IIIT Bhubaneswar

ADVISOR

Dr. Sanjay Saxena

TEAM

B.Prithiraj (B520016)
Nirmit Gupta (B520034)
Sarit Samyak Rath (B520048)

Implementation of AI methods for Alzheimer's disease detection.

Objective

- To **investigate the effectiveness of advanced Artificial Intelligence (AI) techniques in the early detection of Alzheimer's disease** by analyzing various biomarkers, including speech data, neuroimaging data, etc.

- To **develop AI-based diagnostic models and compare the performance of different AI algorithms**, including **deep learning**, **machine learning**, and **hybrid models**, in the detection of Alzheimer's disease.

Background

Alzheimer's disease is a neurodegenerative disorder that affects millions of people worldwide. Various Artificial intelligence (AI) techniques have shown great potential in aiding the detection and diagnosis of Alzheimer's disease.

- **Neuroimaging Analysis:** Neuroimaging techniques, such as magnetic resonance imaging (MRI), positron emission tomography (PET), and functional MRI (fMRI), provide detailed images of the brain's structure and function.
- **Machine Learning:** Machine learning techniques play significant role in Alzheimer's detection. Supervised learning algorithms can be trained on large datasets of neuroimaging data, or clinical data to identify patterns and develop predictive models. These models can then be used to classify individuals as either having Alzheimer's disease or being healthy.
- **Deep learning and Transfer Learning:** A subset of machine learning, involves training artificial neural networks with multiple layers to learn hierarchical representations of data. Convolutional neural networks (CNNs) are commonly used in Alzheimer's detection to analyze neuroimaging data. These networks can automatically extract features from images and classify them as indicative of Alzheimer's disease or healthy brain function.

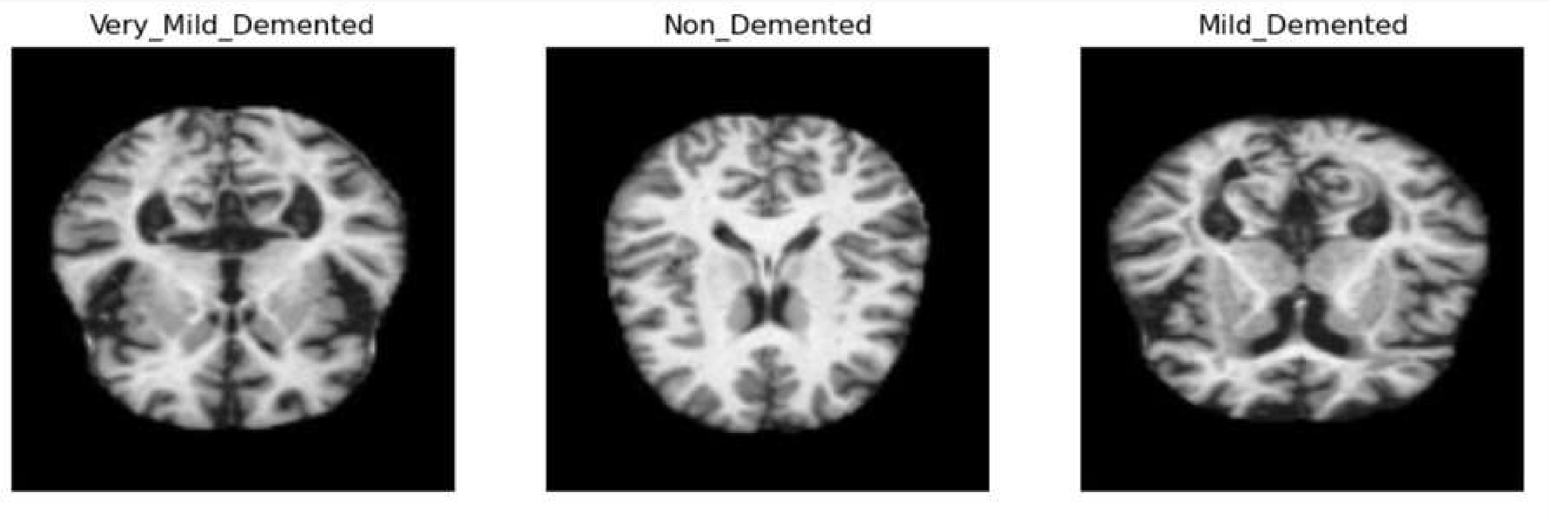
Dataset Used

Alzheimer MRI Preprocessed Dataset

The project utilizes the Alzheimer MRI Preprocessed Dataset obtained from Kaggle. The dataset consists of 6400 preprocessed MRI images, resized to 128 x 128 pixels, representing different stages of Alzheimer's disease.

Dataset Details

- Total Images: 6400
- Classes:
  - Class 1: Mild Demented (896 images)
  - Class 2: Moderate Demented (64 images)
  - Class 3: Non Demented (3200 images)
  - Class 4: Very Mild Demented (2240 images)



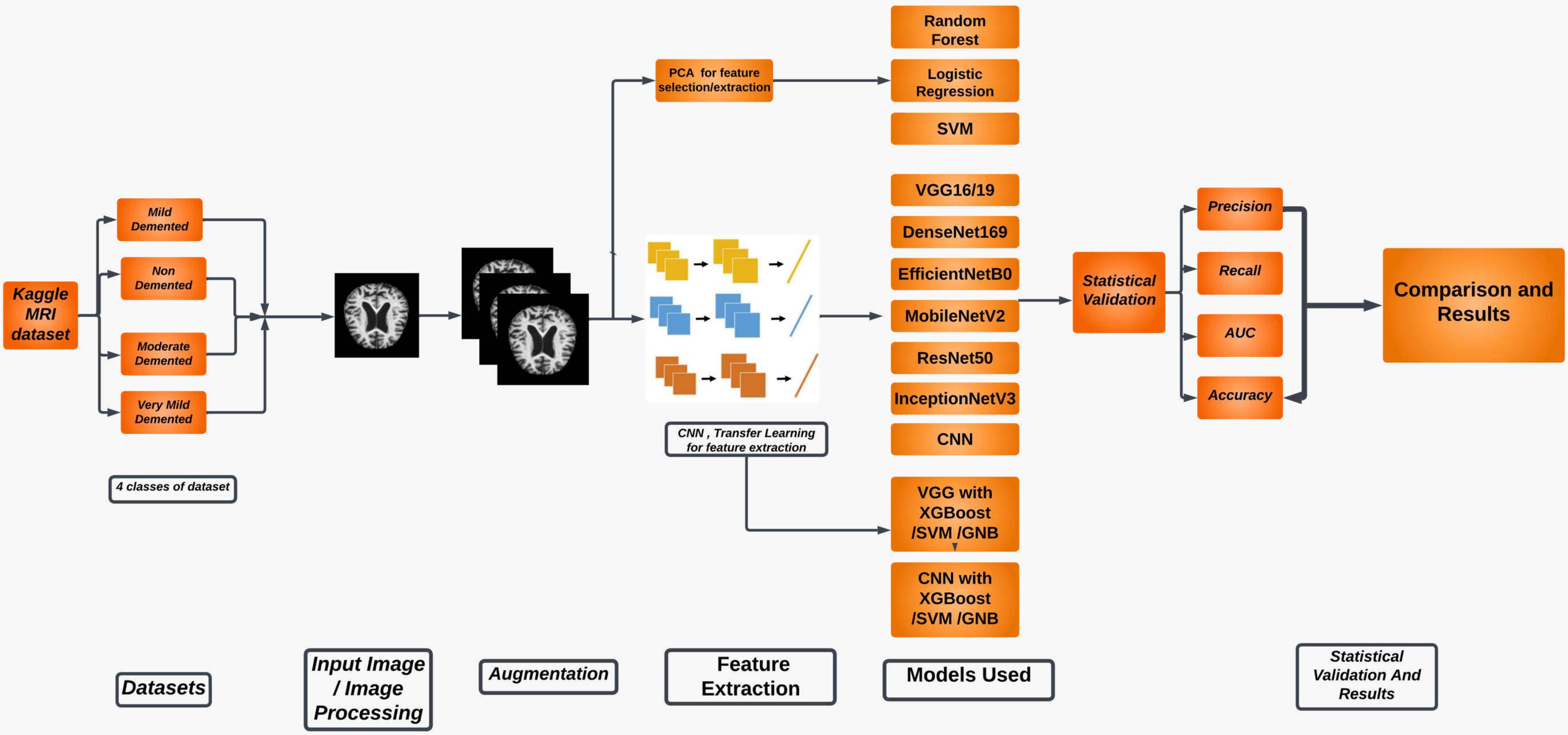
Working Environment

We ran our models and Jupyter Notebooks on the Online Kaggle setup.

Specifications

- CPU with 13GB RAM
- GPU P100 with 15.9GB
- Python Version: 3.9
- Tensorflow: 2.12.0
- SciKit Learn: 1.2.2

Working



Kaggle MRI dataset
Mild Demented
Non Demented
Moderate Demented
Very Mild Demented
4 classes of dataset
PCA for feature selection/extraction
CNN , Transfer Learning for feature extraction
Random Forest
Logistic Regression
SVM
VGG16/19
DenseNet169
EfficientNetB0
MobileNetV2
ResNet50
InceptionNetV3
CNN
VGG with XGBoost /SVM /GNB
CNN with XGBoost /SVM /GNB
Statistical Validation
Precision
Recall
AUC
Accuracy
Comparison and Results
Datasets
Input Image / Image Processing
Augmentation
Feature Extraction
Models Used
Statistical Validation And Results

Working

Step 1: Input dataset

We gathered and prepared our Dataset form Kaggle , organizing them into appropriate directories(Train,Test,Validation), and ensuring proper labeling for them.

Step 2: Preprocessing of images and augmentation

We perform necessary preprocessing steps on the images, such as resizing, normalization, and cropping. Additionally, we applied data augmentation techniques like rotation, flipping, and zooming to increase the diversity and robustness of our training data.

Step 3: Feature Extraction using CNN and PCA

We utilize pre-trained convolutional neural network (CNN) models such as VGG16, VGG19, or Densenet169 to extract meaningful features from our images.We also can apply Principal Component Analysis (PCA) to reduce the dimensionality and retain the most informative components.

Working

Step 4: Models

Implemented and trained various models using the extracted features as input. It included models like VGG16/19, InceptionV3, Densenet169, etc., or any other suitable architectures for image classification tasks.
We trained these models on our labeled training data and fine-tuned the model's parameters to optimize their performance.

Step 5: Statistical validation

Evaluated the performance of our trained models using statistical validation measures such as precision, recall, area under the curve (AUC), and accuracy. These metrics provide insights into how well your models are performing in terms of classification accuracy and the balance between true positives and false positives.

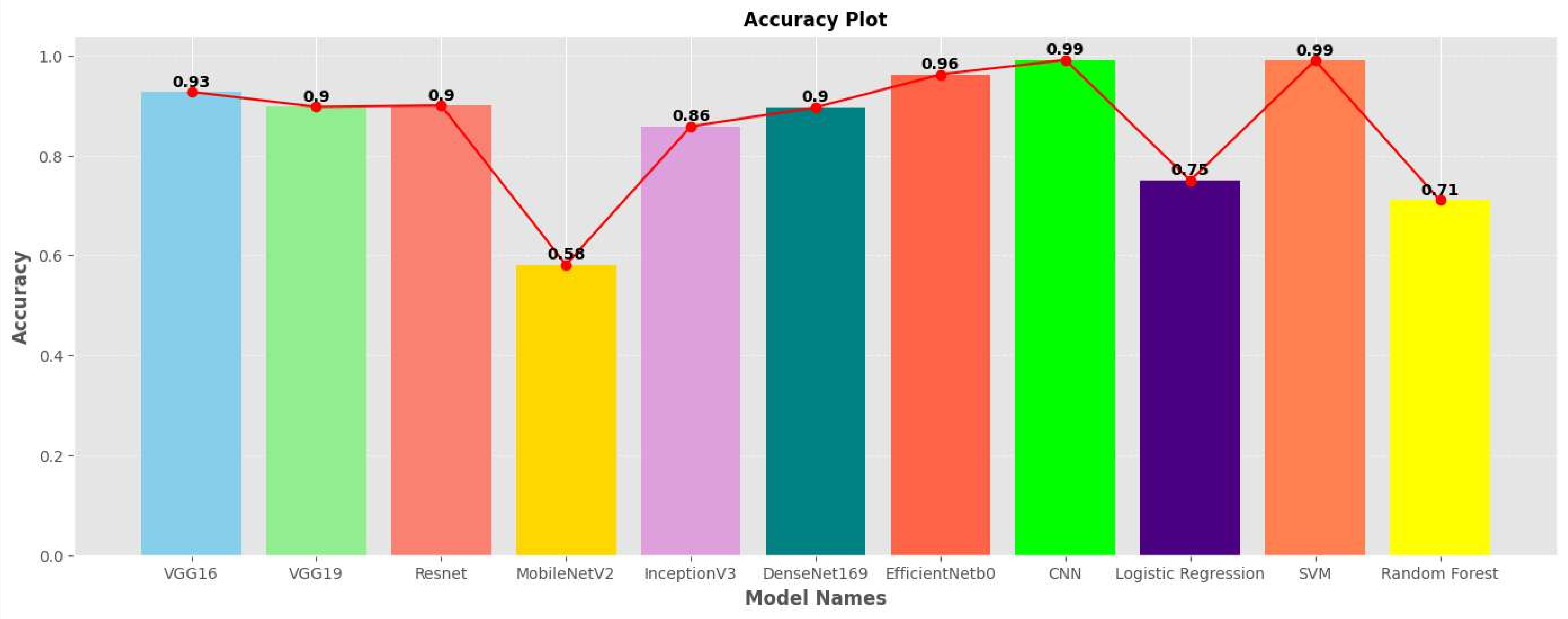
Step 6: Comparison of all models

Compared the performance of different models which we had trained based on the statistical validation measures. Analyzed the strengths and weaknesses of each model, consider factors like training time, model complexity, and interpretability, and make informed decisions about which model(s) to use for your specific image classification task.

Results

We have compared each our model performance based on the following metrics: Precision, Recall, Accuracy, AUC score and also built a confusion matrix above all the metrics mentioned. We have plotted comparison of each model performance on the basis of each of the above metrics.

The figure below shows **Model Performance of all the models trained on basis of accuracy.**



Results

The tables below show the respective **test accuracy, test precision, test recall, test AUC score** and **test loss** of the various ML and DL models implemented in our project.

Transfer Learning and Conventional CNN

Model	Test Loss	Test Accuracy	Test AUC	Test Precision	Test Recall
VGG16	0.193	0.927	0.993	0.928	0.924
VGG19	0.279	0.897	0.986	0.898	0.891
ResNet	0.324	0.900	0.982	0.903	0.897
MobileNetV2	0.941	0.581	0.842	0.620	0.483
InceptionV3	0.426	0.858	0.974	0.867	0.852
DenseNet169	0.304	0.896	0.981	0.899	0.889
EfficientNetb0	0.110	0.962	0.997	0.964	0.962
CNN	0.035	0.991	0.999	0.991	0.991

Machine Learning Models

Model	Accuracy	Precision	Recall
Logistic Regression	0.75	0.81	0.73
SVM	0.99	0.99	0.99
Random Forest	0.71	0.64	0.42

Discussion

MODEL PERFORMANCES:

As we can see from the plotted comparisons of different models based on their performance on basis of various metrics, our **custom CNN architecture model seems to outperform the other models by giving an accuracy of over 99 percent**.

Different Transfer Learning models have also performed good ,out of which notably EfficientNetB0 giving 96% accuracy, ResNet giving 90% and VGG16 giving 92% etc.

The PCA-SVM model also seems to have performed pretty good, also achieving an accuracy of almost 99%, better than many deep learning architectures!

However, Hybrid deep learning- machine learning models have somehow failed to perform well with very low accuracies <55%. Maybe more training on more powerful CPUs & GPUs, and probably a different approach could get us better results than the present ones.

Conclusion and Future Scope

- **Larger and more diverse datasets:** Acquiring larger and more diverse datasets can help improve the performance and generalizability of the CNN model.

- **Multi-modal data fusion:** Incorporating multiple imaging modalities, such as functional MRI (fMRI), positron emission tomography (PET), or cerebrospinal fluid (CSF) biomarkers, along with MRI data, can provide complementary information for more accurate prediction.

- **Longitudinal analysis:** Alzheimer's disease is a progressive condition that evolves over time. Incorporating longitudinal data and analyzing disease progression can offer valuable insights into the temporal patterns and changes in brain structures.

- **Integration with clinical data:** Combining MRI data with clinical information, such as cognitive test scores, medical history, genetic data, or lifestyle factors, can lead to a more comprehensive and accurate prediction model.

Thank You