B.Tech. Project (8th semester) PRESENTATION

*of the project entitled* "Prediction of Cardiovascular Risk Factors from retinal fundus images using deep learning algorithms"

*by*

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# OUTLINES

- Introduction
- Literature Review
- Research Gap
- Technical Novelty
- Challenges
- Objectives
- Methodology
- Evaluation Metrics
- Results
- Future Work Plan
- Acknowledgement
- References

# INTRODUCTION

- **<u>What is Cardiovascular Disease?</u>**
- Cardiovascular disease (CVD) refers to a class of diseases that involve the heart or blood vessels (arteries and veins).
- These diseases can impair the normal functioning of the cardiovascular system, which is responsible for pumping blood throughout the body, delivering oxygen and nutrients to cells, and removing waste products.
- **<u>WHAT IS RETINAL FUNDUS IMAGE :</u>**
- A retinal fundus image is a specialized medical image that captures a detailed view of the back of the eye, including the retina, optic disc, blood vessels, and surrounding structures.
- **<u>Types Of Cardiovascular Diseases:</u>**

1.Coronary Artery Disease (CAD)
2.Heart Failure
3.Arrhythmias
4.Hypertension (High Blood Pressure)
5.Heart Valve Disease
6. Peripheral Artery Disease (PAD)

# INTRODUCTION

## CHANGES IN RETINAL FUNDUS IMAGE DUE TO CARDIOVASCULAR DISEASE:

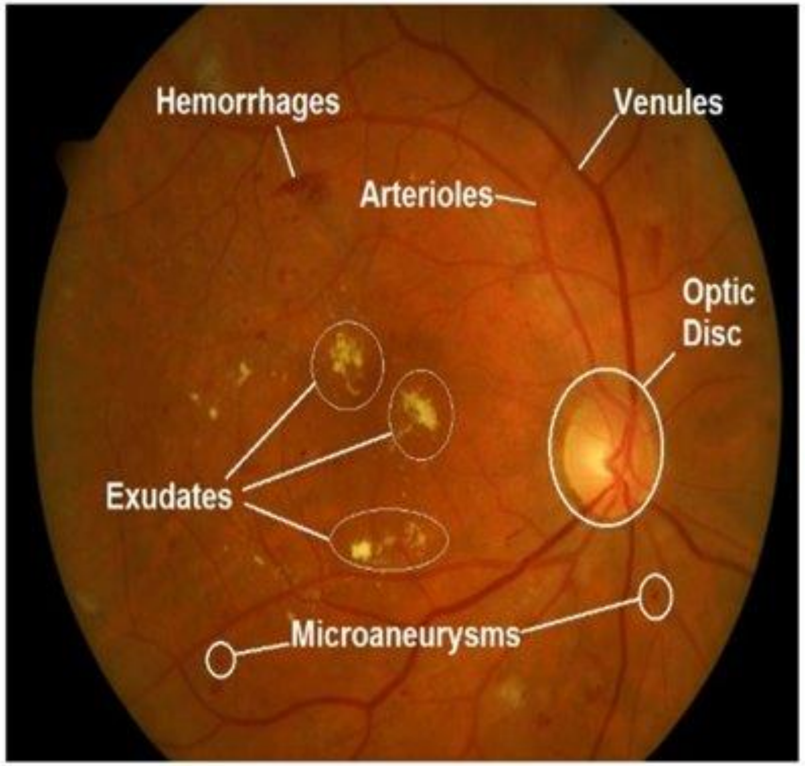


Fig: Parts of Retinal Fundus Image

- 1.Retinal Vascular Changes
- 2.Microvascular Abnormalities
- 3.Arteriovenous Nicking
- 4.Atherosclerosis
- 5.Embolisms

- Cardiovascular Risk Factors :
- High blood pressure (Hypertension).
- High cholesterol levels.
- Smoking.
- Diabetes.

# LITERATURE REVIEW

| S. NO | Research Paper | Methodology | Limitations |
|---|---|---|---|
| 1. | Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning | Inception-v3 neural-network architecture was used. | • Very small Datasets.<br>• Inputs to existing cardiovascular risk calculators were missing from the datasets like lipid panels, blood pressure, HbA1c and accurate diagnosis of diabetic status. |
| 2. | Validation of a deep learning based retinal biomarker (Reti-CVD) in the prediction of cardiovascular disease: data from UK Biobank | The deep-learning algorithm of binary classification. It is based on a probability score derived from retinal photographs and CT scans. | • Misclassification Bias<br>• Variability in Retinal Photograph Quality<br>• Limited Generalizability, Lack of External Validation. |
| 3. | Diagnosing Cardio Vascular Disease (CVD) using Generative Adversarial Network (GAN) in Retinal Fundus Images | Ensemble Deep Learning Models for Heart Disease Classification. | Lack of Clinical Validation, Limited Sample Size, Lack of Comparative Analysis, Lack of External Validation, Limited Explanation of Methodology, |

| S. NO | Research Paper | Methodology | Limitations |
|---|---|---|---|
| 4. | Deep-learning-based cardiovascular risk stratification using coronary artery calcium scores predicted from retinal photographs. | A deep-learning algorithm was trained to predict the presence of CAC (Cervical Arterial Conjunctival Cell) using retinal photographs . The algorithm was tested using Cox proportional hazards models | • More CAC data are needed to test the performance changes for CAC prediction and directly compare CVD risk prediction between CT-measured CAC score and RetiCAC. |
| 5. | Development and validation of a deep learning algorithm using fundus photographs to predict 10-year risk of ischemic cardiovascular diseases among Chinese population | The deep learning architecture used Inception-Resnet-v2, with an input size of 299x299. Performance matrix and AUC curve used. | • The 10-year ICVD risk was calculated , which limited reliability of the algorithm.<br>• Data on current smoking status was absent in the development dataset. |
| 6. | Cardiovascular Risks Detection Using Fundus Image | Pre-processing methods like Manual Cropping, Vessel Enhancement and Outlier Removal employed. Pre-trained networks involved and model architectures taken into account are Mobile Net, Mobile Net V2, NASNet Mobile and InceptionV3. | A clear limitation comes from the fact that the labels used were obtained with the SCORE calculator. This limits the results of only being able to be as good as this calculator, which is reported to have a 0.72 AUC |

# RESEARCH GAP

- The dataset used in the first paper we reviewed, is relatively small, which limits the accuracy and generalizability of the models. Additionally, important inputs such as lipid panels and diagnosis of diabetic status were missing from the datasets, which could have improved the performance of cardiovascular risk prediction. Variables like blood pressure and HbA1c, were available for only one dataset and smoking habits were self-informed. Hence, datasets with confirmed patient history and grouped accordingly can yield more accurate results.
- Requirement of a larger and more diverse dataset, so that a single model can be generalized for a larger population. Considering the differences in risk factor patterns and cardiovascular disease profiles between different populations, further research is required to assess the applicability of the algorithm in different ethnic groups.
- Limited existence of prediction models for CVD risk factors compared to direct CVD which limits the validation of the model and comparison with other risk assessment tools.


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# TECHNICAL NOVELTY

- Early methods of detecting CVD include Electrocardiogram (ECG) , MRI, Blood Test, Echocardiography, etc. We can detect the early CVD risk factors efficiently through this process--

1. **Integration of Medical Imaging and AI :** This project merges medical imaging with advanced AI techniques to analyze retinal fundus images for cardiovascular risk assessment.
2. **Non-Invasive Early Detection :** Retinal imaging offers a non-invasive approach to detect cardiovascular risks at an early stage, improving the chances of timely intervention.
3. **Deep Learning and CNN :** Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), are employed to automatically extract intricate features from retinal images, aiding in the identification of subtle risk factors.
4. **Multimodal Data Fusion :** The project combines retinal images with patient clinical data, enhancing the accuracy of risk prediction models by considering various factors like age, gender, medical history, and lifestyle.

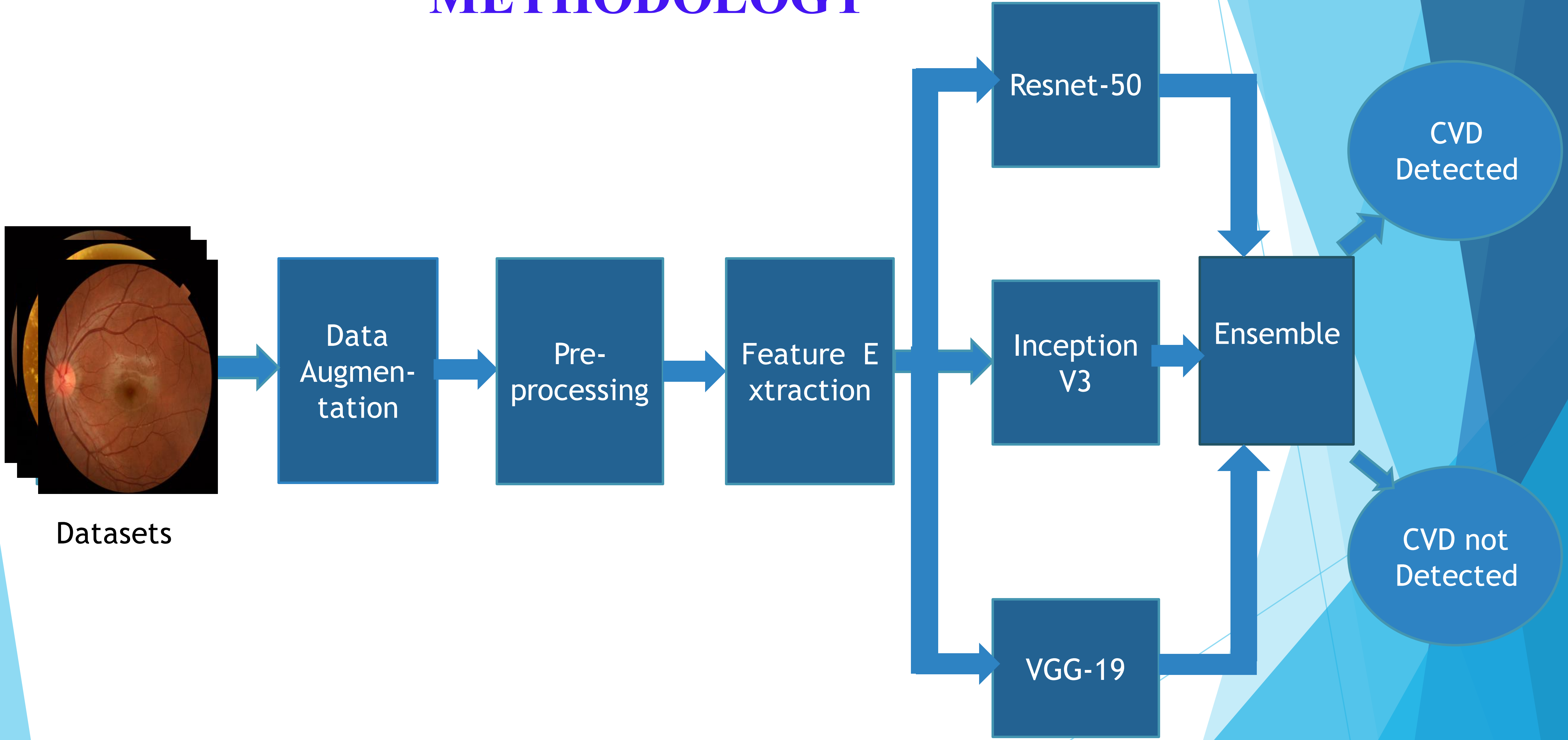
# CHALLENGES

- **Limited and imbalanced datasets :** Obtaining a large and diverse dataset of retinal fundus images with comprehensive cardiovascular health information can be challenging. Also, diagnosed patients' medical history like blood pressure,Hba1c levels, blood pressure, smoking status and family history of CVD is hard to obtain.
- **Interpretability :** Understanding the relationship between retinal changes and cardiovascular risk factors can be complex.
- **Feature Extraction and Selection :** Identifying relevant features or patterns in retinal images that are indicative of cardiovascular risk factors can be challenging.
- **Cost and Accessibility :** Getting datasets from UK Biobank and Implementing retinal imaging as a routine screening tool can be expensive.

# OBJECTIVE

- To collect real-time datasets of retinal Fundus images which are related to Cardiovascular disease because of the limited availability of the datasets.
- To integrate retinal imaging and non-imaging patient data to implement CAD (Computer-aided diagnosis) and make assessment and prediction of the patient’s condition.
- To develop a prototype that screens cardiovascular diseases risks through the automatic analysis of retinal fundus images and expand its potential use by further validation and comparison with risk-assessment tools.

# METHODOLOGY



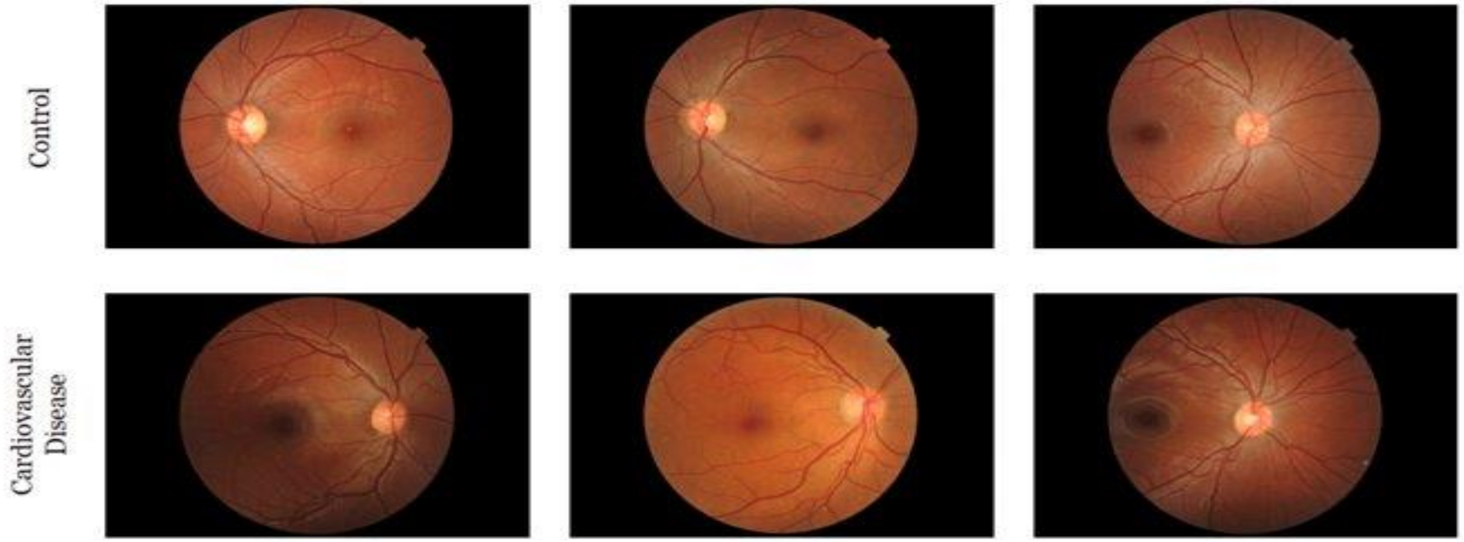
# METHODOLOGY

- **IMAGE PREPROCESSING :**
- Resizing images to a fixed resolution and then normalizing the pixel range values are the steps involved in image standardization.
- We resized images to 256 x 256 pixels to match the pretrained model input layer requirements.

- **Three Deep Learning architectures were implemented in this project :-**
  - VGG-19
  - RESNET-50
  - INCEPTION V3
  - ENSEMBLE MODEL

# METHODOLOGY

- **DATASET ACQUISITION:-**
- We acquired retinal fundus images dataset from publicly available datasets on the internet. The dataset which includes different types of Cardiovascular Diseases(CVD). These images will be used to train and test the pretrained models like Inception V3, Resnet-50, VGG-19 and Ensemble model.
- **SOURCES OF DATASET ACQUISITION:-** CHASE_DB1 ,STARE, MESSIDOR DATASETS .
- **TOTAL IMAGES COLLECTED:-** 770 IMAGES (AFTER AUGMENTATION, TOTAL IMAGES - 3400).




- Fig: Control (Normal) and CVD affected retinal fundus image

# METHODOLOGY

- **VGG-19:**
- **VGG 19** Is a CNN architecture that is 19 layers deep used for image classification.
- It employs 3x3 convolutional filters for feature extraction.
- The VGG19 has 3 **fully connected** layers.

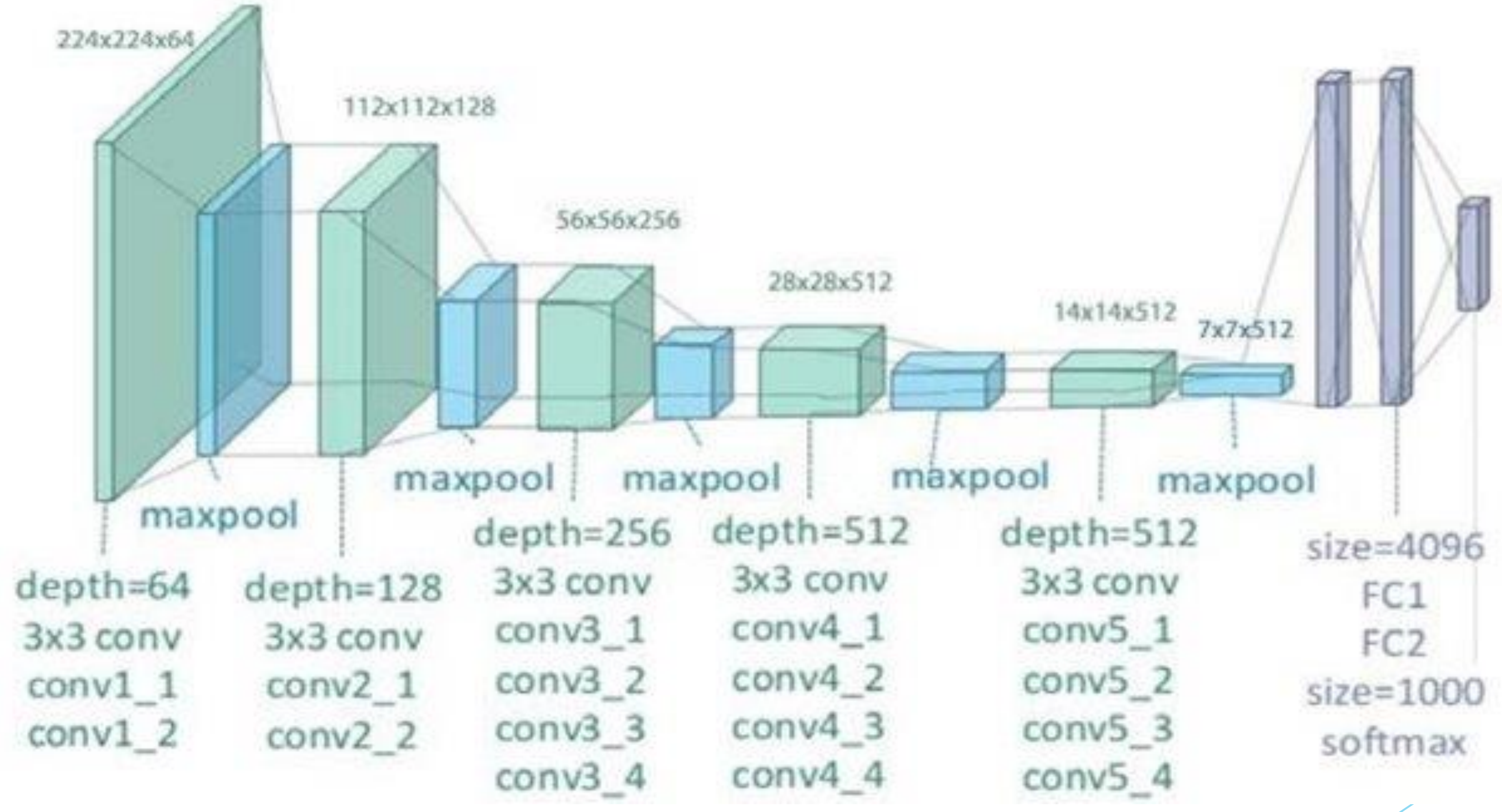



Fig :- VGG-19 Architecture

# METHODOLOGY

## ResNet-50 :

- ResNet-50 is a convolutional neural network that is 50 layers deep. ResNet, short for Residual Networks is a classic neural network used as a backbone for many computer vision tasks. The fundamental breakthrough with ResNet was it allowed us to train extremely deep neural networks with 150+layers.

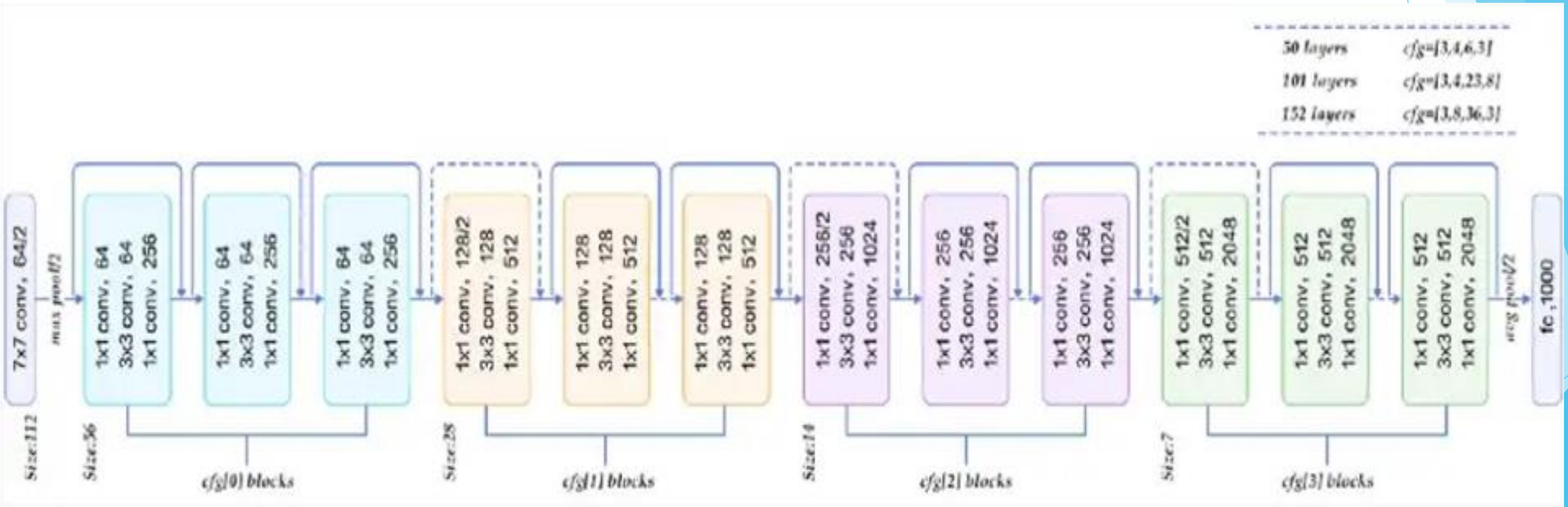



**Fig:- ResNet-50 Architecture**

# METHODOLOGY

- **Inception V3:**
- Inception V3 is a deep CNN architecture developed by Google in 2015 and has been trained on large datasets such as ImageNet.
- The architecture of Inception V3 includes 48 convolutional layers and 3.5 million parameters.
- Inception V3 also incorporates other techniques such as batch normalization, residual connections, and global average pooling, which help to improve its accuracy and performance on large-scale image classification tasks.

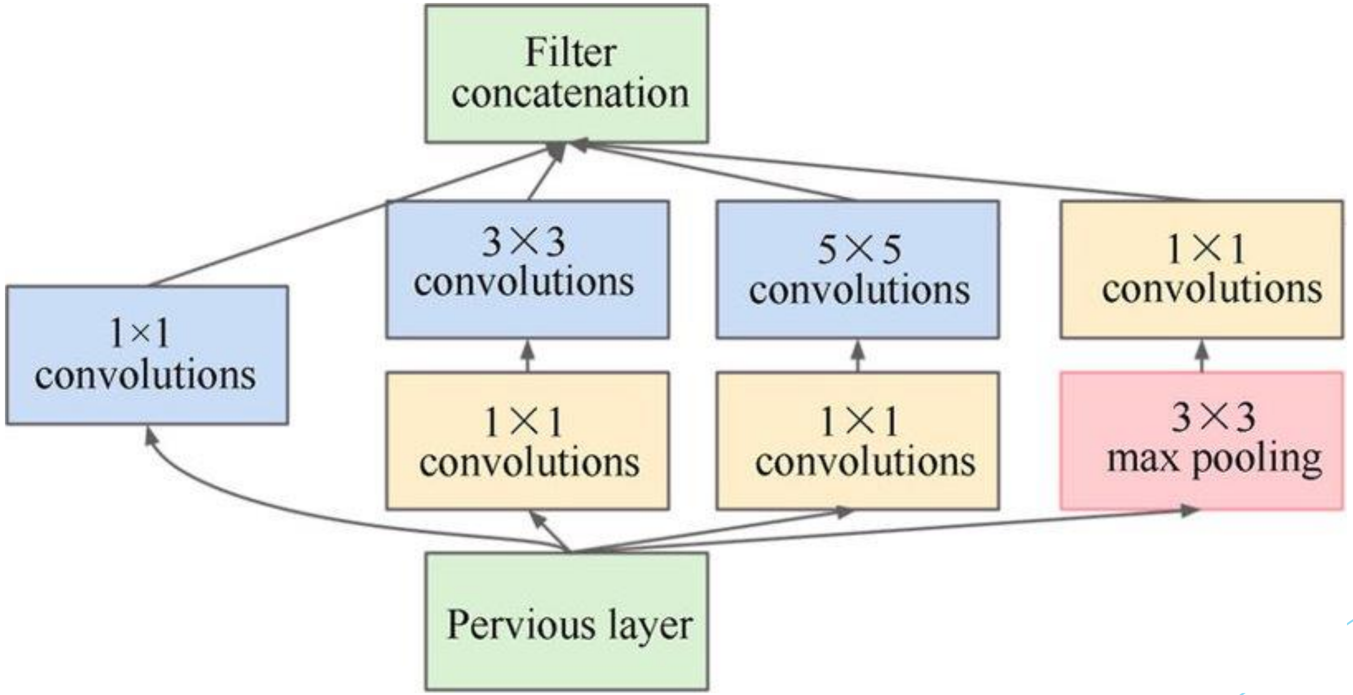



**Fig:- Inception module**

# METHODOLOGY

- **WORKING OF THE ENSEMBLE MODEL:-**

- Input image undergoes preprocessing specific to each model.
- Features are extracted from the image by Inception V3, ResNet 50 and VGG 19.
- Predictions are generated by each model based on the extracted features.
- Predictions from all three models are combined using a suitable method(e.g., averaging probabilities).
- The combined prediction serves as the final output of the ensemble model.

# METHODOLOGY

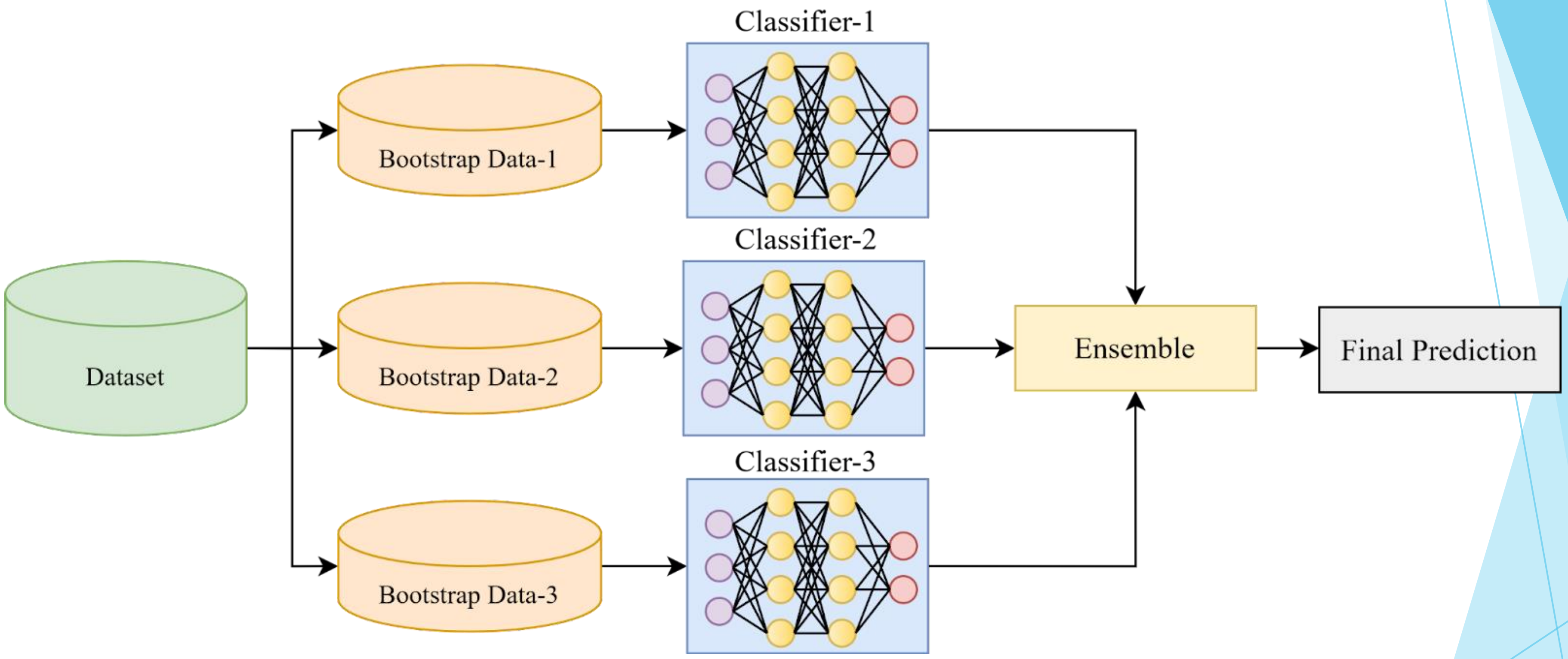



Fig:- Ensemble model Architecture

# EVALUATION METRICS

- **Plot loss (or error) vs. epoch or accuracy vs. epoch graphs**
- For neural network models, it is common to examine learning curve graphs to decide on model convergence. Generally, we plot loss (or error) vs. epoch or accuracy vs. epoch graphs. During the training, we expect the loss to decrease and accuracy to increase as the number of epochs increases. However, we expect both loss and accuracy to stabilize after some point.

- **Precision**
- The number of correct documents returned by our ML model.
- **Precision = TP/(TP+FP)**

- **Recall / Sensitivity**
- Recall may be defined as the number of positives returned by our ML model.
- **Recall = TP/(TP+FN)**

- **F1 Score**
- This score will give us the harmonic mean of precision and recall. Mathematically, F1 score is the weighted average of the precision and recall. The best value of F1 would be 1 and worst would be 0.
- $$\mathbf{F1} = 2 * (\boldsymbol{precision} * \boldsymbol{recall}) / (\boldsymbol{precision} + \boldsymbol{recall})$$

# RESULTS

**Overview of various models implemented:-**

| Parameters | Resnet-50 | VGG-19 | INCEPTION-V3 | ENSEMBLE MODEL |
|---|---|---|---|---|
| ACCURACY | 89.88 | 82.35 | 87.29 | 92.71 |
| PRECISION | 92.30 | 90.90 | 100 | 92.30 |
| RECALL | 92.30 | 83.33 | 92.85 | 92.30 |
| F1-SCORE | 92.30 | 86.95 | 96.29 | 92.30 |

# RESULTS

## Accuracy, Loss, Recall and Precision graphs of the models :-

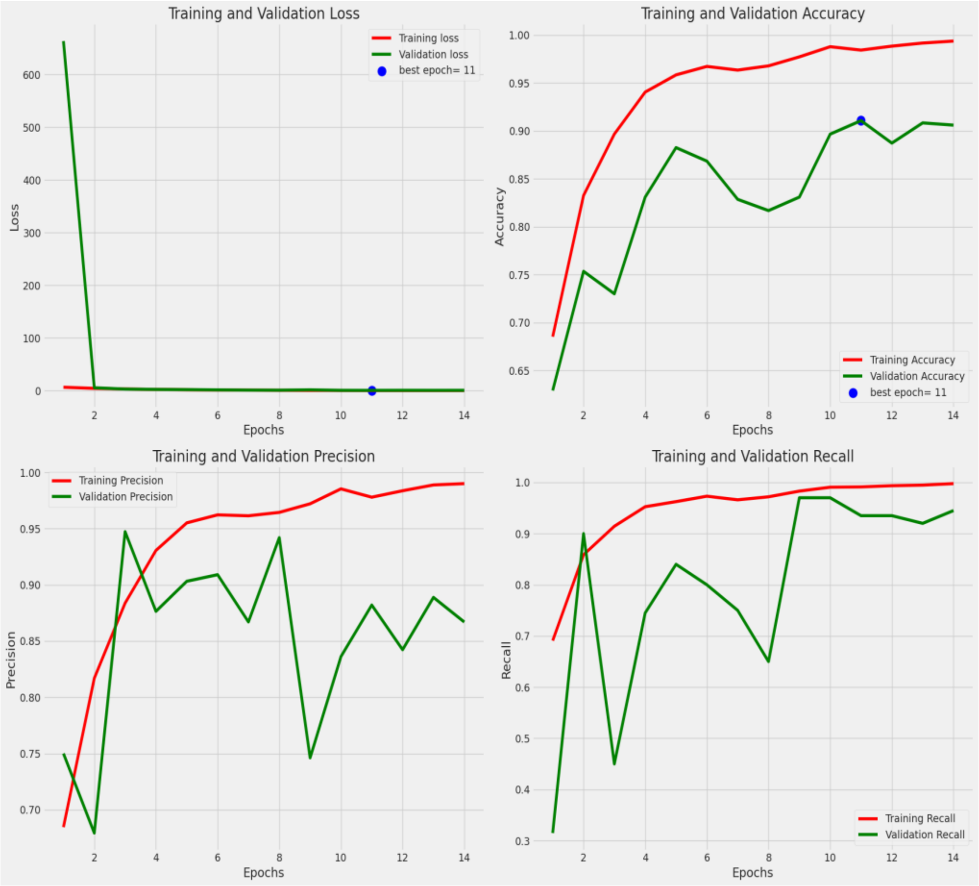



Fig:- Accuracy ,Loss, Recall and Precision graphs of Inception V3

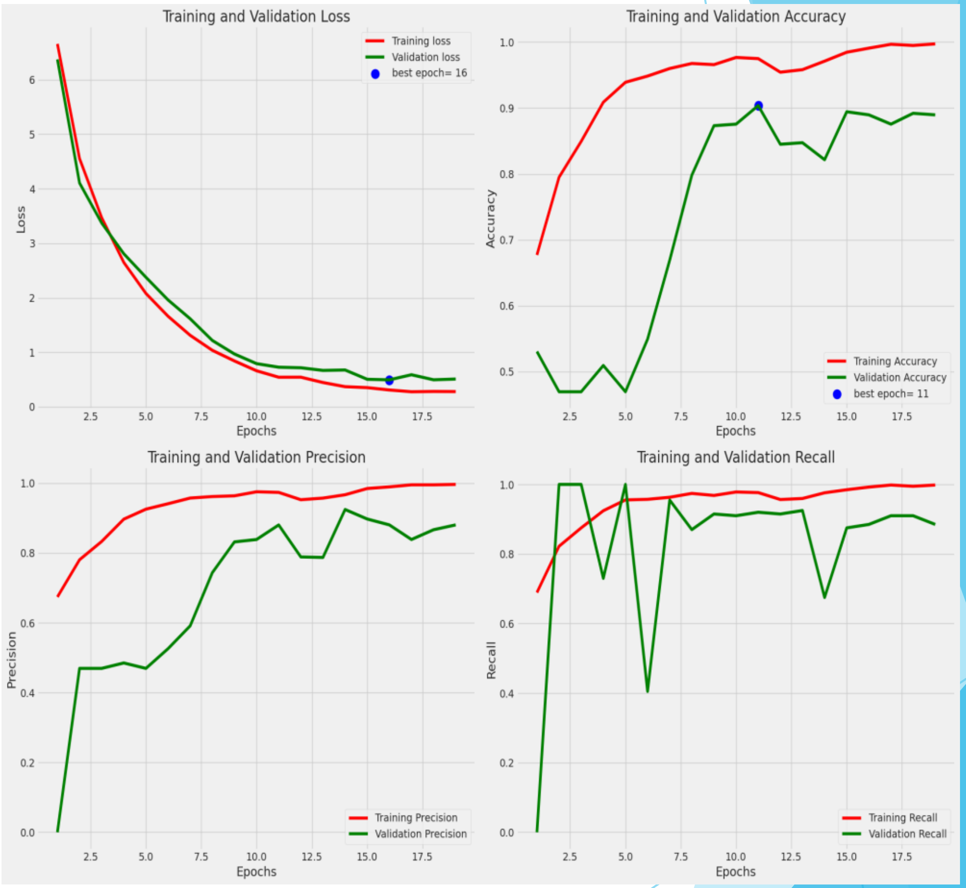



Fig:- Accuracy, Loss, Recall and Precision graphs of ResNet50

# RESULTS

- **Accuracy, Loss, Recall and Precision graphs of the models :-**

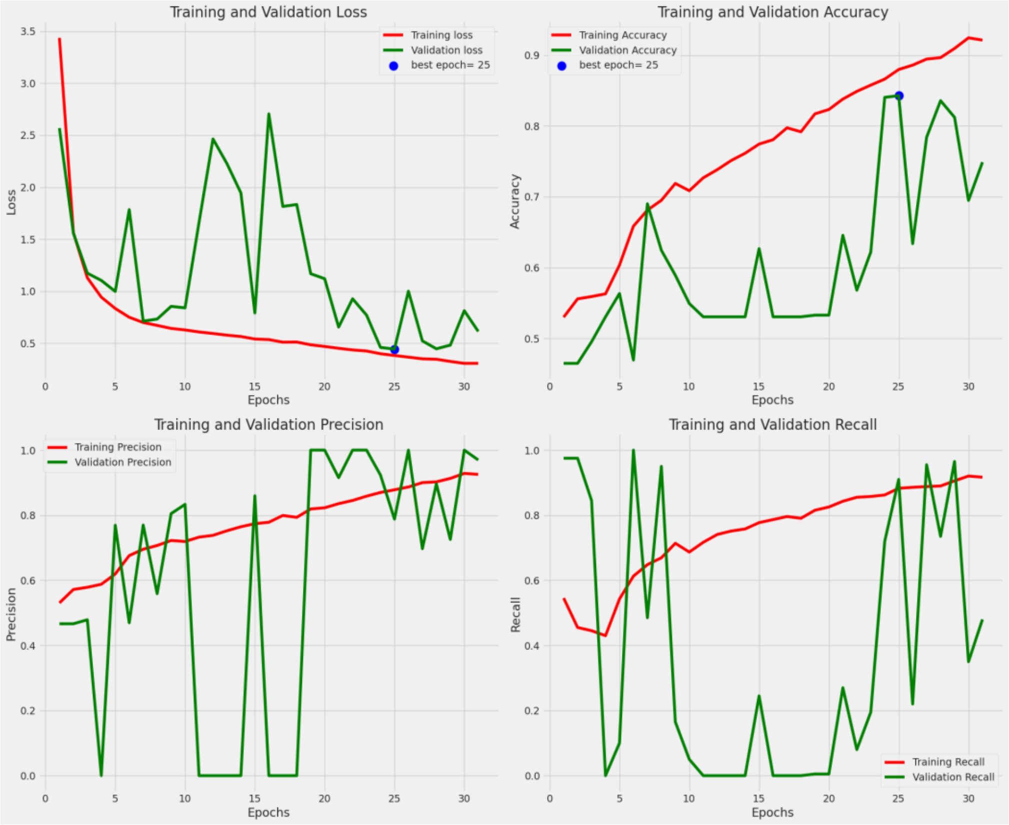



Fig:- Accuracy ,Loss, Recall and Precision graphs of VGG19

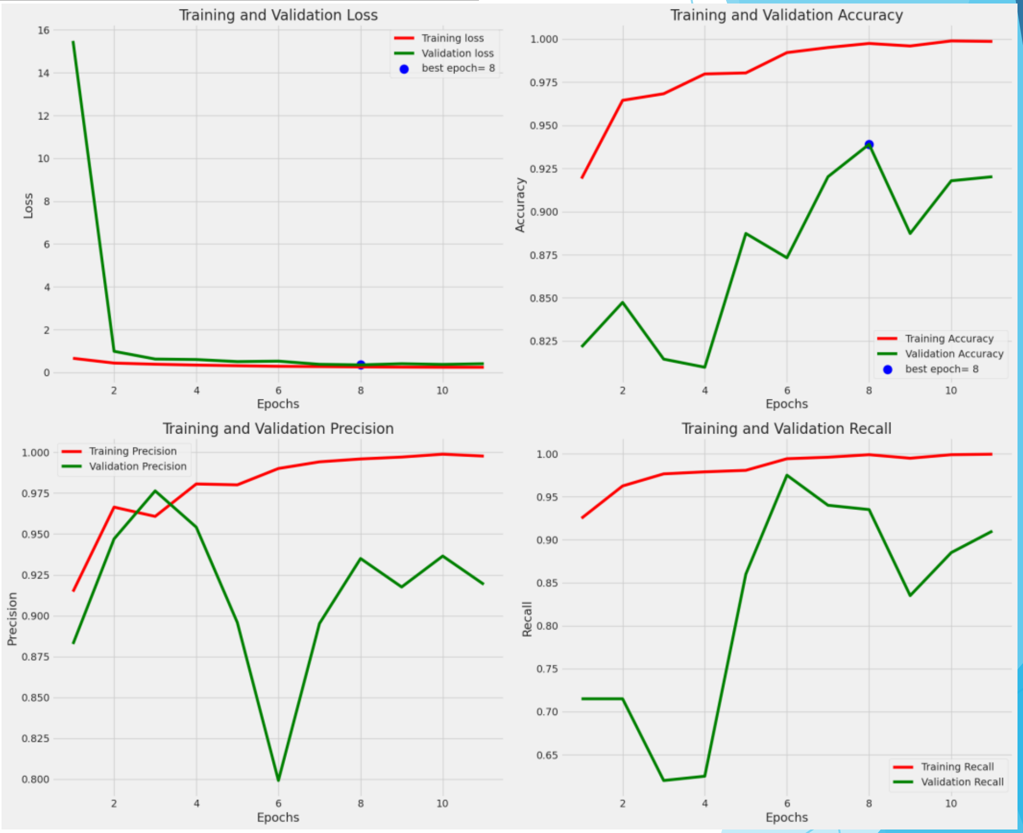
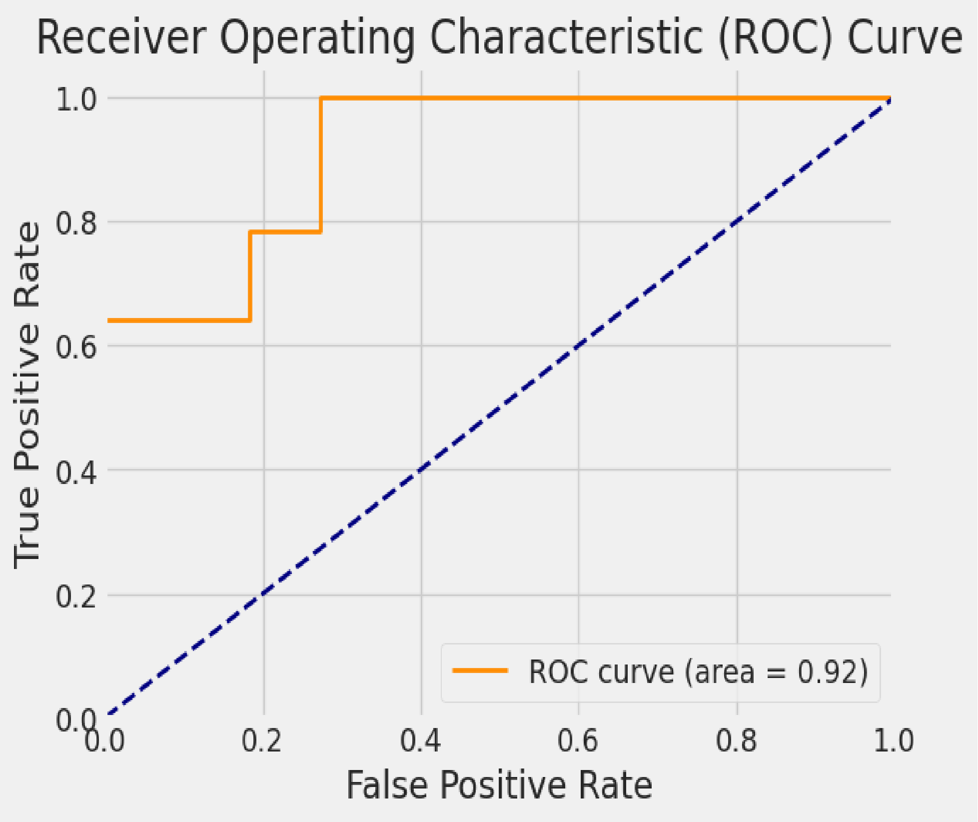



Fig:- Accuracy ,Loss, Recall and Precision graphs of Ensemble model

# RESULTS

## <u>ROC curve and confusion matrix of VGG-19 model:-</u>



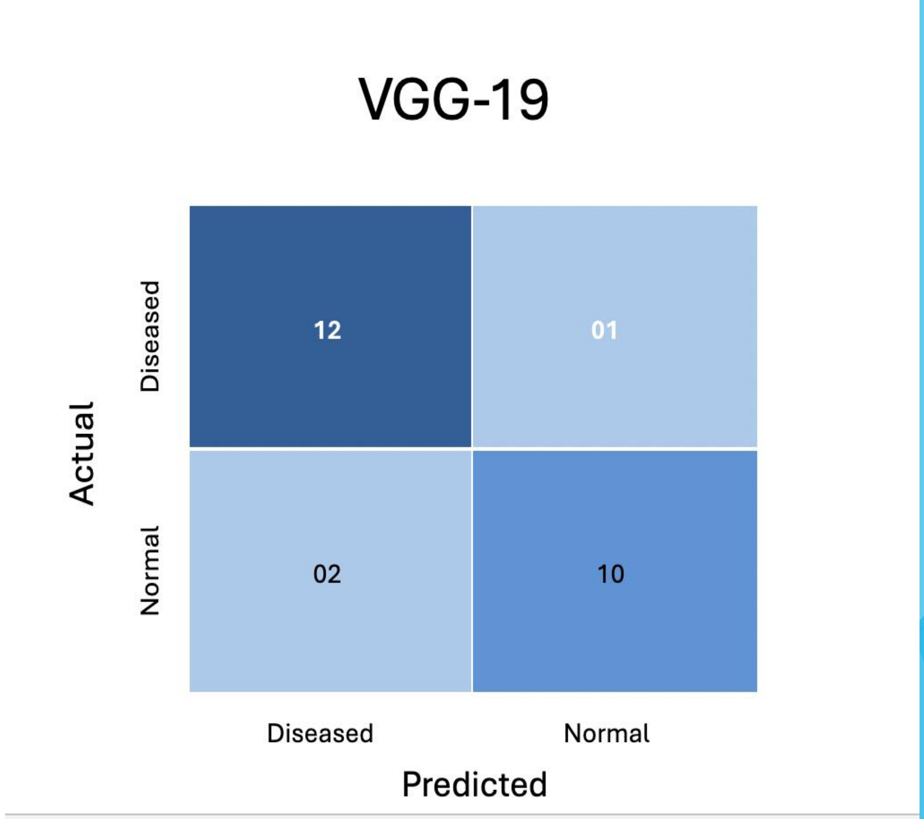




**Fig:- ROC curve of VGG-19 model with parameters (Precision,Recall,F1-Score)**

**Fig:- Confusion Matrix of VGG-19 model**

# RESULTS

## ROC curve and confusion matrix of resnet-50 model:-

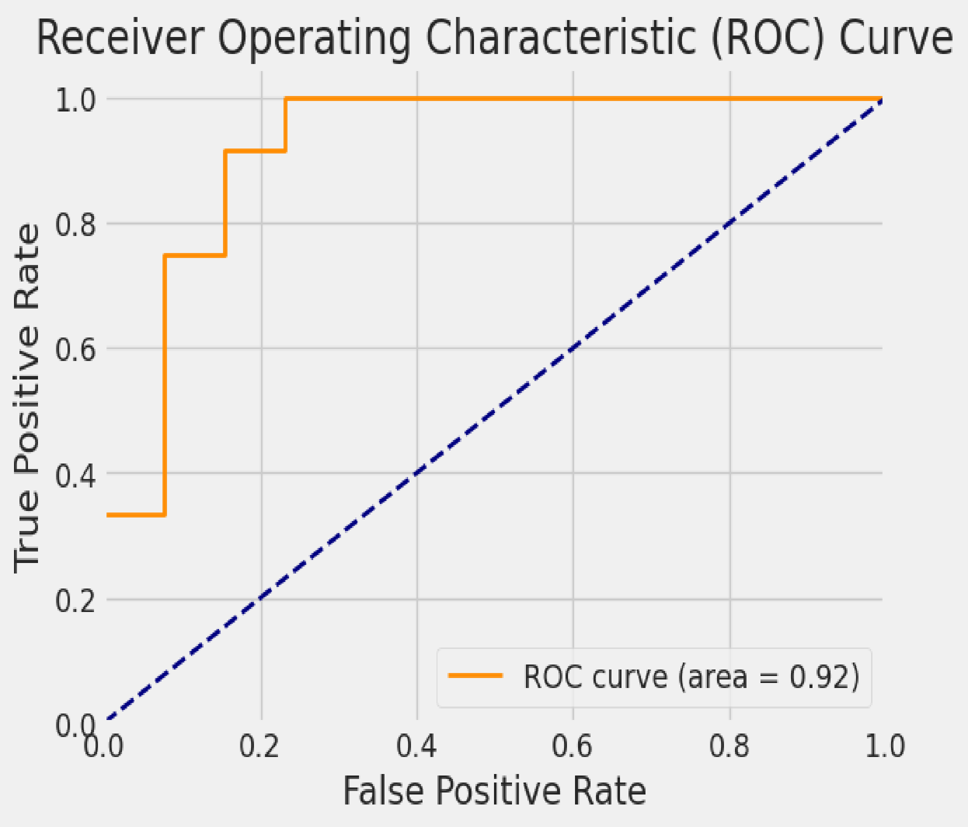



Fig:- ROC curve of Resnet-50 model with parameters (Precision,Recall,F1-Score)

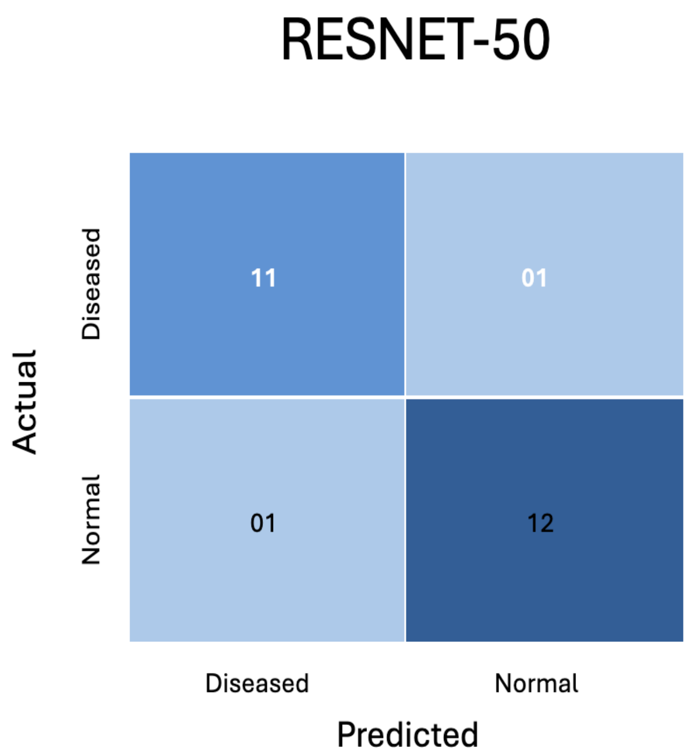



Fig:- Confusion Matrix of Resnet-50 model

# RESULTS

## ROC curve and confusion matrix of Inception-V3 model:-

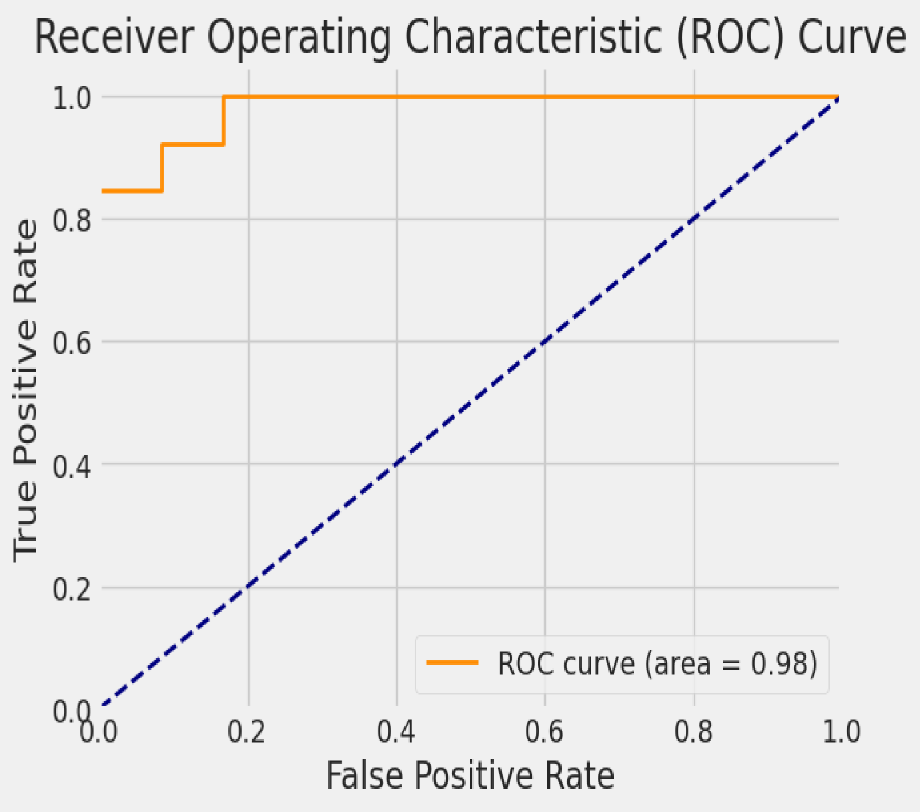



Fig:- ROC curve of Inception-V3 model with parameters (Precision,Recall,F1-Score)

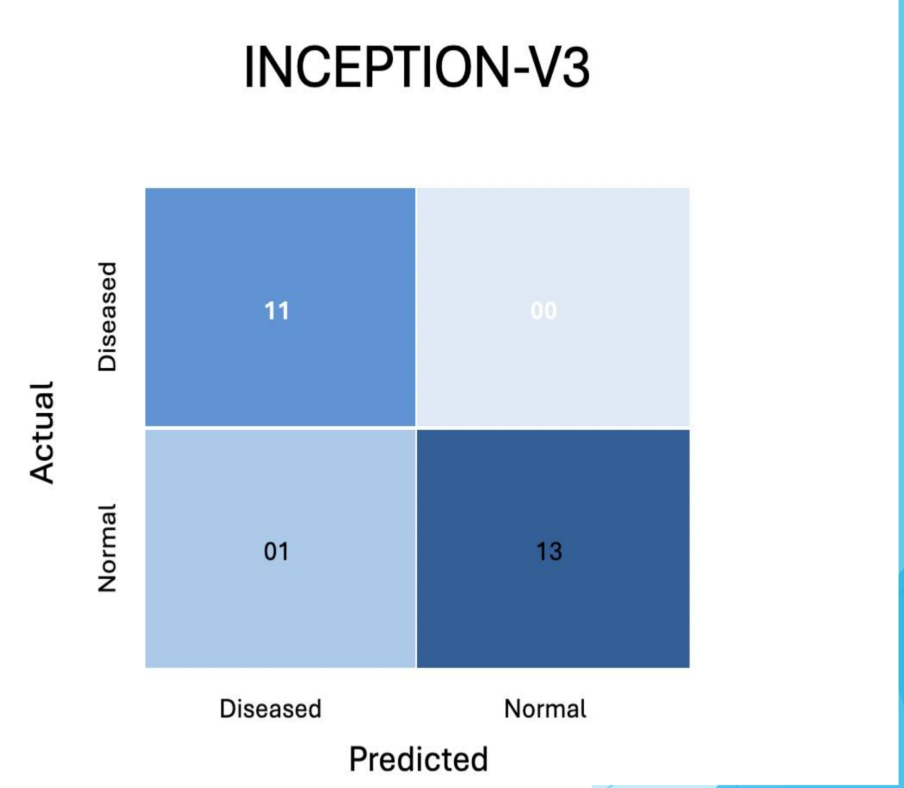



Fig:- Confusion Matrix of Inception-V3 model

# RESULTS

## ROC curve and confusion matrix of Ensemble model:-

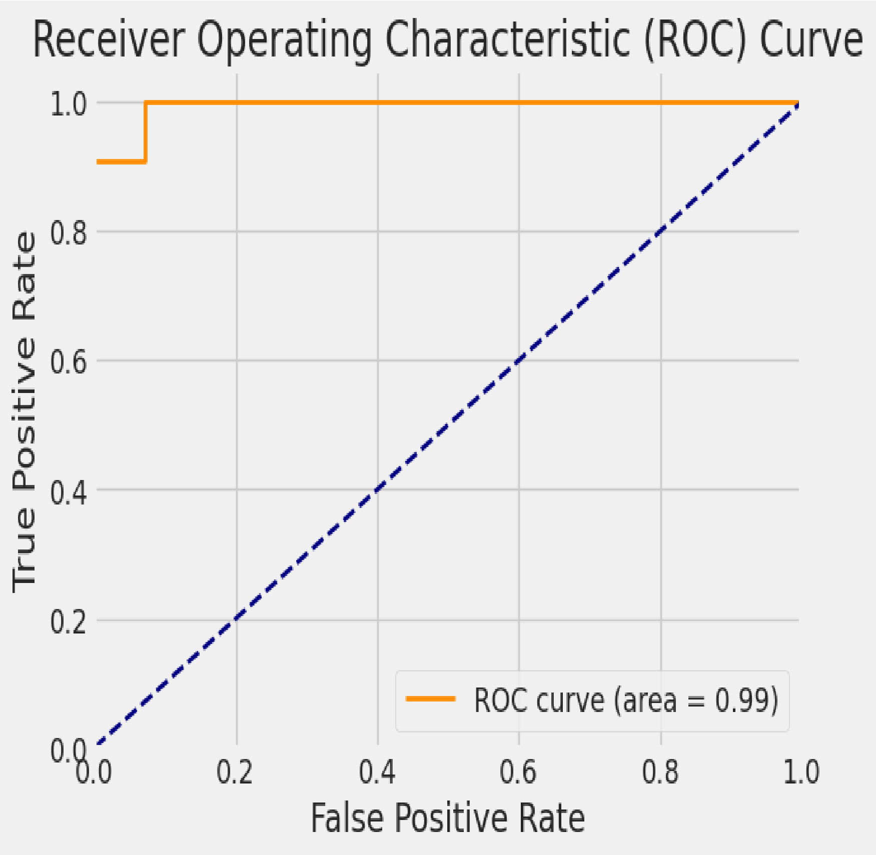



Fig:- ROC curve of Ensemble model with parameters (Precision,Recall,F1-Score)

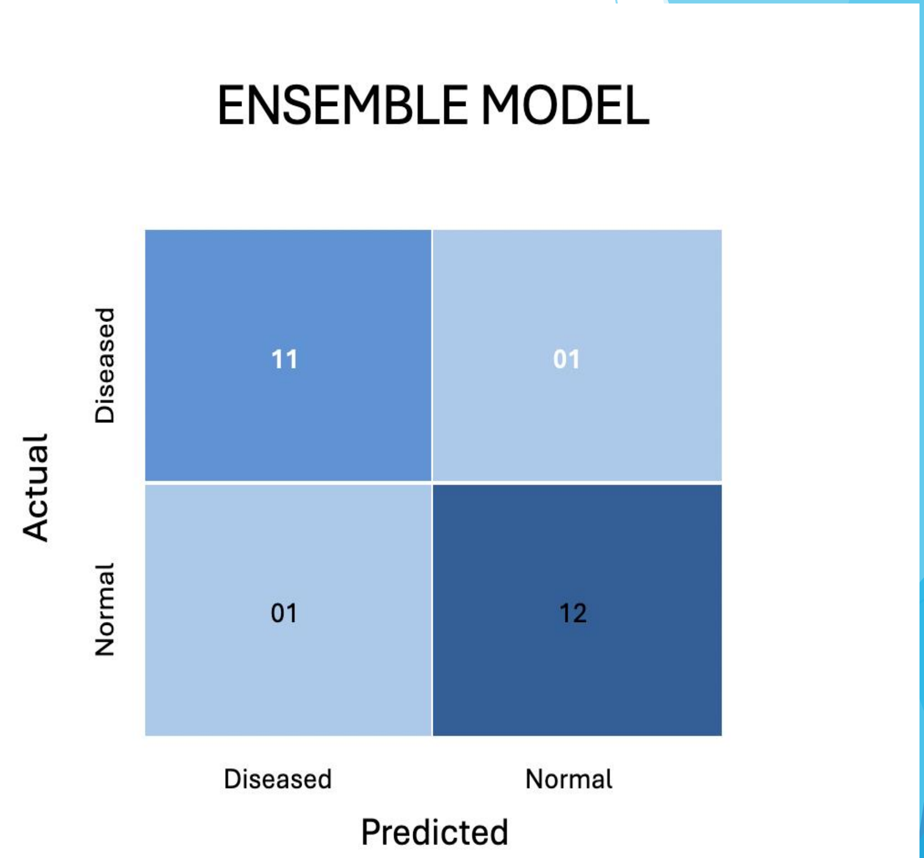



Fig:- Confusion Matrix of Ensemble model

# CONCLUSION

In conclusion, the use of deep learning algorithms for the detection of cardiovascular risk prediction is a promising area of research. We have explored the effectiveness of three popular convolutional neural network architectures: ResNet-50, VGG-19, and Inception V3, and have shown that all three models can achieve high accuracy in detecting cardiovascular diseases from retinal fundus images. ResNet-50 model achieved the highest accuracy of 89.88% among all these models on testing dataset.

Furthermore, we have increased the accuracy of our predictions to 92.71% by integrating these models using an ensemble approach (average of the pre-trained weights of the preceding three models). The ensemble model demonstrates the importance of leveraging multiple models for complex tasks such as medical diagnosis, where combining the strengths of individual models can help compensate for their respective weaknesses

# FUTURE PLAN OF WORK

- Compared to the dataset we used till now, that is obtained from publicly available sources online, we intend on reaching out to more real-time datasets from hospitals wherever possible.
- Upon creation of the final model there will be further attempt to optimize the performance of our models for different populations and clinical settings
- The resulting software model will subsequently be loaded on hardware for prototyping.
- Finally, the output of the developed diagnostic model will need to be evaluated and validated with the aid of experts.

# ACKNOWLEDGEMENT

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# REFERENCES


- [1] Poplin, R., Varadarajan, A.V., Blumer, K., Liu, Y., McConnel, M.V., Corrado, G.S., Peng, L. and Webster, D.R., 2018. "Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning." Nature Biomedical Engineering, 2(3), pp.158-164.
- [2] Wood, D., 201. Established and emerging cardiovascular risk factors. American heart journal, 141(2), pp.S49-S57.
- [3] Castelli, W.P., Wilson, P.W., Levy, D. and Anderson, K., 1989. Cardiovascular risk factors in the elderly. The American journal of cardiology, 63(16), pp. 12-19.
- [4] Ruben G. Barriada, David Masip, Jae-Ho Han . An Overview of Deep-Learning-Based Methods for Cardiovascular Risk Assessment with Retinal Images.
- [5] Rachel Marjorie Wei Wen Tseng1,2†, Tyler Hyungtaek Rim1,3,4*† , Eduard Shantsila5. Validation of a deep learning based retinal biomarker (Reti-CVD) in the prediction of cardiovascular disease: data from UK Biobank.
- [6] David Joel Nogueira Azevedo. “Cardiovascular Risks Detection Using Fundus Image.” 19 July 2019.

# THANK YOU