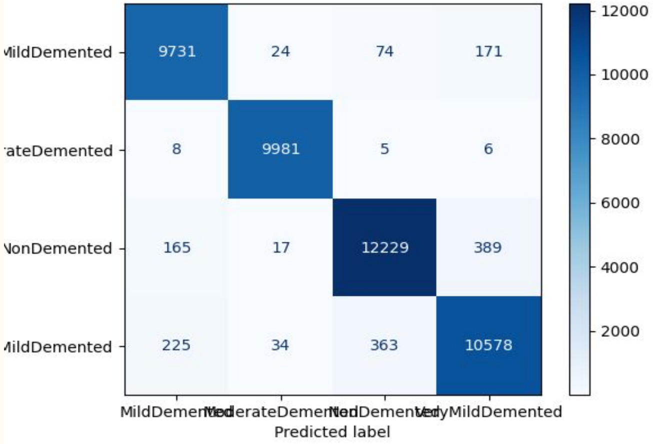


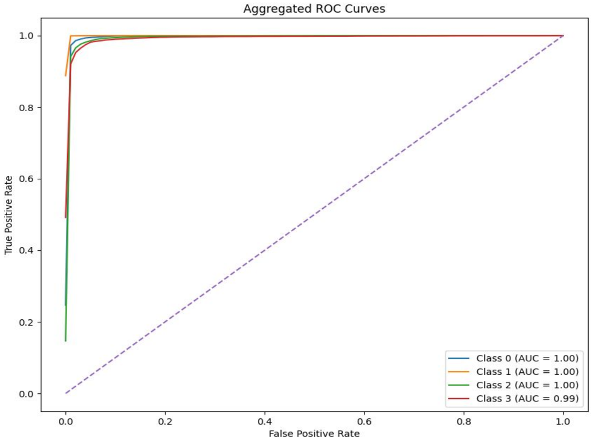
8-Conv Layers





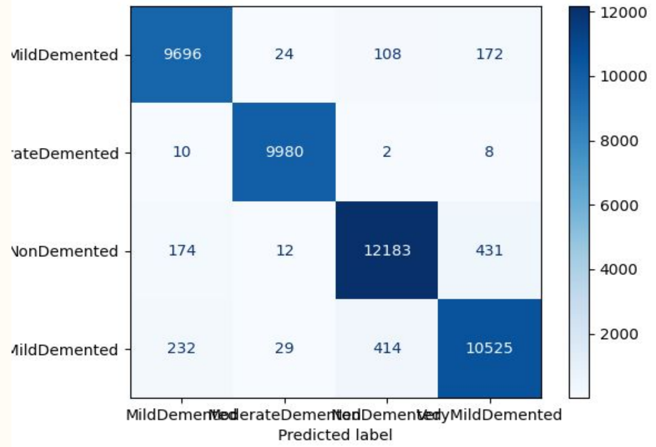
9-Conv Layers

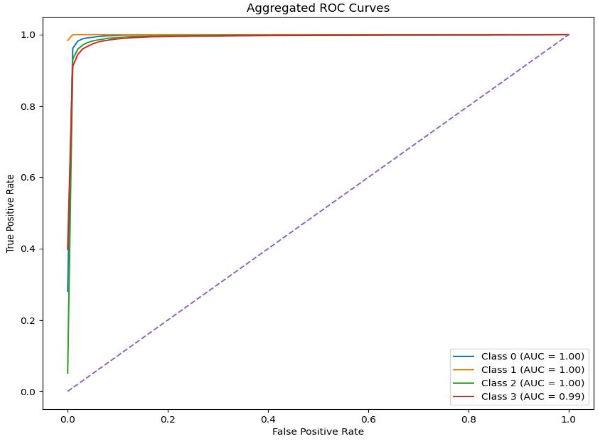




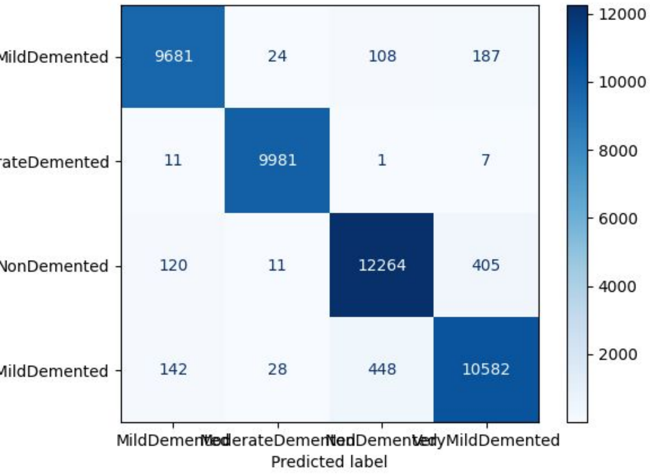
10-Conv Layers

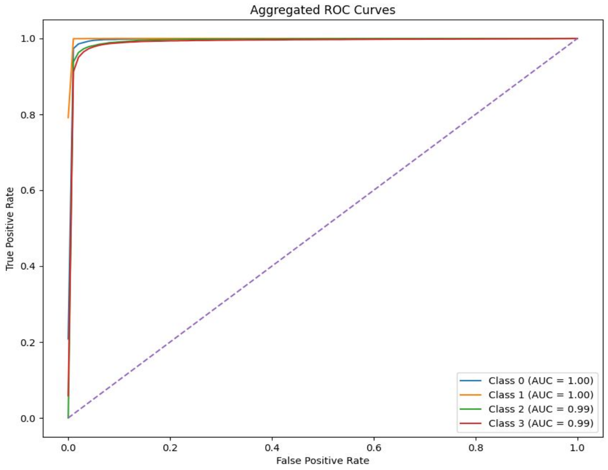
11-Conv Layers

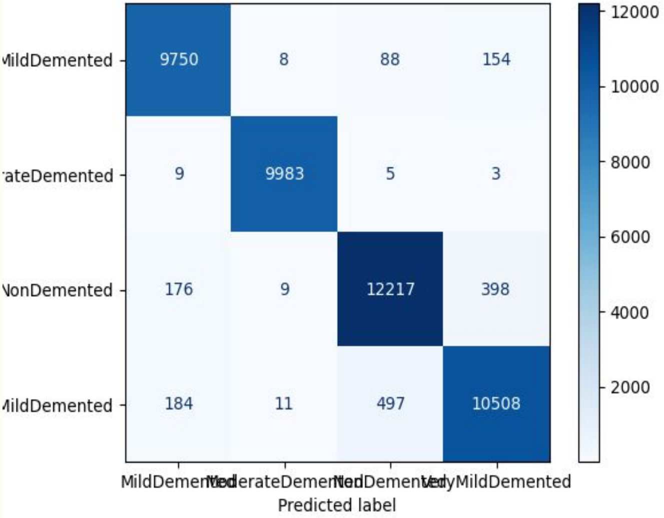


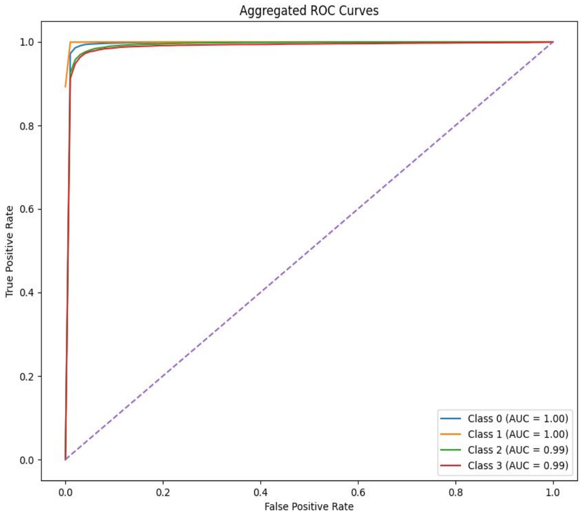


12-Conv Layers





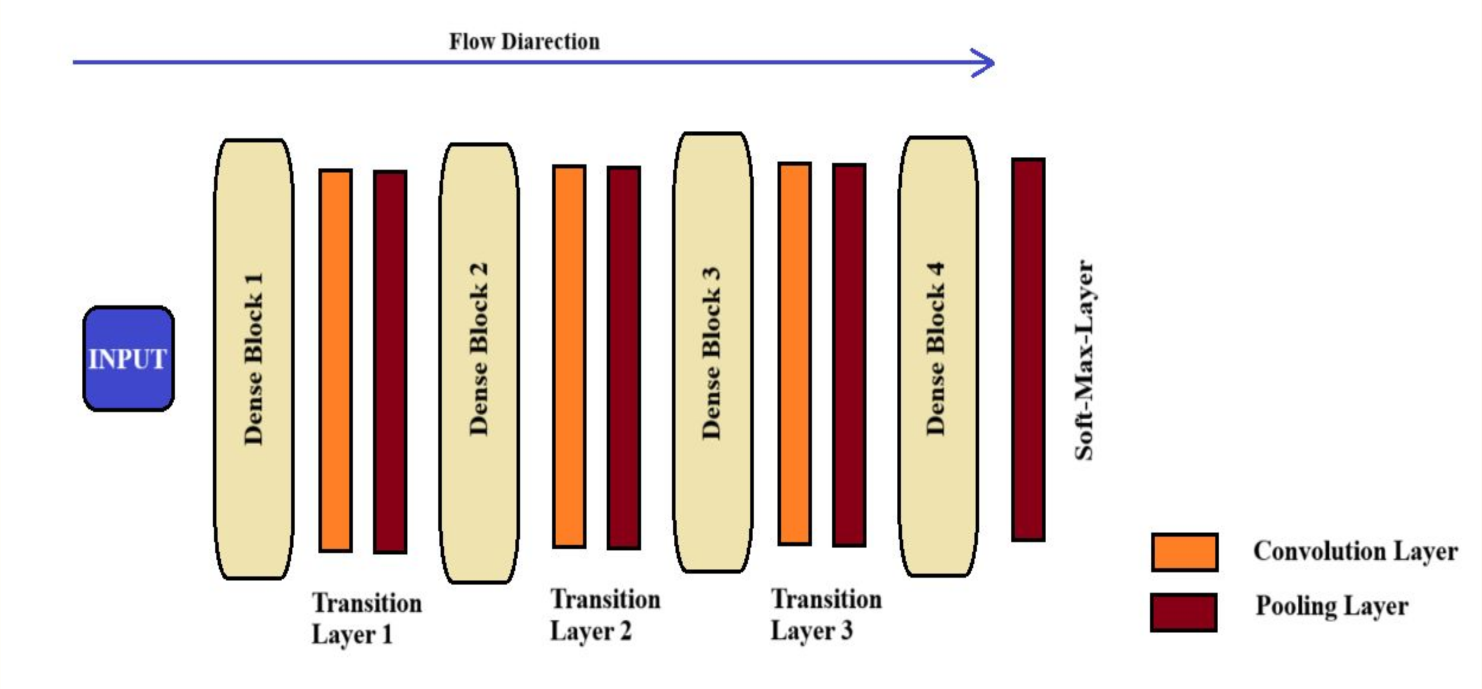




13-Conv Layers

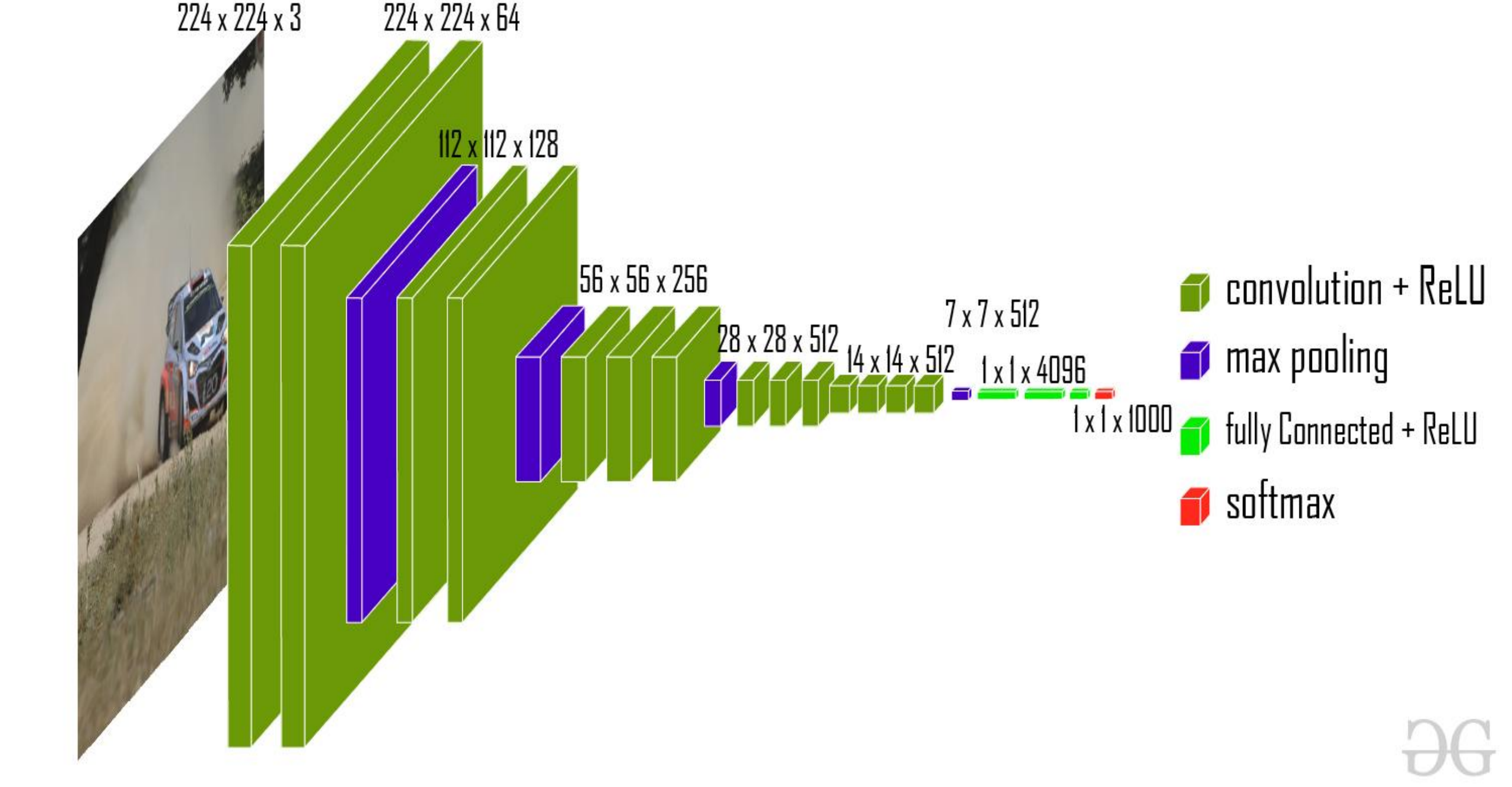
Pretrained Models

DenseNet-121



Here we freeze till Dense Block 3 and then apply fine tuning .
Image source → https://images.app.goo.gl/HPNJw9B6LDyPd31j9

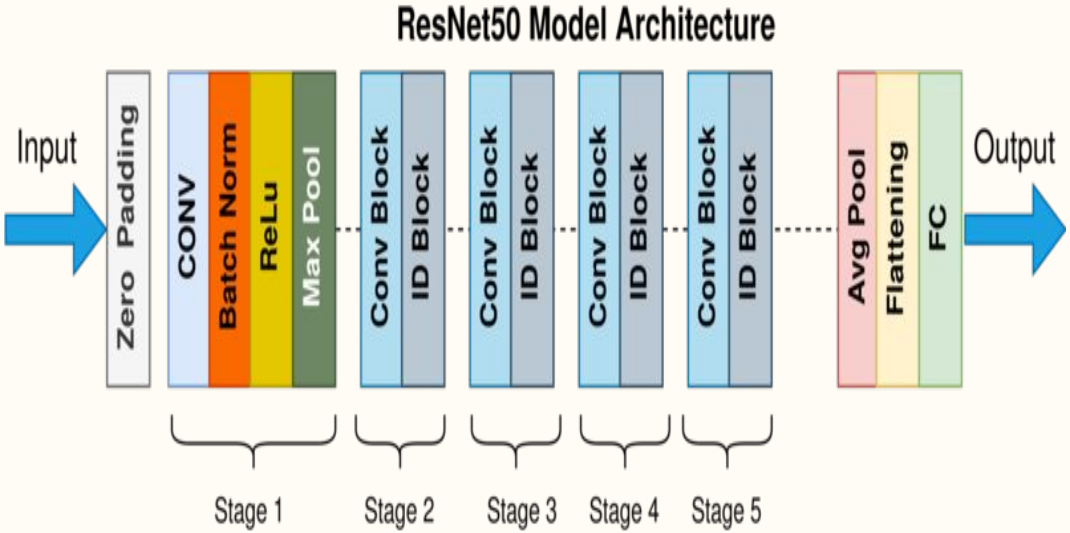
VGG16



No fine tuning → All layers are freezed

Image Source → [Link]

ResNet50



First 40 convolution layers are freezed .

Image source → [Link]

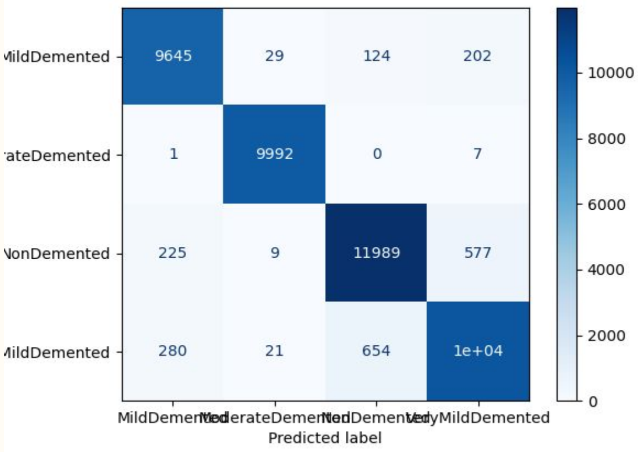
MobileNetV2

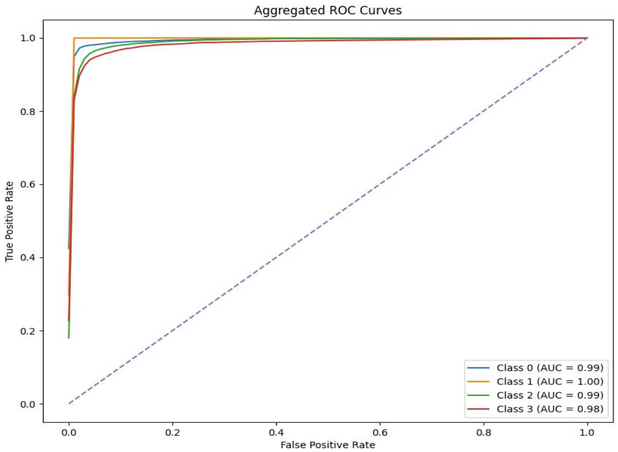
First 13 Convolution Layers are freezed.

Model	Accuracy	Precision	F1-Score	Specificity
VGG16	95.16%	0.9532	0.9533	0.9836
ResNet50	92.80%	0.9307	0.9304	0.9757
MobileNetV2	96.34%	0.9645	0.9646	0.9877
DenseNet-121	98.01%	0.9807	0.9809	0.9933

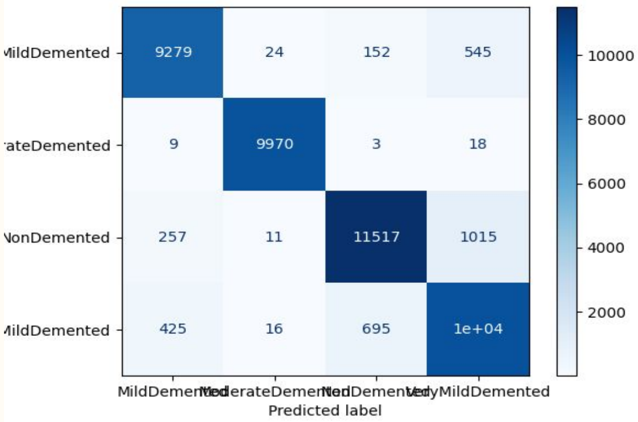
AUC , ROC curves & Confusion Matrix

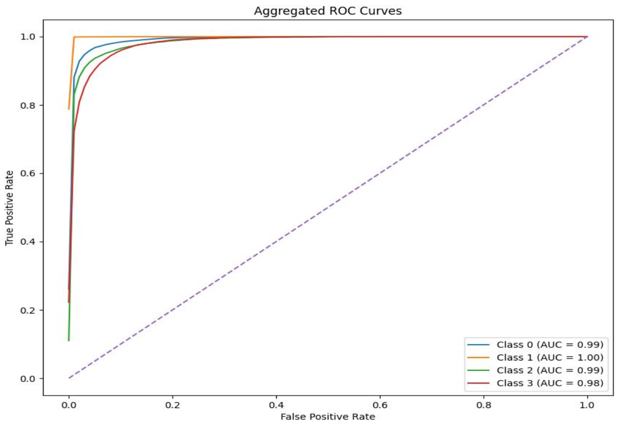
VGG16



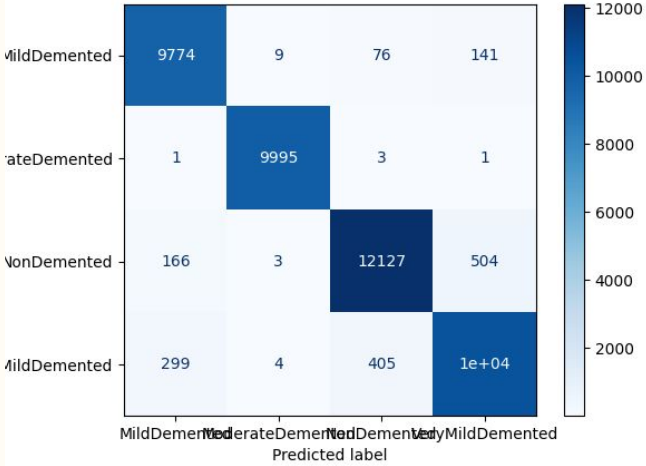


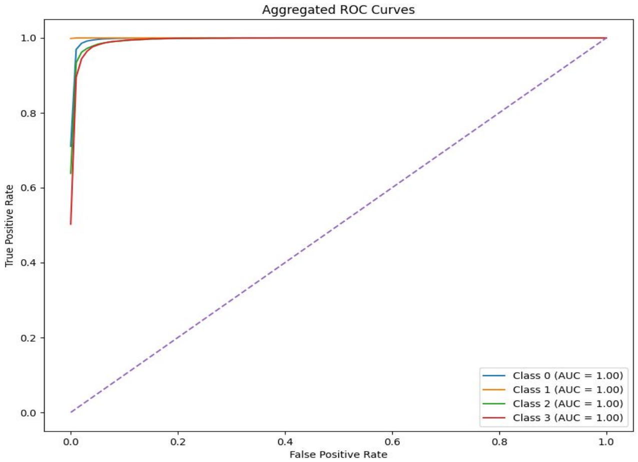
ResNet50



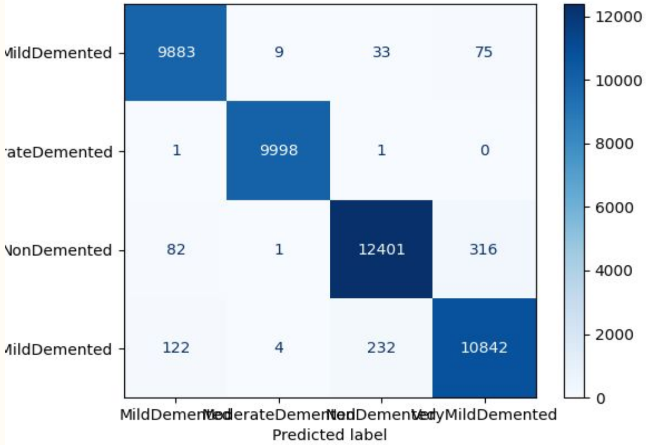


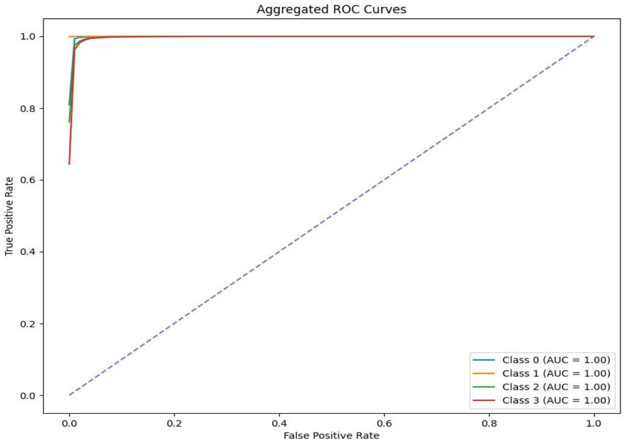
MobileNetV2



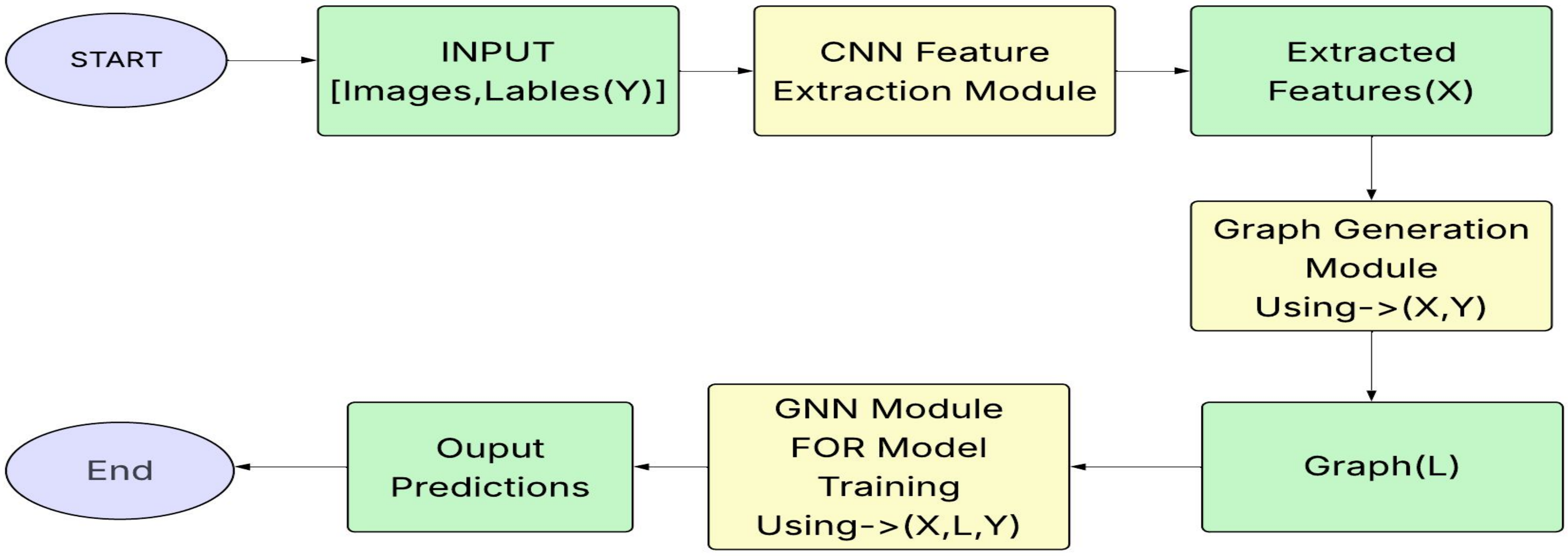


DenseNet121





Future Deliverable



Conclusion

We conclude that :-

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

References

- Fig-CNN-1   Source Link -> https://www.upgrad.com/blog/image-classification-in-cnn/
- GFG-CNN -> https://www.geeksforgeeks.org/
- Stanford University-CNN -> https://youtu.be/vT1JzLTH4G4?feature=shared
- CampusX-DL -> https://youtu.be/2dH_qjc9mFg?feature=shared
- PyTorch -> https://pytorch.org/
- Fig-1 -> Link
- Fig-2 -> https://i.sstatic.net/BBlAb.png
- Paper 1 -> https://link.springer.com/chapter/10.1007/978-3-319-70772-3_20
- Paper 2 -> https://ieeexplore.ieee.org/abstract/document/9364155
- Paper 3 -> https://www.mdpi.com/2075-4418/12/7/1531
- Paper 4 -> https://www.nature.com/articles/s41598-025-86635-2

THANK YOU