HIDDEN HUNGER DETECTION USING DEEP LEARNING APPROACHES

Under the guidance of:

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OUTLINE

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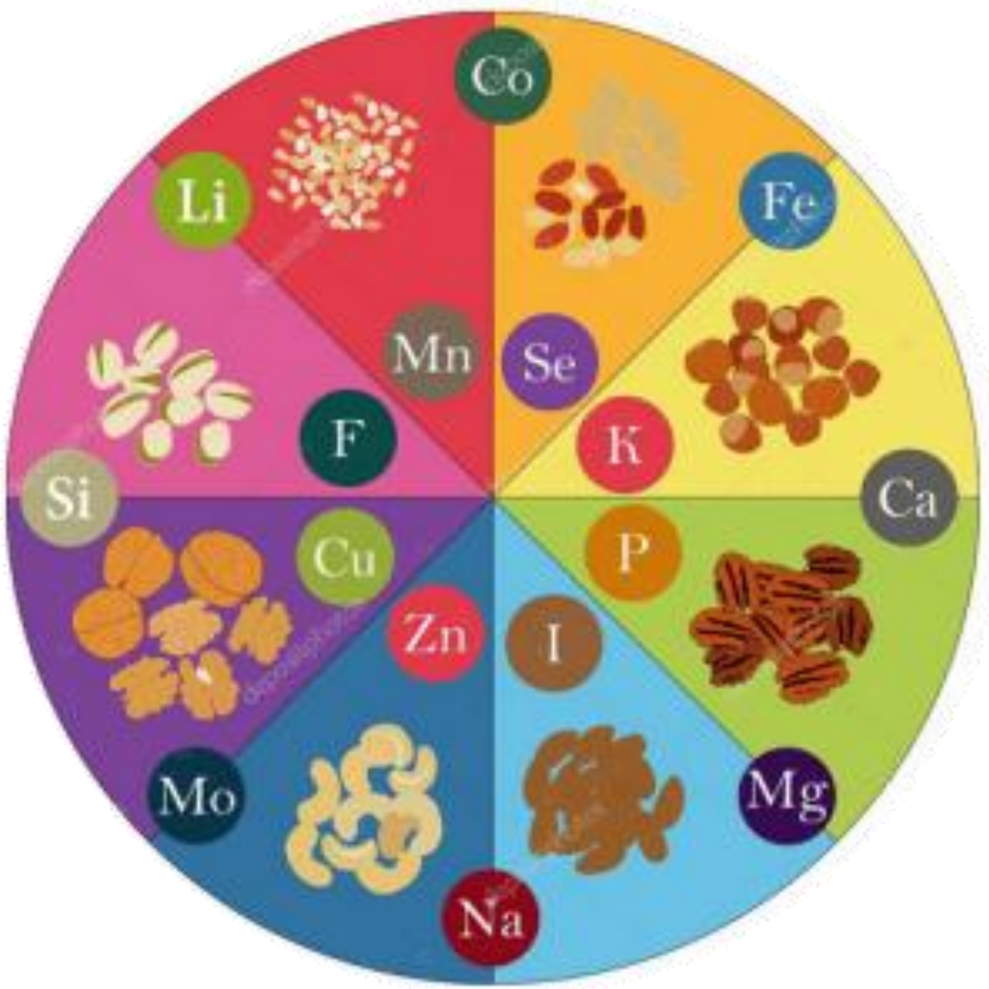
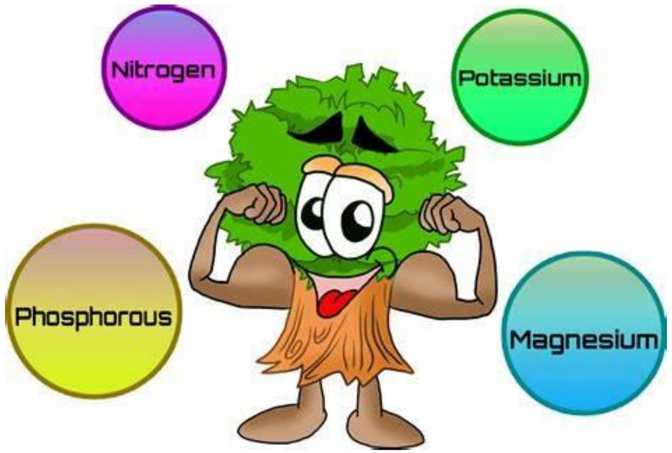
- Need
- Why this topic
- Literature survey
- Objectives
- Methodology
- Block diagram
- Results and discussion
- Conclusion and future scope
- References

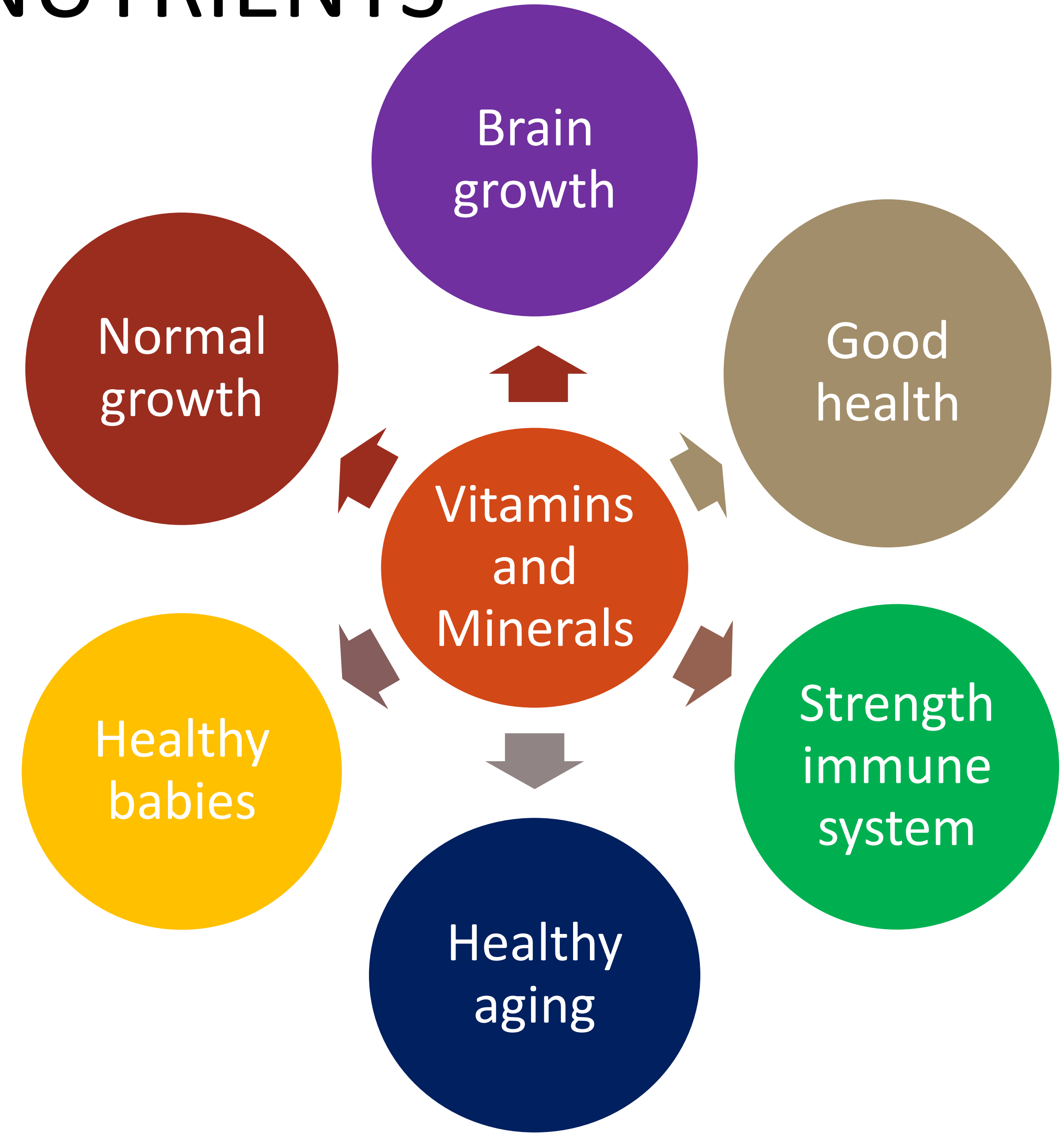


INTRODUCTION

- ‘Hidden hunger’ - describe deficiencies in essential vitamins and minerals, also known as micronutrients
- Major Micronutrients:
  - In Human-Vitamin A,C,D,Fe,Ca,Mg,Iodine
  - In Plants-Zn,Fe,Mn,B



ROLE OF MICRONUTRIENTS



HIDDEN HUNGER ACROSS THE WORLD

- Micronutrient deficiencies affect an estimated two billion people, or almost one-third of the world's population.

Preschool children		People Worldwide	
30%	Vitamin A deficiency	30%	Iodine deficiency
18%	Fe-deficiency	17%	Zn-deficiency

HIDDEN HUNGER IN CROPS AND SOIL ACROSS INDIA

Crops and Soil	
49%	Zn-deficiency
12%	Fe-deficiency
5%	Mn-deficiency

Crops and Soil	
3%	Cu-deficiency
33%	Boron deficiency
11%	Molybdenum deficiency

NEED:

- Human Health implications:
  - To improve the health and well-being of individuals- children and pregnant women.
- Plant disease:
  - Identify micronutrient deficiencies-Plant susceptible to diseases.
  - For the development of sustainable agriculture practices- Promote plant health and reduce the risk of plant diseases.

WHY THIS TITLE?

- All the existing methods focus on diagnosing macronutrient deficiencies
- No awareness among people on micronutrient deficiencies
- Micronutrient deficiency also causes serious damage to the growth of the plant/crop.

LITERATURE SURVEY:

Title of the paper	Year	Author and Journal	Description	Summary
Ensemble Averaging of Transfer Learning Models for Identification of nutritional deficiency in Rice plants	2022	Mayuri Sharma,Keshab Nath,Rupan Kumar Sharma et all MDPI-Electronics	• Detect the nutrient deficiency in plants • Host a high end system in cloud • Used six CNN based DL architectures	Limitations: • Detect only 3 mineral deficiency • No ML classifier is used Summary: • Highest performance InceptionResNetV2(90%) and Xception(95.83%)

Title of the paper	Year	Author and Journal	Description	Summary
A comparative Study of Deep CNN in Forecasting and Classifying the Macronutrient Deficiencies on Development of Tomato Plant	2019	Trung-Tin Tran,Jae-Won Choi,Thein-Tu Huynh Le and Jong-Wook Kim MDPI-applied sciences	• Calcium,Nitrogen, Potassium deficiency in tomato plant • ANN model is used • Inception ResnetV2, • Autoencoder and Ensemble Averaging are the 3 models which are used	Accuracy rate obtained 87.27% -Inception-Resnet v2 79.09% - Autoencoder to 91% - ensemble averaging.

Title of the paper	Year	Author and Journal	Description	Summary
Using Deep Convolutional Neural Network for Image Based Diagnosis of Nutrient Defeciencies in Plants Grown in Aquaponics	2022	Mohamed Farag Taha et all MDPI- chemosensors	• Diagnoses the nutrient status(N,P,K,FN) of lettuce in aquaponics • It integrate color imaging and deep convolution neural network(DCNNs)	• SegNet for segmentation, Inceptionv3 and Resnet18 for classification • Highest classification accuracy-96.5% • Real time disease detection

Title of the paper	Year	Author and Journal	Description	Summary
Deep Learning for Non Invasive Diagnosis of Nutrient Deficiencies in Sugar Beet Using RGB images	2020	Jinhui Yi ,Lukas Krusenbaum et all MDPI-Sensors	• Determine the nutrient deficiency (N,P,K) in sugar beet • Five CNN based DL architectures	• Accurate detection is not possible by non invasive methods • Recognizing deficiency during growing stages is difficult

Title of the paper	Year	Author and Journal	Description	Summary
Deep Learning Based Disease, Pest Pattern and Nutritional Deficiency Detection System For “Zingiberaceae” Crop	2022	Hamna Waheed,Noureen Zafar,Waseem Akram,Awais Manzoor,Abdullah Gani MDPI-agriculture	• Determine the soft rot disease,deficiency and pest pattern in ginger plant leaf • ANN and CNN are used • MobileNetV2 and VGG are the training algorithms	• 3 types-deficiency and healthy,Pest pattern and Healthy,Soft rot disease and healthy • VGG-16 accuracy 96% - pest pattern • ANN accuracy 97%-deficiency

Title of the paper	Year	Author and Journal	Description	Summary
Identifying Individual Nutrient Deficiencies of Grapevine Leaves using Hyperspectral Imaging	2021	Sourabhi Debnath,Manoranja Paul et all MDPI-remote sensing	• Determine the N,K,Mg nutrient deficient in grapevine • SVM is used to demonstrate the feature • Features applied-reflectance ratio,mean derivative reflectance,variation index,mean spectral ratio,normalized difference vegetation index	• Average F measure for SVM algorithm - 93.19% • Confusion matrix – visualize the performance

Title of the paper	Year	Author and Journal	Description	Summary
Nutritient Deficiency detection in maize(Zea Mays L.) leaves using image processing	2022	Nurbaity Sabri,Nurul Shafekah kassim,Shafaf Ibrahim,Rosniza Roslan,Nur Nabilah Abu IAES International Journal of AI(IJ-AI)	• Determine nutrient deficiency(Mg,N,P) maize plant leaf • Random forest were used as classifier to achieve accuracy of 78.35% • Combination of GLCM hu and color histogram	Limitations: • Result of P detection affected by its similarity with Mg features Future Scope: • Some deficiency have same trait • More data can be collected

Title of the paper	Year	Author and Journal	Description	Summary
Detection and classification of nutrient deficiencies in plants using machine learning	2021	Anu Jose,S Nandagopalan,Vidya Ubalanka and Dhanya Viswanath ICMMCMSE 2020 Journal of Physics	• Detect the deficiency (N,Mg,P,K,S,C) • Image can be uploaded on server • Processed by image processing system (ANN model) • Image Sementation,Feature extraction and classification is done	• Best model- Features from Hue based segmentation • ANN accuracy- 88.27% • Design of CNN can give better accuracy

Title of the paper	Year	Author and Journal	Description	Summary
Plant Nutrient Deficiency Detection Using Deep Convolutional Neural Network	2019	Lili Ayu Wulandhari,Alexander Agung et all ICIC International	• Recognize and predict healthy and deficiency okra • Inception Resnet architecture & fine tuning from ImageNet dataset is applied	• Accuracy – 97% & 86% for testing and training • Improvement can ben done by Mobilenet to implement in mobile

Title of the paper	Year	Author and Journal	Description	Summary
A nutrient Deficiency Prediction Method using Deep learning on development of Tomato fruits	2018	Choi Jae-Won,Tin Tran Trung et all International Conference on Fuzzy Theory and its application iFuzzy	• Recognize and predict calcium and potassium deficiency • CNN with Inception ResV2 network • Uses Digital camera to capture image	• High accuracy • Algorithm can be upgraded to detect accurately

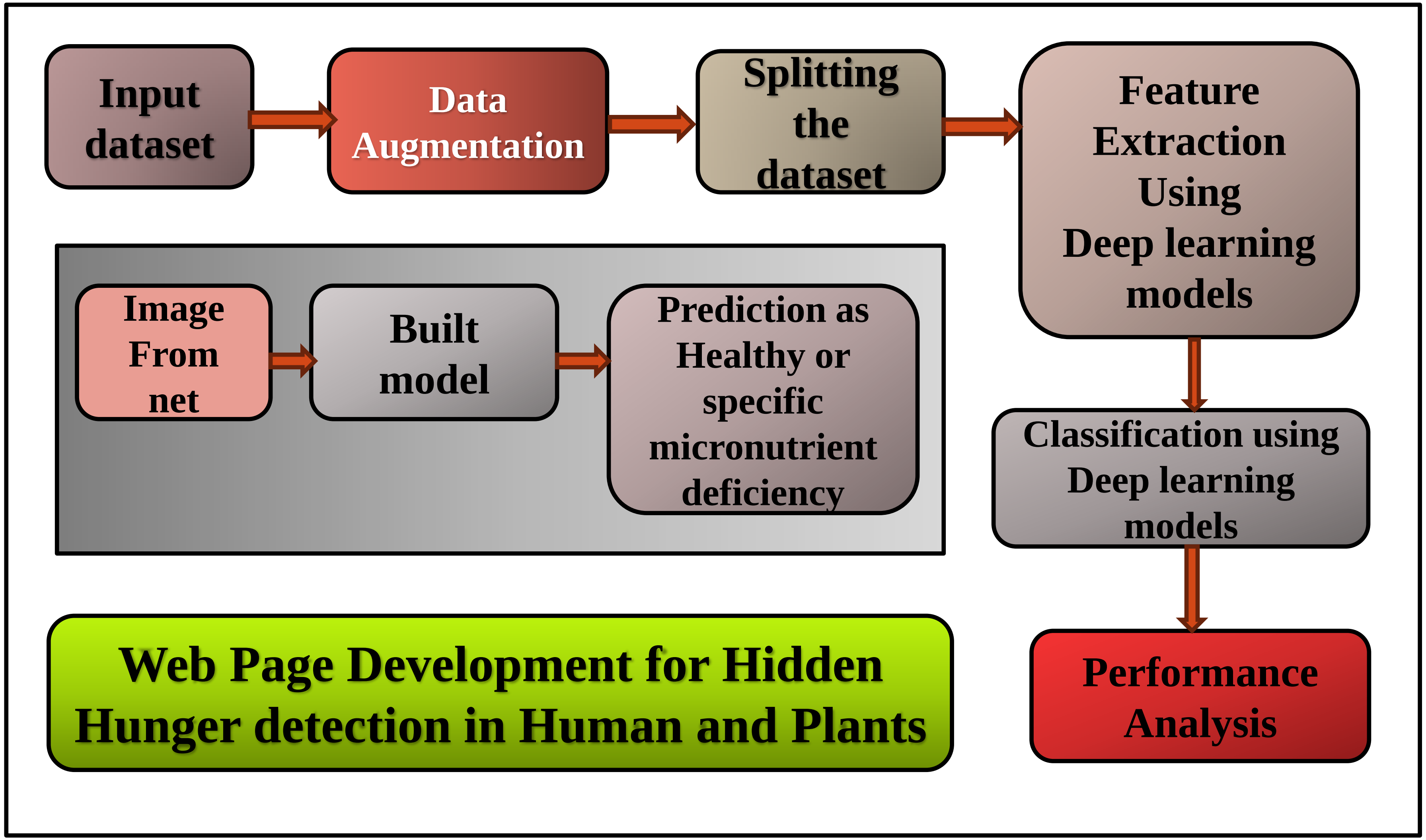
GAP IN LITERATURE SURVEY

- All the paper majorly focus only on macronutrient deficiency detection.
- Only few research work have been done in the field of micronutrient deficiency detection.

OBJECTIVES

- To detect hidden hunger at early stages using image processing techniques.
- To determine the micronutrient deficiency in human and plants.
- To implement various deep learning model and analyze its performance.
- To create a webpage for the developed model.

BLOCK DIAGRAM



DATA AUGMENTATION

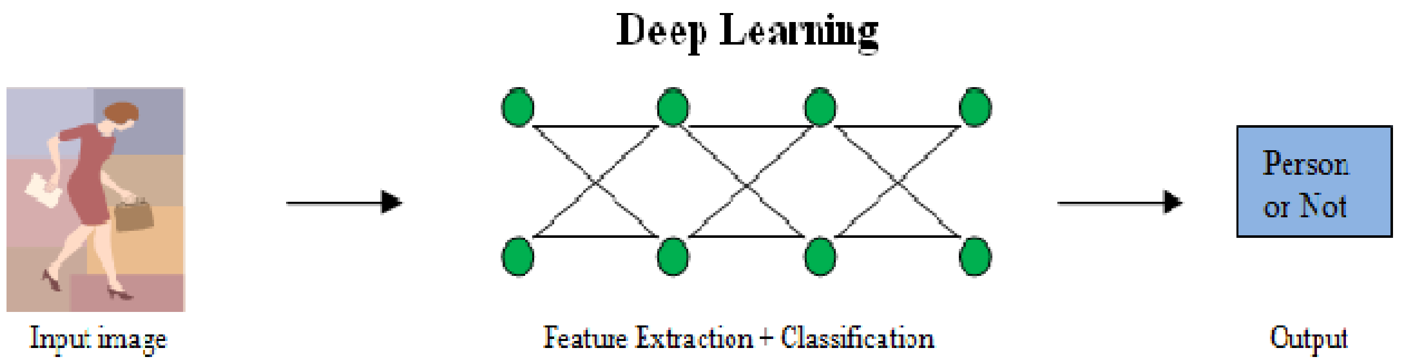
- Artificially increasing the training set by creating modified copies of a dataset using existing data
- Geometric & color space transformations (flipping, resizing, cropping, brightness, contrast)
- Prevents model from overfitting, improve the accuracy

SPLITTING THE DATASET

- Data splitting - avoid overfitting
- Overfitting-If our model does much better on the training set than on the test set
- Training set, testing set, validation set

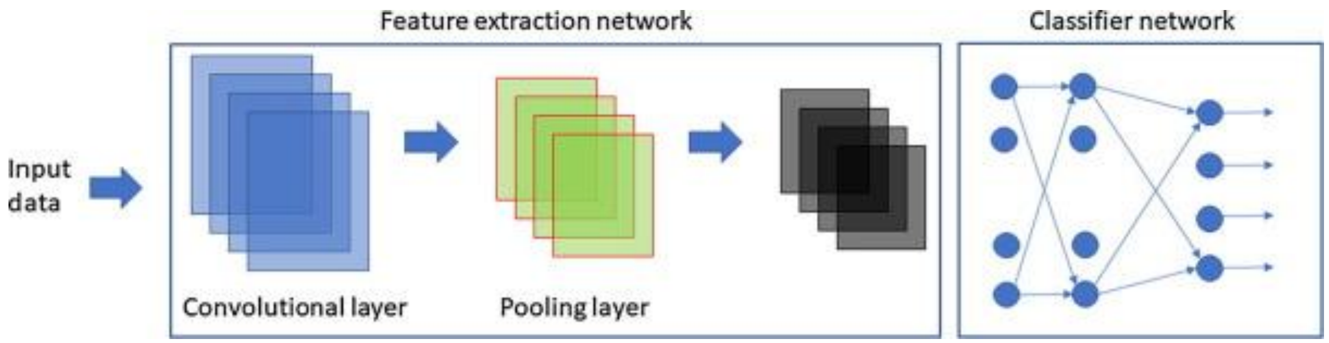
DEEP LEARNING MODEL

- Deep learning uses neural networks to learn useful representations of features directly from data
- Machine is trained to perform tasks using an algorithm or a predefined set of steps



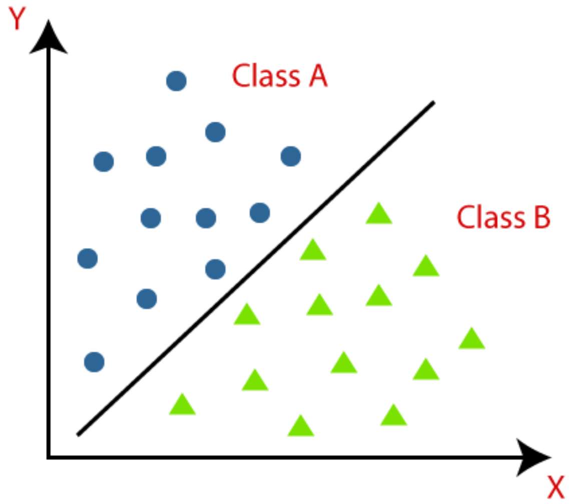
FEATURE EXTRACTION

- The process of transforming raw data into numerical features
- This technique is used to detect features in digital images such as edges , shapes or motion



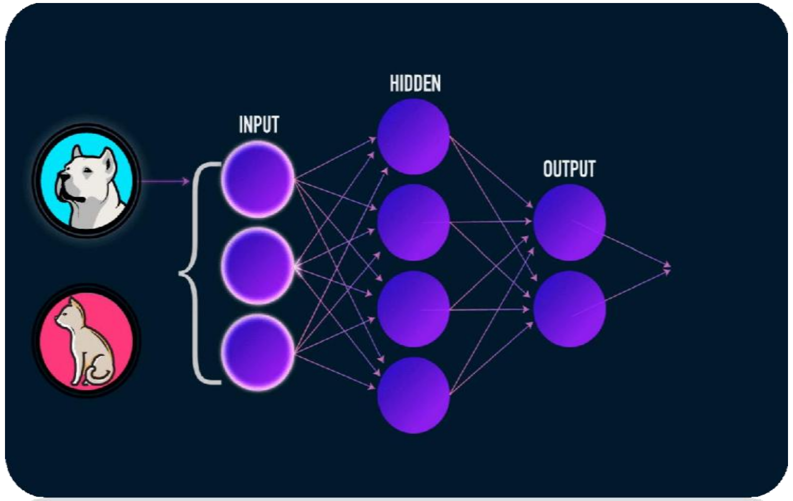
CLASSIFICATION

- A supervised learning technique that categorizes a set of data into classes
- The objective is to identify and portray as a unique gray level , the features occurring in an image

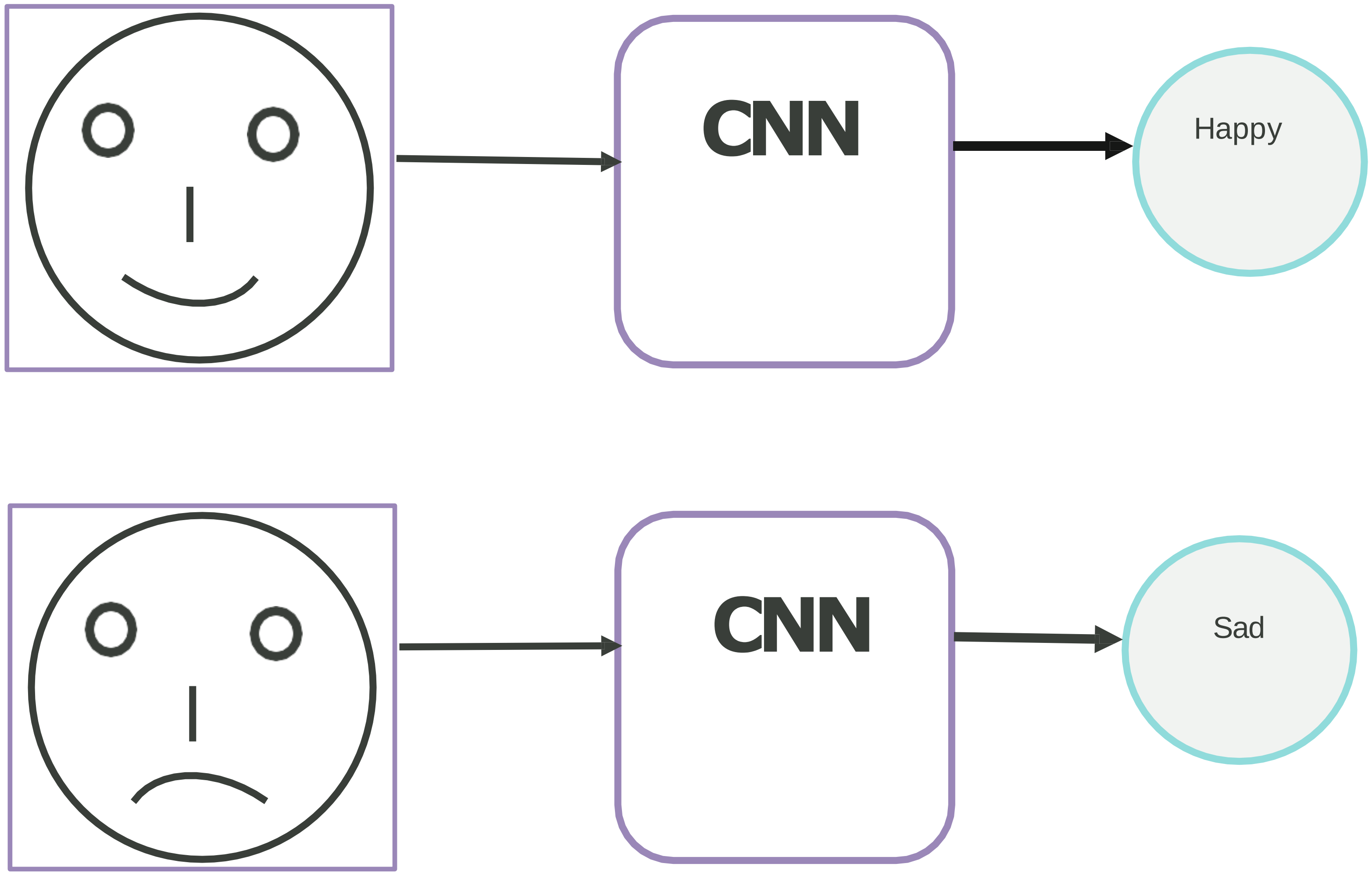


CONVOLUTION NEURAL NETWORK

- CNN ⟶ Deep learning neural network
- Process structured arrays of data such as images
- Used in visual applications such as image classification



How CNN Operates?



CNN Layers

Convolution layer

Pooling layer

Flatten layer

Fully connected layer

CONVOLUTION LAYER

Image

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

*

Feature Detector

1	-1	-1
-1	1	-1
-1	-1	1

=

Feature map

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

MAX POOLING LAYER

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

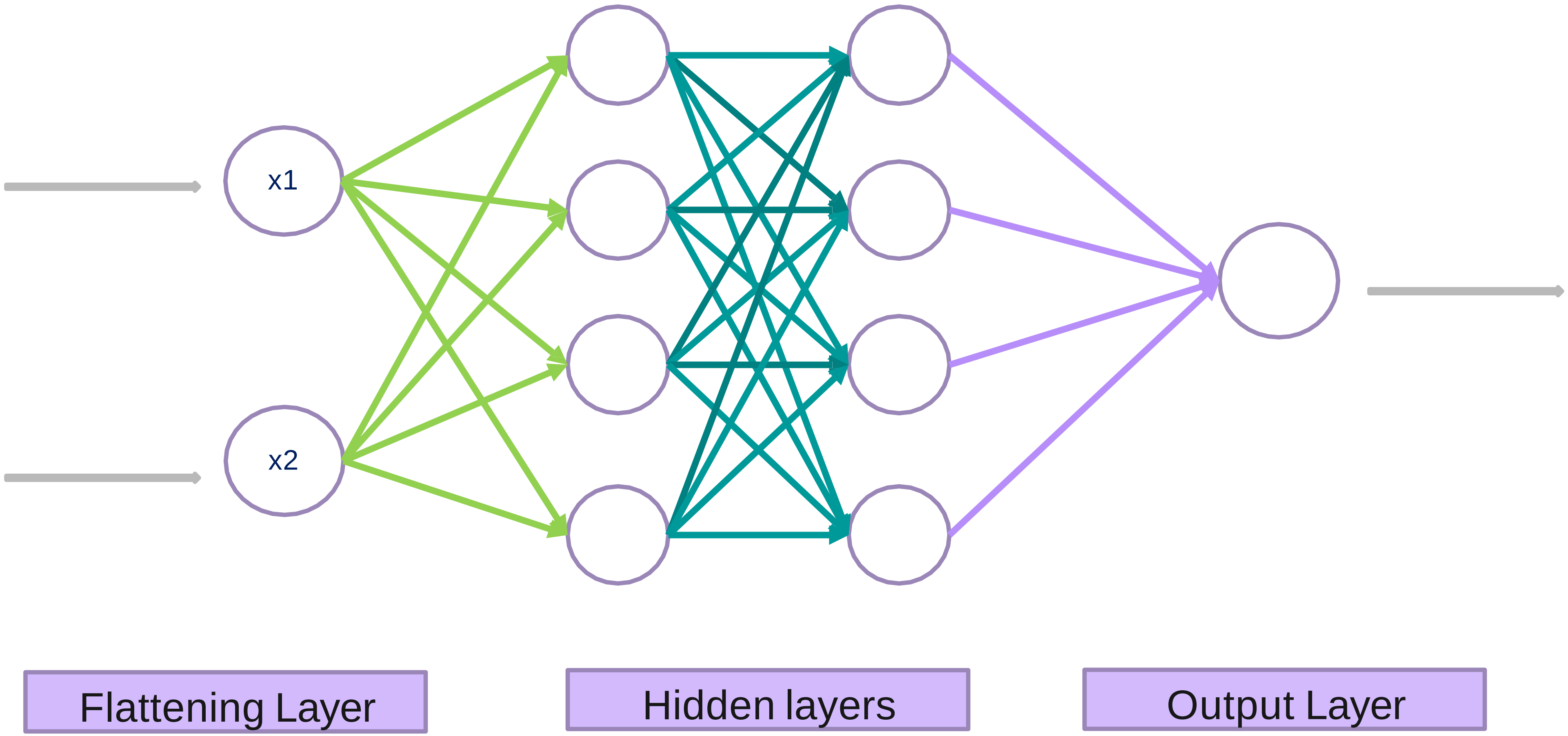
3	1	0
1	1	1
3	0	1

FLATTENING LAYER

3	1	0
1	1	1
3	0	1

3
1
0
1
1
1
3
0
1

FULLY CONNECTED LAYER



RELU(RECTIFIED LINEAR UNIT)

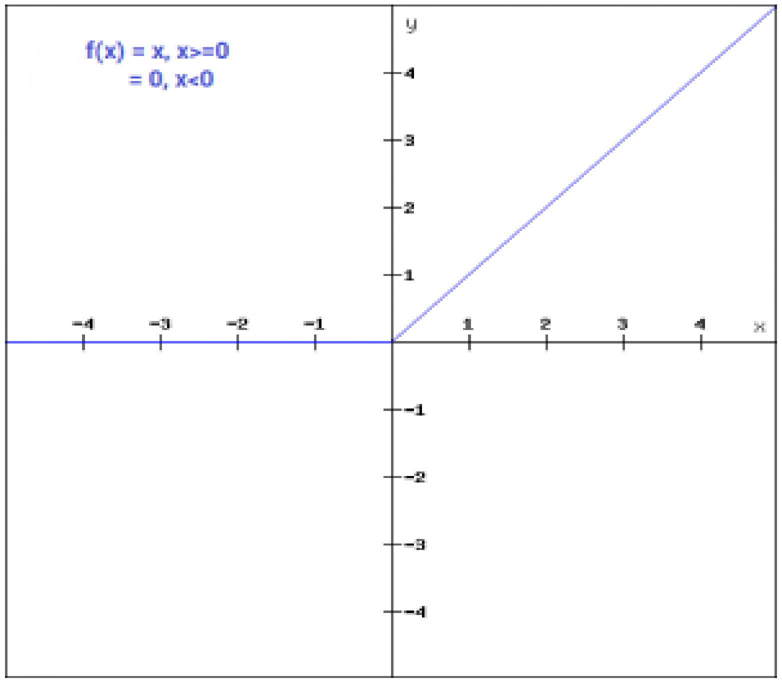
- ReLU is a commonly used activation function
- Returns zero if the input is negative
- The input value itself if it is positive
- Mathematically, it is expressed as

$$f(x) = \max(0,x)$$

where,

x -input to the function

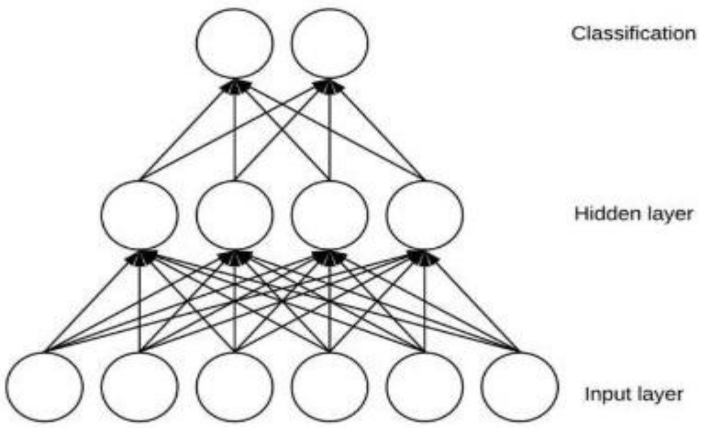
f(x)-output



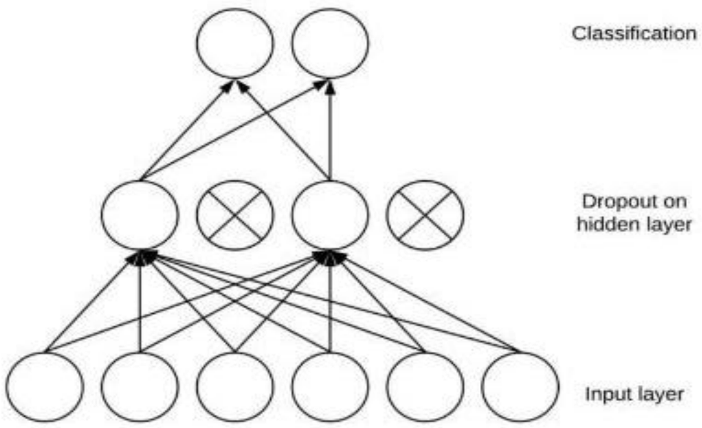
- Prevent the vanishing gradient problem

DROPOUT LAYER

- The Dropout layer nullifies the contribution of some neurons towards the next layer and leaves unmodified all others
- Prevent overfitting on the training data



Without Dropout



With Dropout

SOFTMAX LAYER

- Placed before the output layer in a neural network
- It converts the scores to a normalized probability distribution
- Used as the activation function for multi-class classification problems

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

σ = softmax

$\vec{z}$ = input vector

e^{z_i} = standard exponential function for input vector

K = number of classes in the multi-class classifier

e^{z_j} = standard exponential function for output vector

e^{z_j} = standard exponential function for output vector

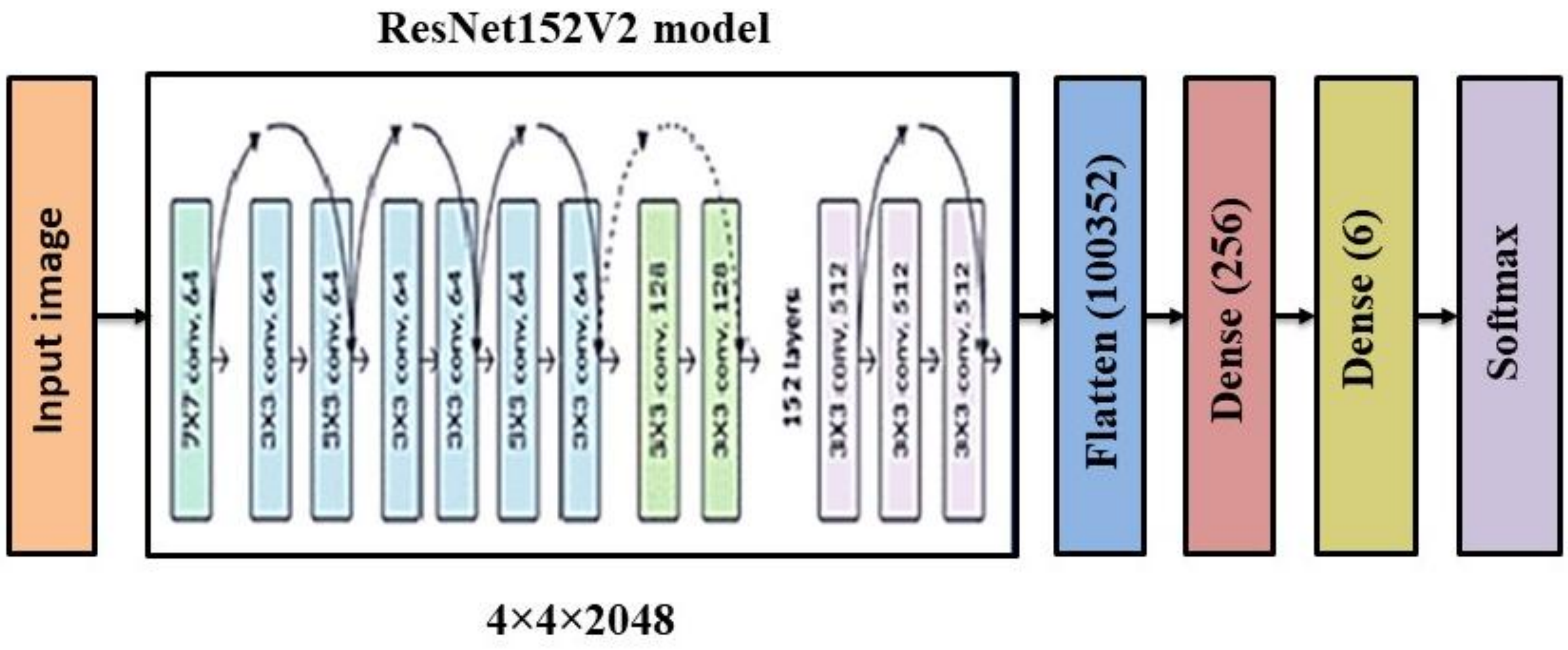
RESNET

- It is a Convolutional Neural Network (CNN) architecture designed to support hundreds or thousands of convolutional layers

RESNET152V2

- Resnet152v2 process the input image by 152 convolutional layers and the image is reshaped.

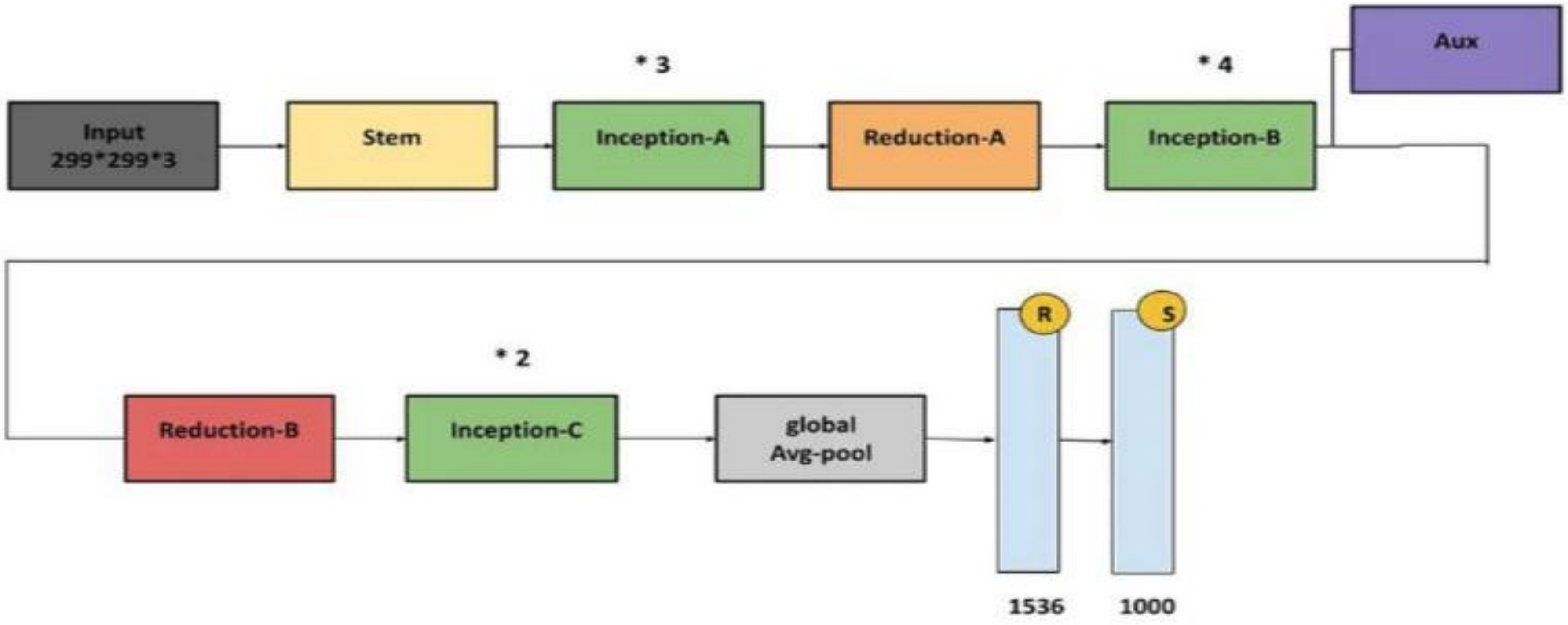
RESNET152V2 ARCHITECTURE



INCEPTION V3

- Inception v3 is a deep neural network architecture for image classification, developed by Google in 2015.
- The Inception v3 architecture uses a CNN with multiple layers of convolutional and pooling layers, followed by several fully connected layers.

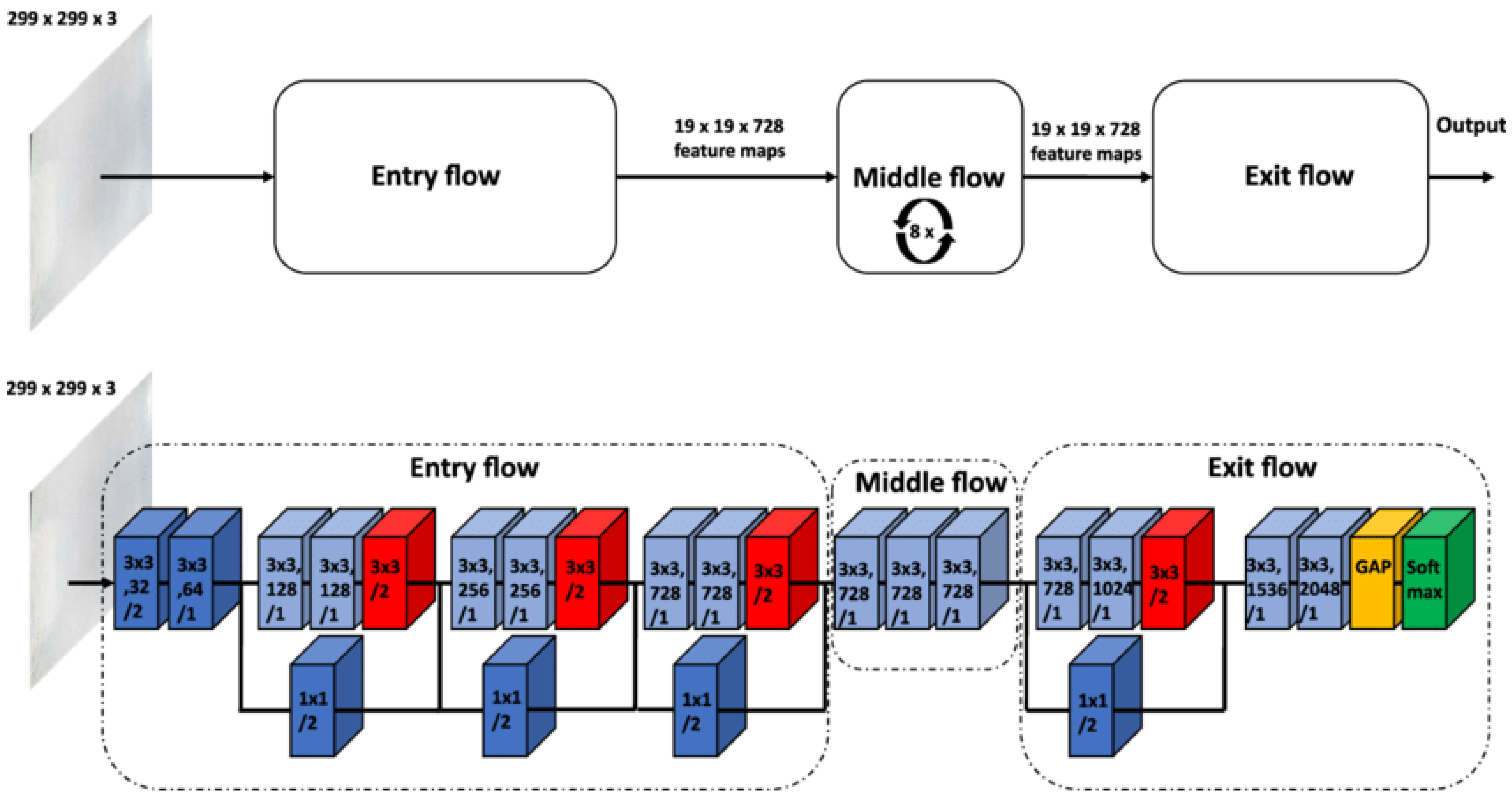
INCEPTION ARCHITECTURE



XCEPTION

- Xception is a deep convolutional neural network architecture that involves depthwise separable convolutions.
- Xception is also known as extreme version of inception module.

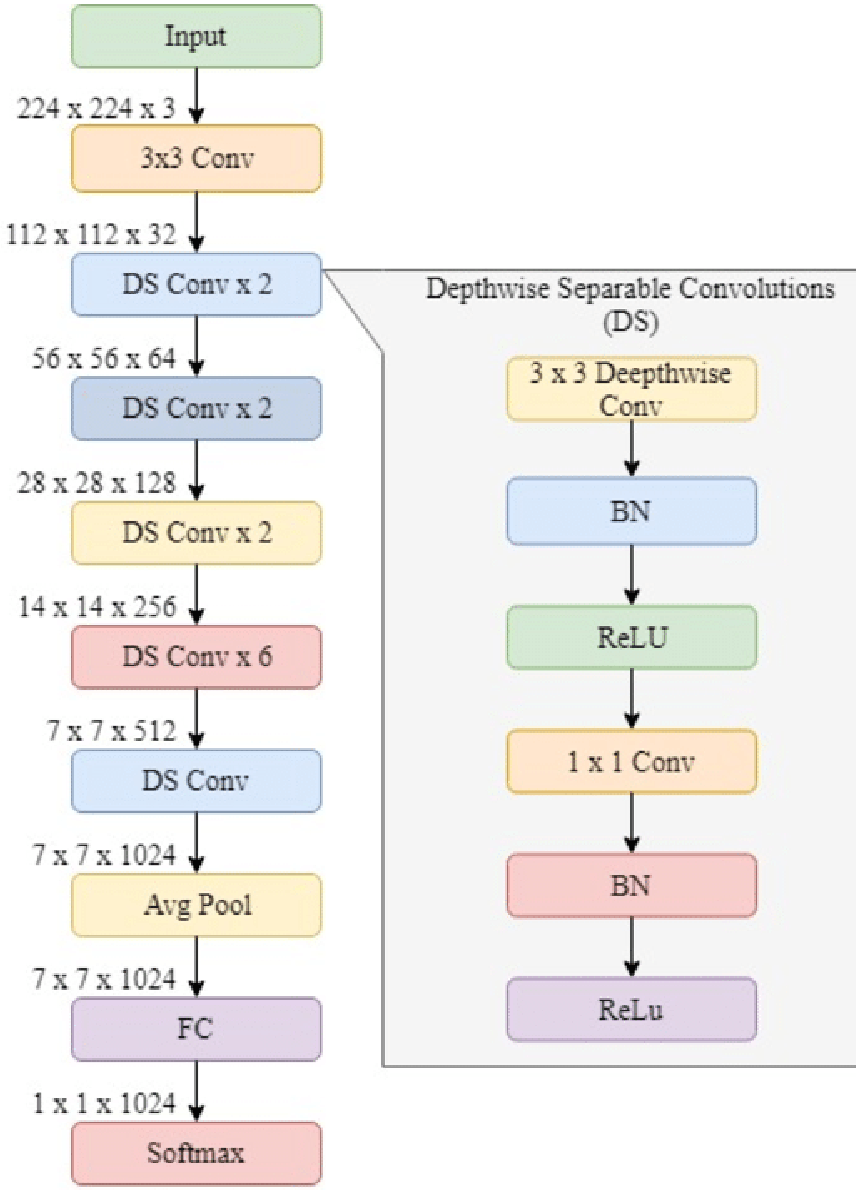
XCEPTION ARCHITECTURE



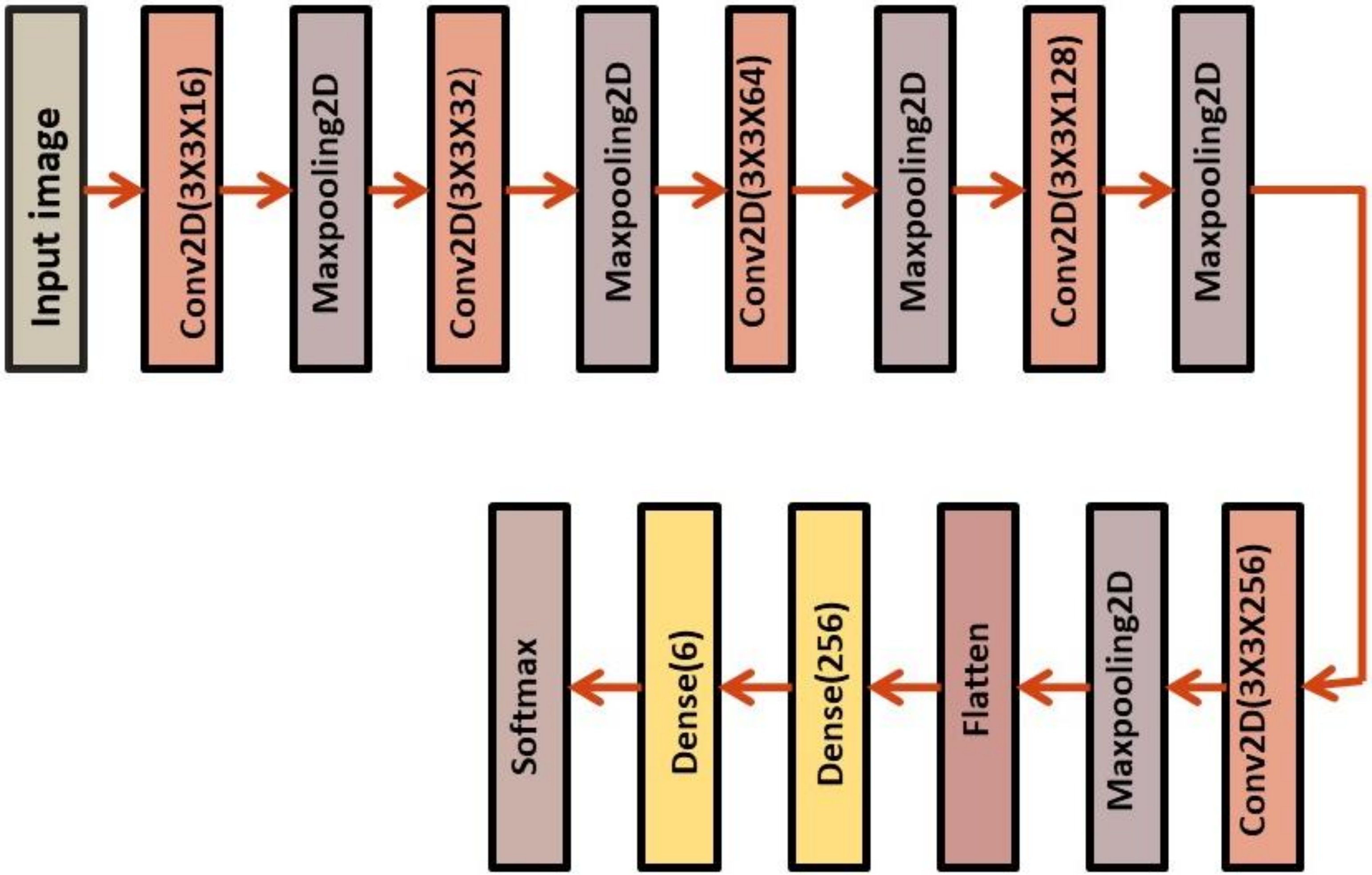
MOBILE NET

- An efficient & portable CNN architecture used in real world applications.
- Uses depthwise seperable convolutions in place of the standard
- MobileNets introduce two new global hyperparameters(width multiplier and resolution multiplier)

MOBILENET ARCHITECTURE



CNN MODEL ARCHITECTURE

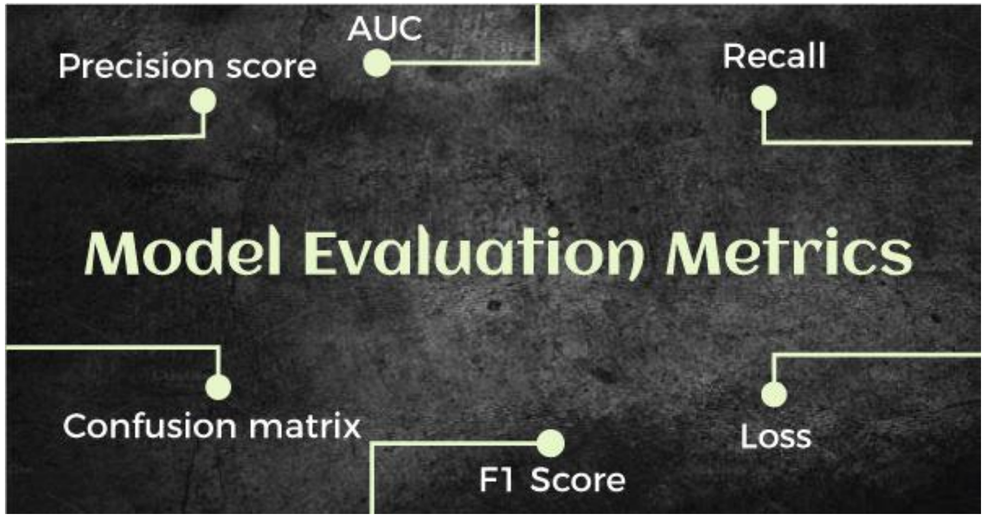


PREDICTION

- The process of using a trained model to estimate or forecast an unknown or future outcome based on input data.
- It involves applying the learned patterns and relationships in the training data to make an informed inference about new, unseen data.

PERFORMANCE MEASUREMENT

- Performance metrics are used to determine the effectiveness of image processing technique in achieving expected results.



CONFUSION MATRIX

- A technique for summarizing the performance of a classification algorithm

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

RECALL

- Recall tells us about how well the model identifies true positives

$$\frac{TP}{FN+TP}$$

PRECISION

- The precision of the model is the proportion of correct positive predictions

$$\frac{TP}{FP+TP}$$

F1-SCORE

F1 Score is a weighted average of precision and recall

$$\text{F1-Score} = \frac{2 \text{ x precision x recall}}{\text{precision+recall}}$$

SUPPORT

- Number of occurrences of each class in the true responses
- calculate it by summing the rows of the confusion matrix

RESULTS AND DISCUSSION

HIDDEN HUNGER DETECTION IN HUMAN

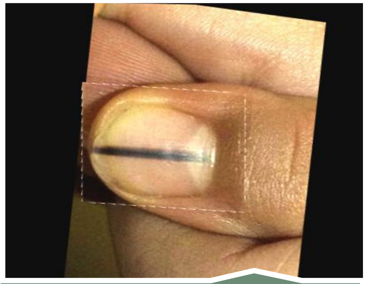
INPUT DATA

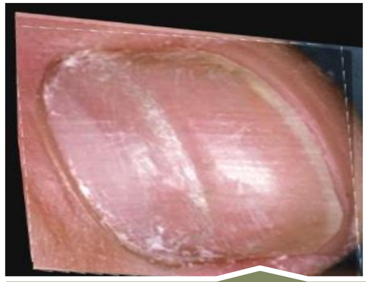
Sample images from each classes in nail dataset


Iodine


Iron


Vitamin B12


Vitamin D


Zinc


Healthy

Sample input from each classes in eye dataset

Vitamin D-Deficiency

Healthy Eye

DATASET SOURCE

- **Roboflow -** https://universe.roboflow.com/knm/nail-disease-detection-mxoqy
- **Kaggle -** https://www.kaggle.com/datasets/kondwani/eye-disease-dataset

DATA AUGMENTATION

Augmentation techniques used

❖ Zoom

❖ Flip

❖ Random Brightness

Sample Images After Data Augmentation

Zoom

Flip Top-Bottom

Random Brightness

DATA AUGMENTATION ON HUMAN DATASET

- 80% TRAIN
- 20% VALIDATION

DATA	BEFORE AUGMENTATION (3500)	AFTER AUGMENTATION (5000)	AFTER AUGMENTION (7000)
Iodine	574	912	1189
Iron	567	851	1188
Vitamin B12	572	840	1236
Vitamin D	584	883	1194
Zinc	455	705	975
Healthy	558	809	1218
TOTAL IMAGES	3500	5000	7000

HIDDEN HUNGER DETECTION IN PLANTS

INPUT DATA

Sample input from each classes in eye dataset

Boron

Iron

Manganese

Zinc

DATASET SOURCE

❖**Mendeley-**https://data.mendeley.com/datasets/7vpdrbdkd4

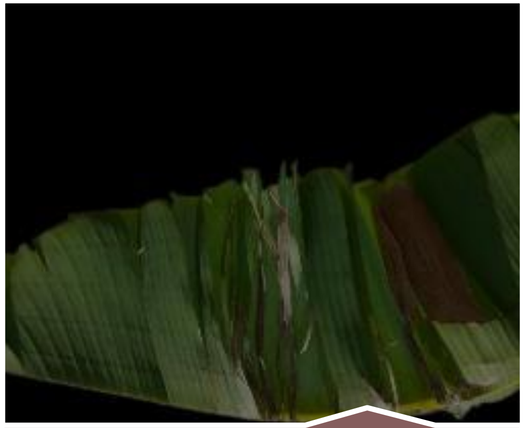
DATA AUGMENTATION

Augmentation techniques used

- ❖ Zoom
- ❖ Flip top bottom
- ❖ Random Brightness
- ❖ Random Distortion

Sample Images After Data Augmentation

Zoom



Flip

Random brightness

Random distortion

DATA AUGMENTATION ON LEAF DATASET

70%	TRAIN
10%	VALIDATION
20%	TEST

DATA	BEFORE AUGMENTATION	AFTER AUGMENTATION	AFTER AUGMENTATION
Boron	100	800	1200
Iron	86	750	1000
Manganese	24	150	700
Zinc	400	800	900
Healthy	950	1200	1200
TOTAL IMAGES	1560	3700	5000

MODEL BUILDING

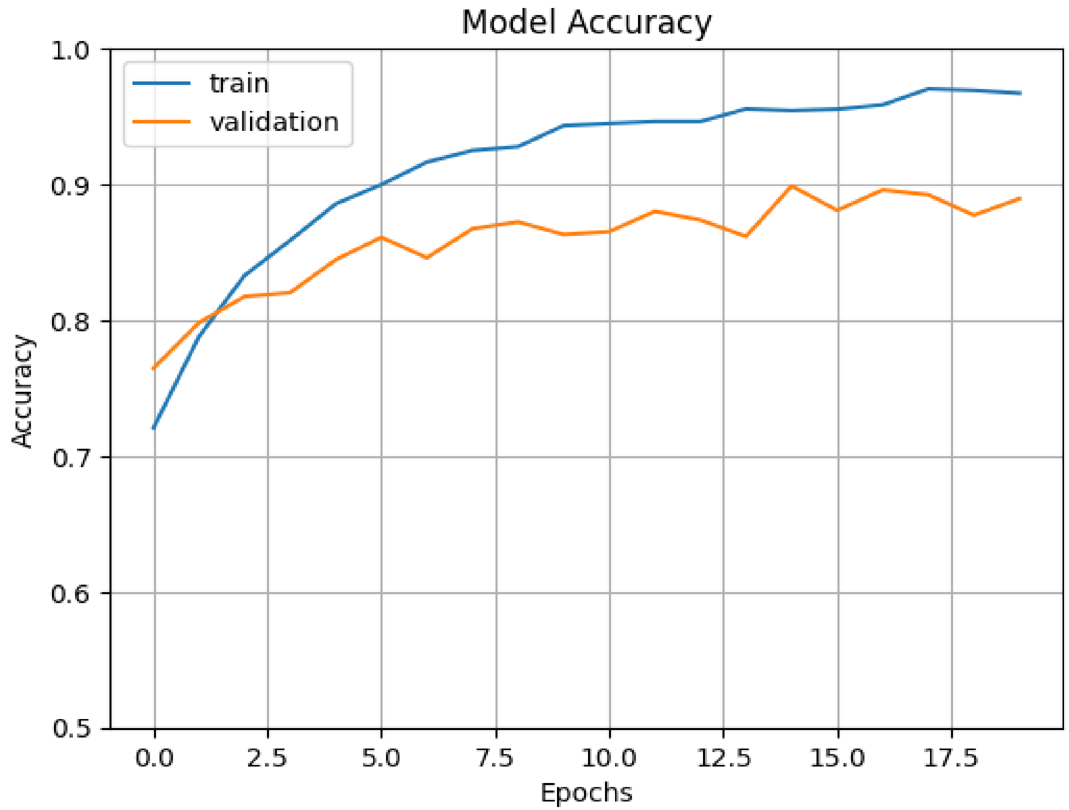
The CNN model we used for model building of nail and eye dataset are

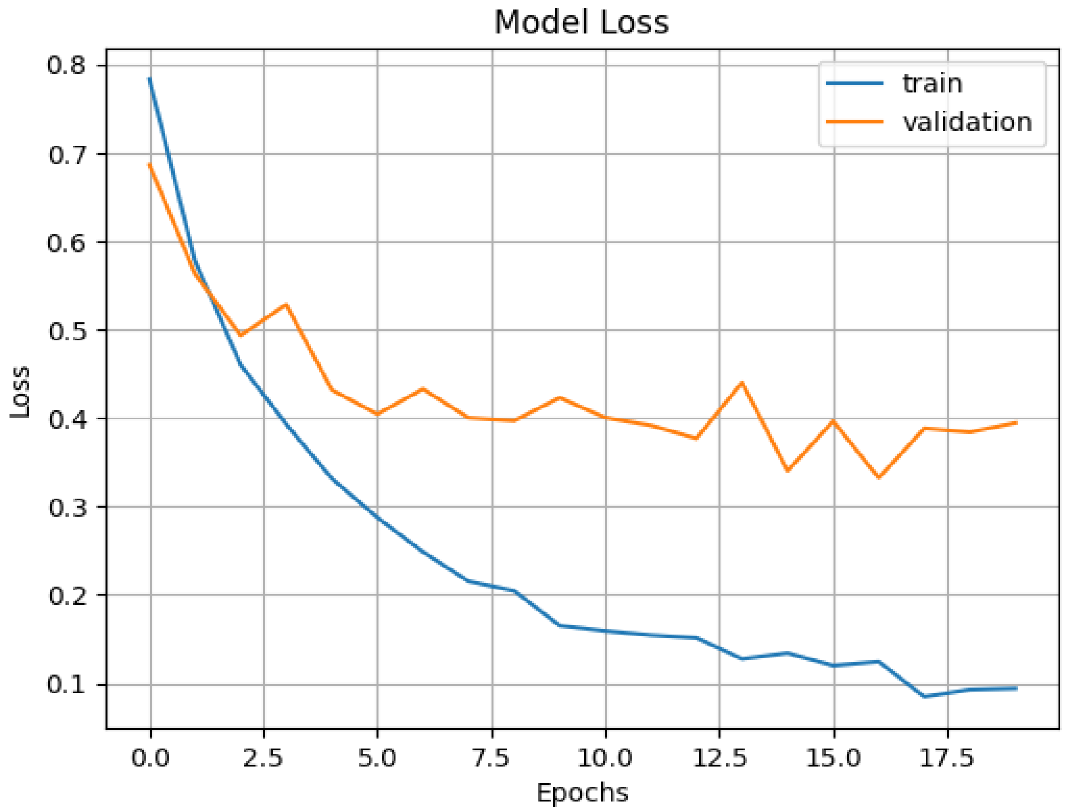
- Inception V3
- Resnet152V2
- CNN model
- Xception
- Mobile net

Resnet152V2	Inceptionv3	Xception	Mobilenet	CNN model
Train accuracy- 96.61	Train accuracy- 92.46	Train accuracy- 94.52	Train accuracy- 95.52	Train accuracy- 86.10
Test accuracy- 90.94	Test accuracy- 83.67	Test accuracy- 83.02	Test accuracy- 83.18	Test accuracy- 68.47

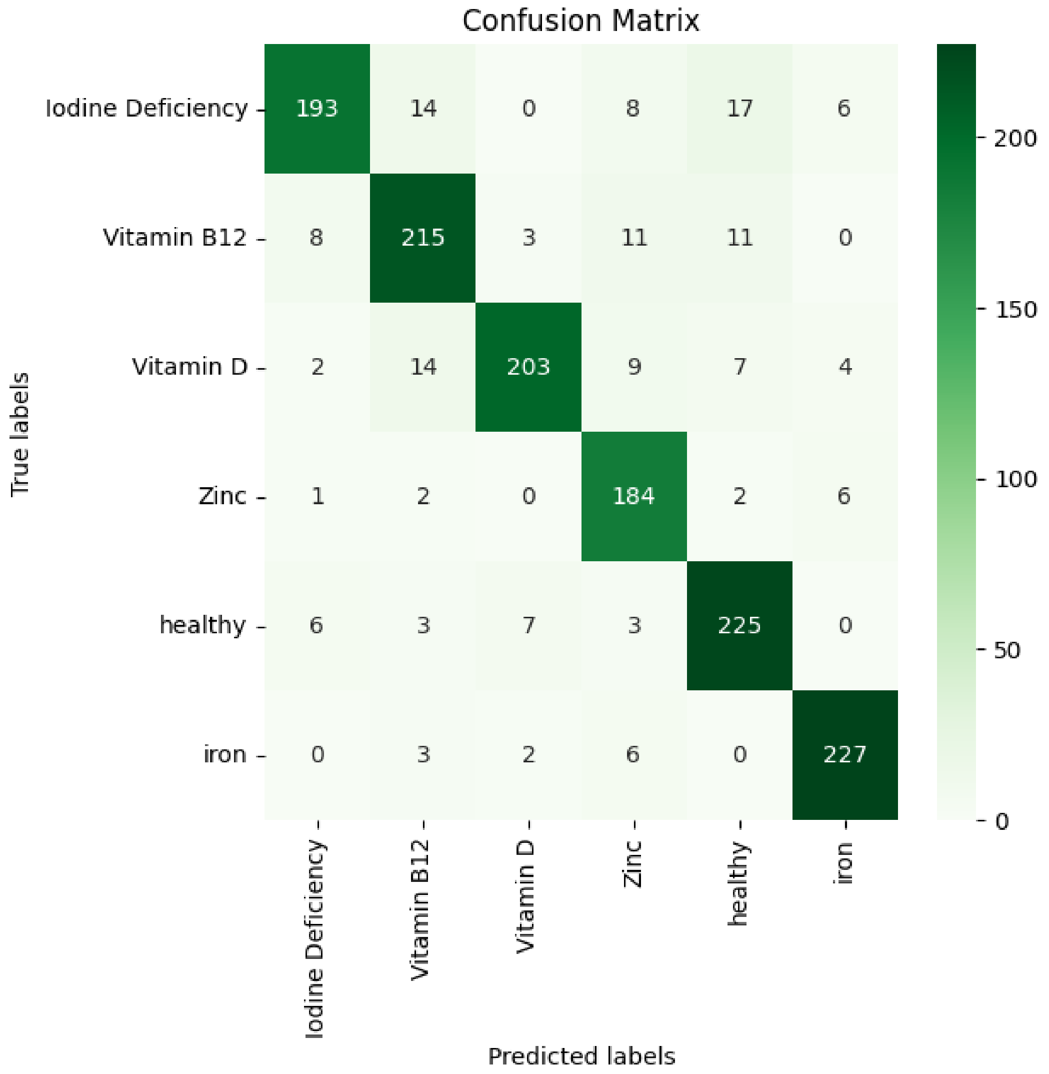
RESNET 152 V2

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20





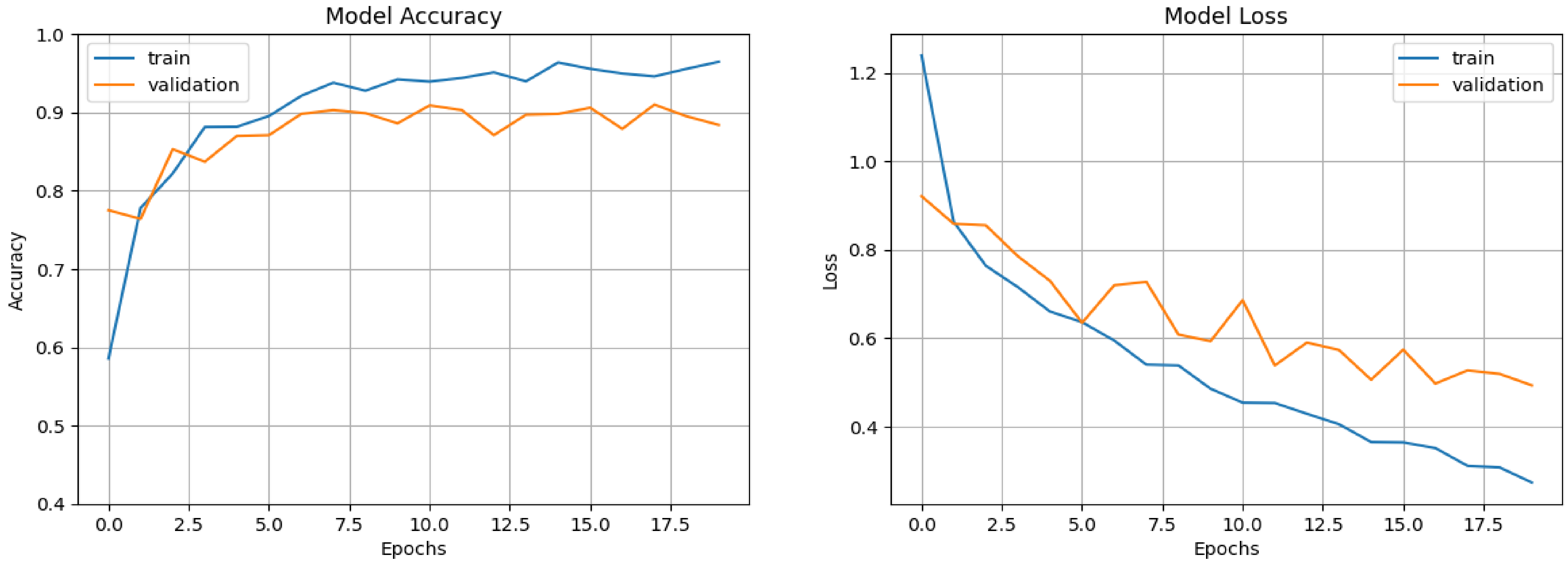
CONFUSION MATRIX



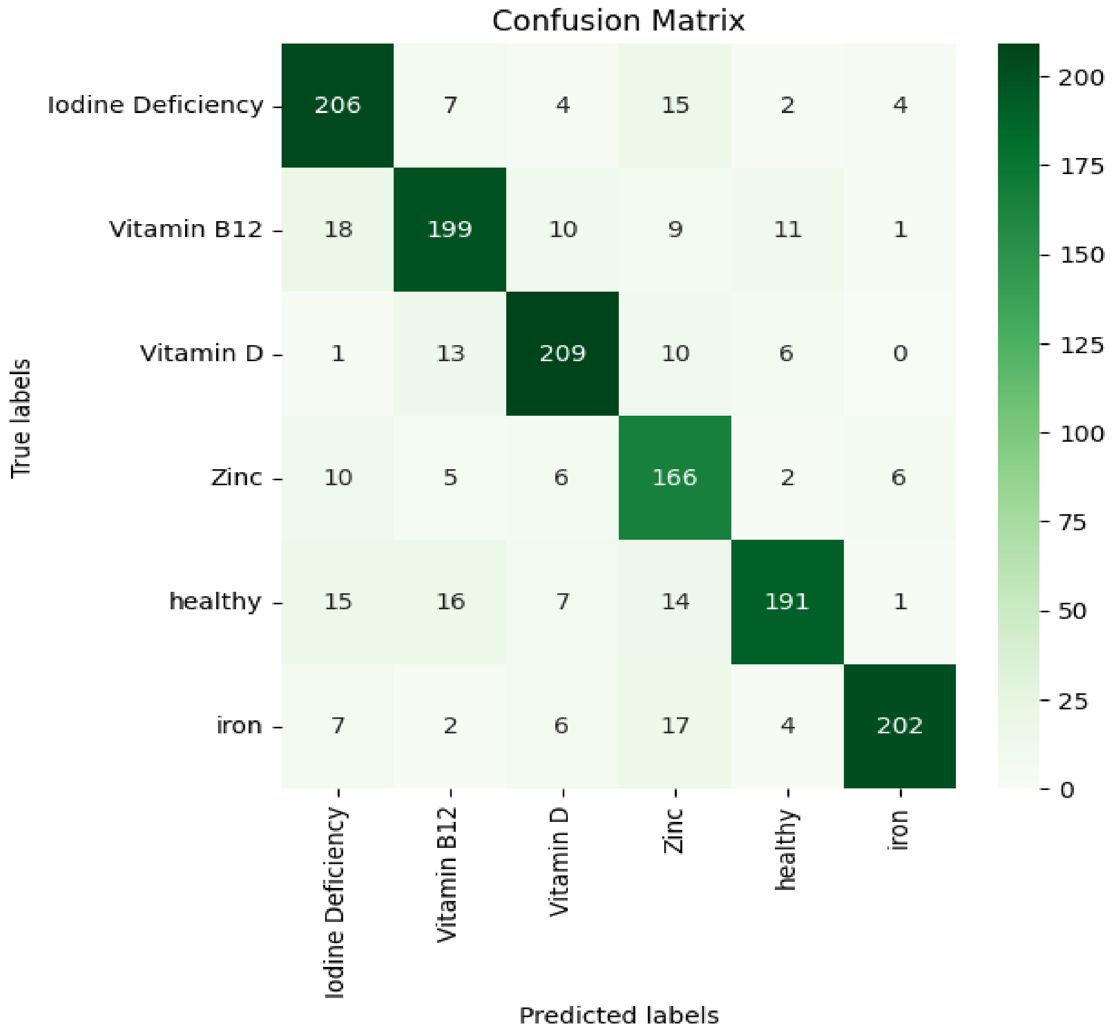
	Precision	recall	F1-score	support
Iodine	0.92	0.81	0.86	238
Vitamin B12	0.86	0.87	0.86	248
Vitamin D	0.94	0.85	0.89	239
Zinc	0.83	0.94	0.88	195
Healthy	0.86	0.92	0.89	244
Iron	0.93	0.95	0.94	238
accuracy			0.89	1402

INCEPTION V3

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20



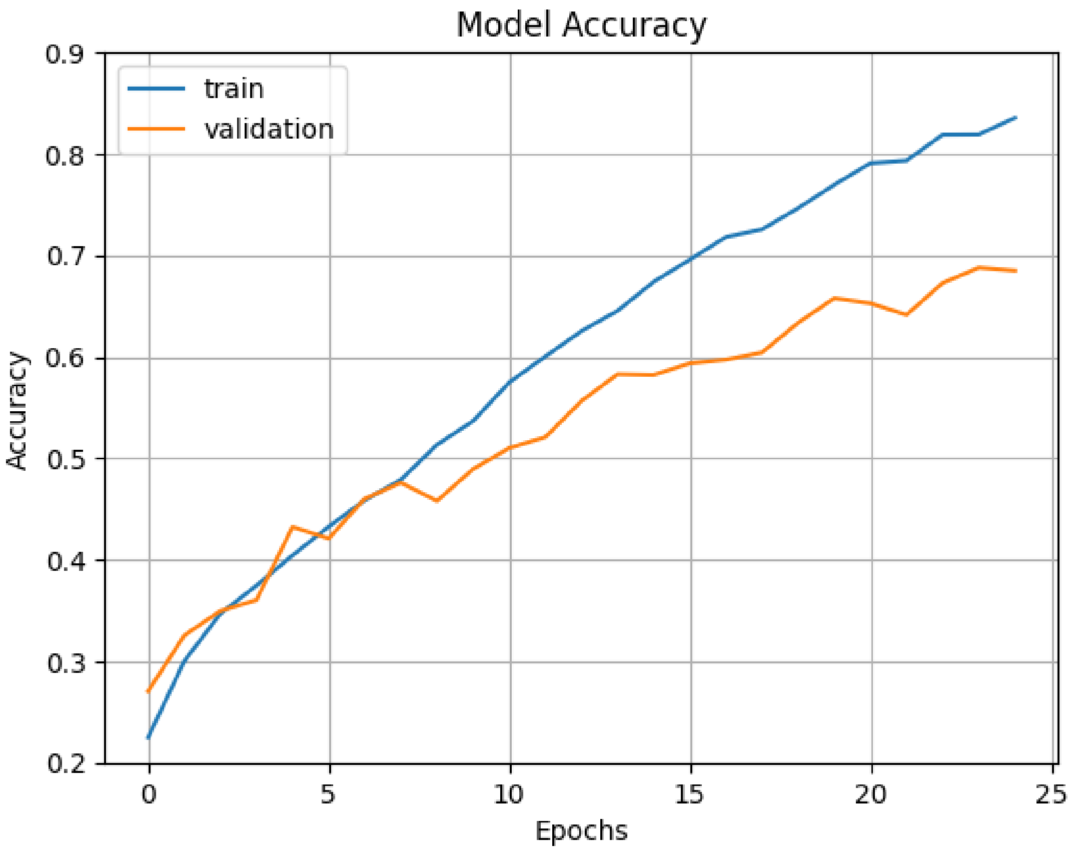
CONFUSION MATRIX

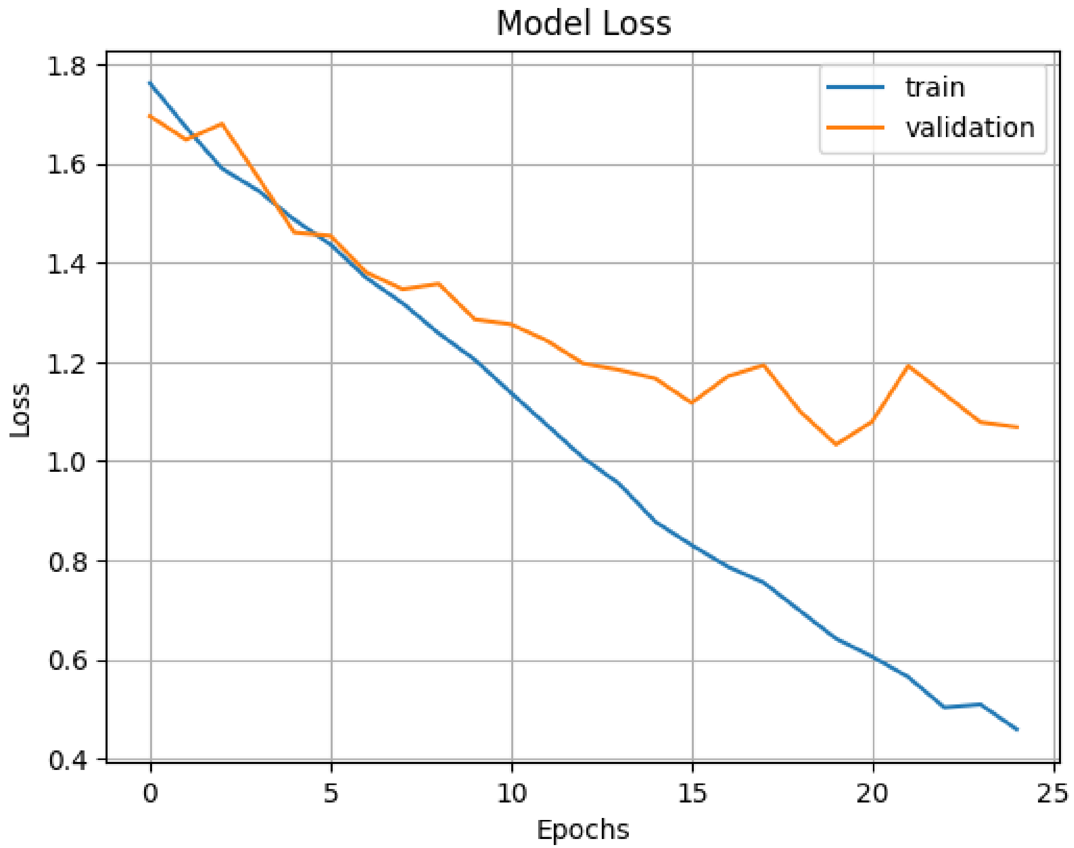


	precision	recall	F1-score	support
Iodine	0.80	0.87	0.83	238
Vitamin B12	0.82	0.80	0.81	248
Vitamin D	0.86	0.87	0.87	239
Zinc	0.72	0.85	0.78	195
Healthy	0.88	0.78	0.83	244
Iron	0.94	0.85	0.89	238
accuracy			0.84	1402

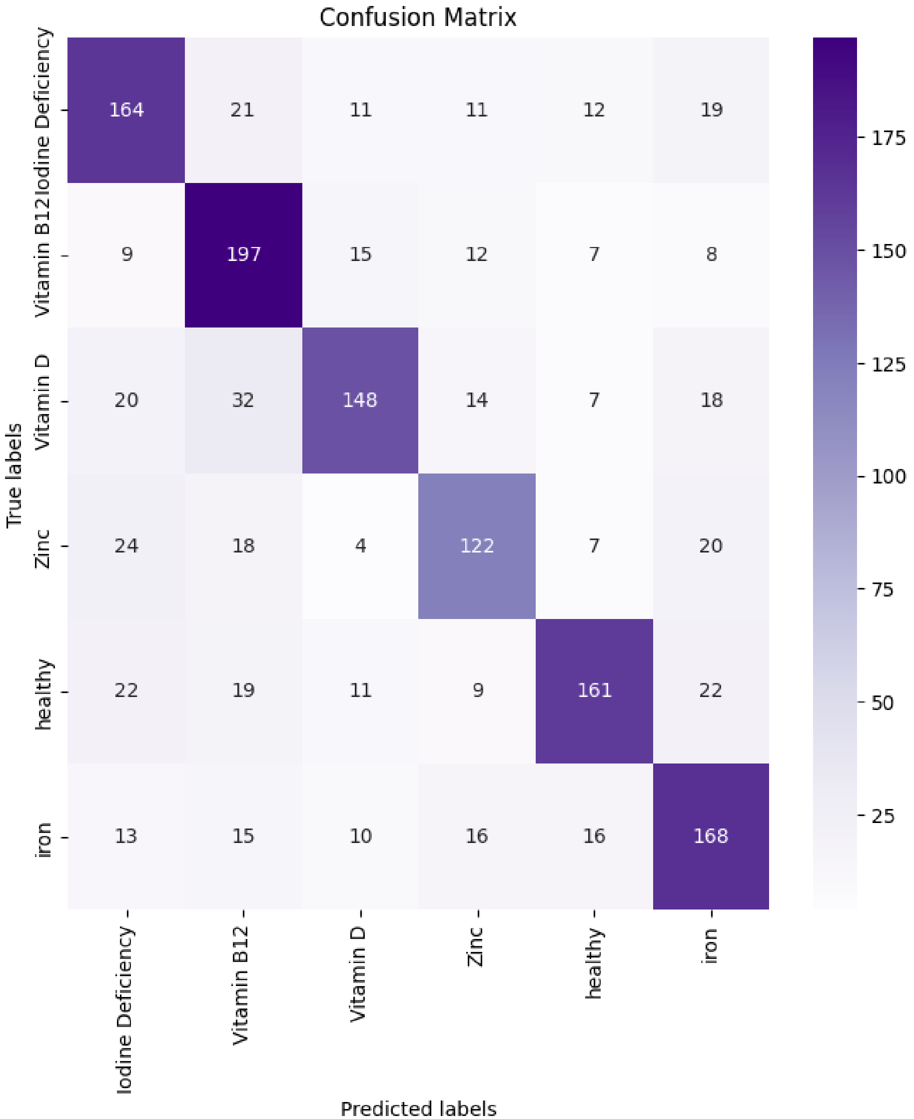
CNN Model

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20





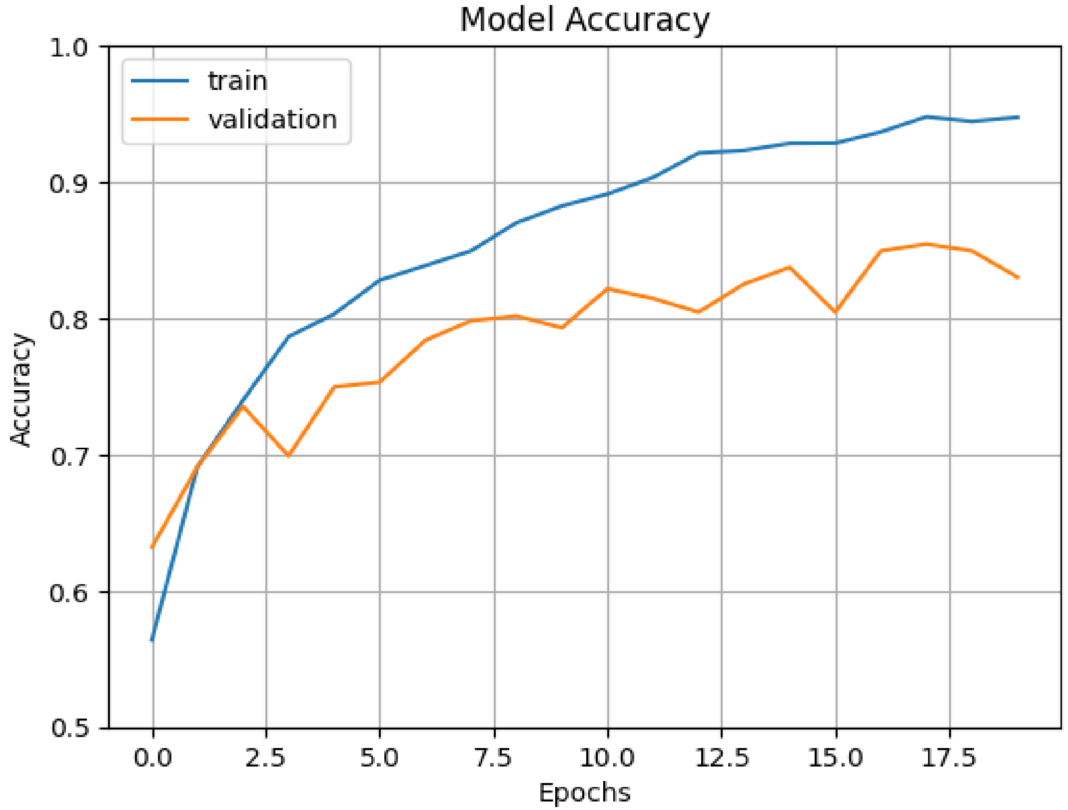
CONFUSION MATRIX

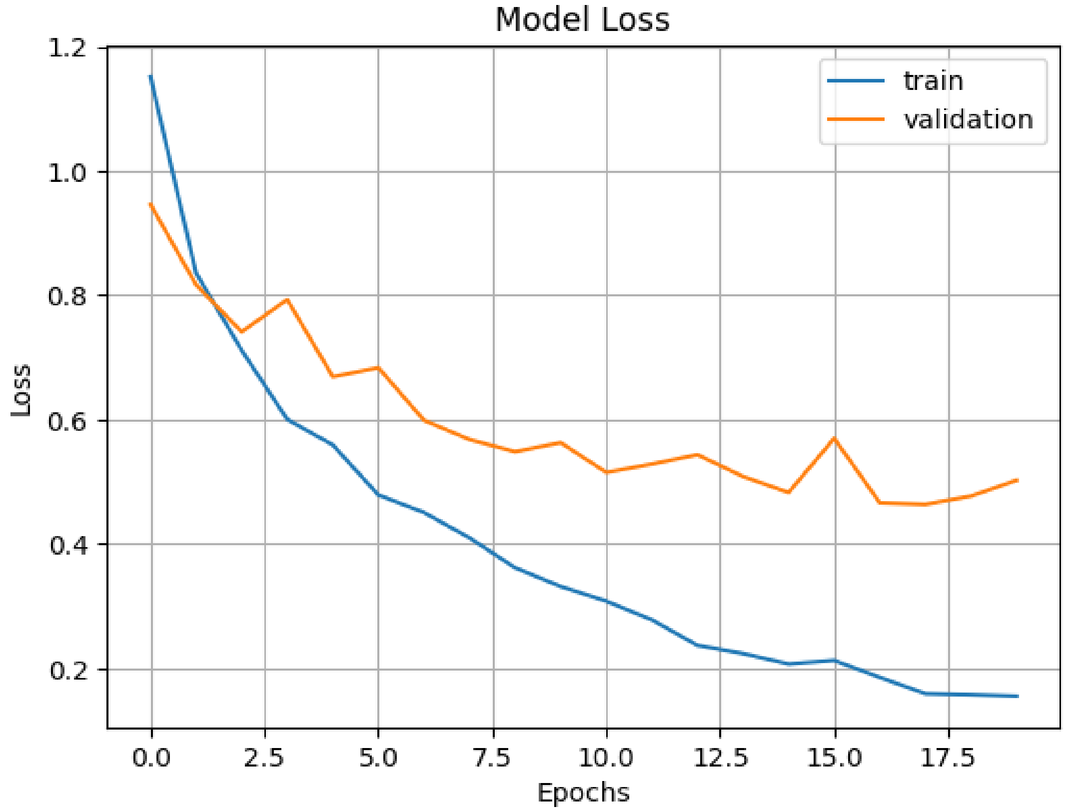


	precision	recall	F1-score	support
Iodine	0.65	0.69	0.67	238
Vitamin B12	0.65	0.79	0.72	248
Vitamin D	0.74	0.62	0.68	239
Zinc	0.66	0.63	0.64	195
Healthy	0.77	0.66	0.71	244
Iron	0.66	0.71	0.68	238
accuracy			0.68	1402

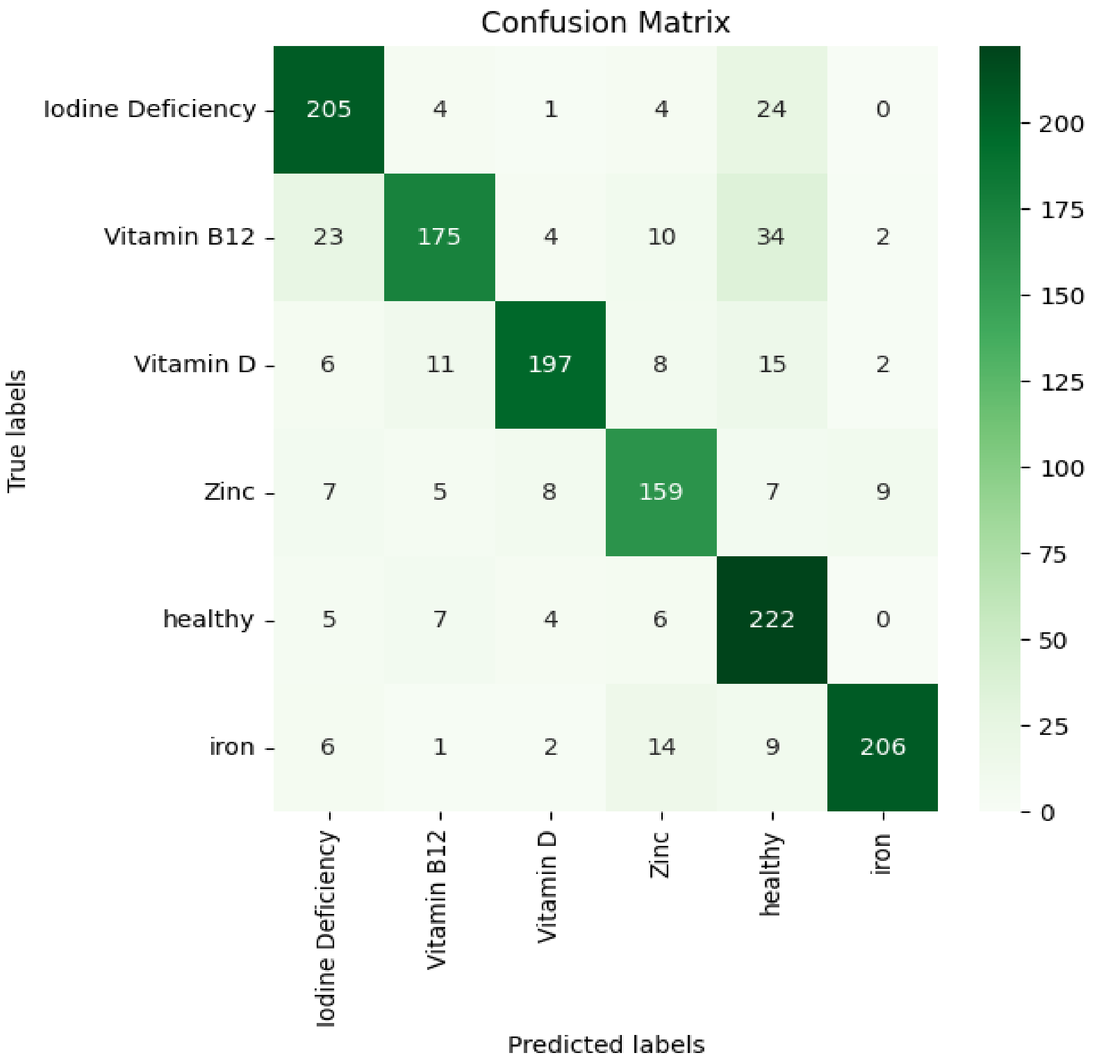
XCEPTION NET

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20





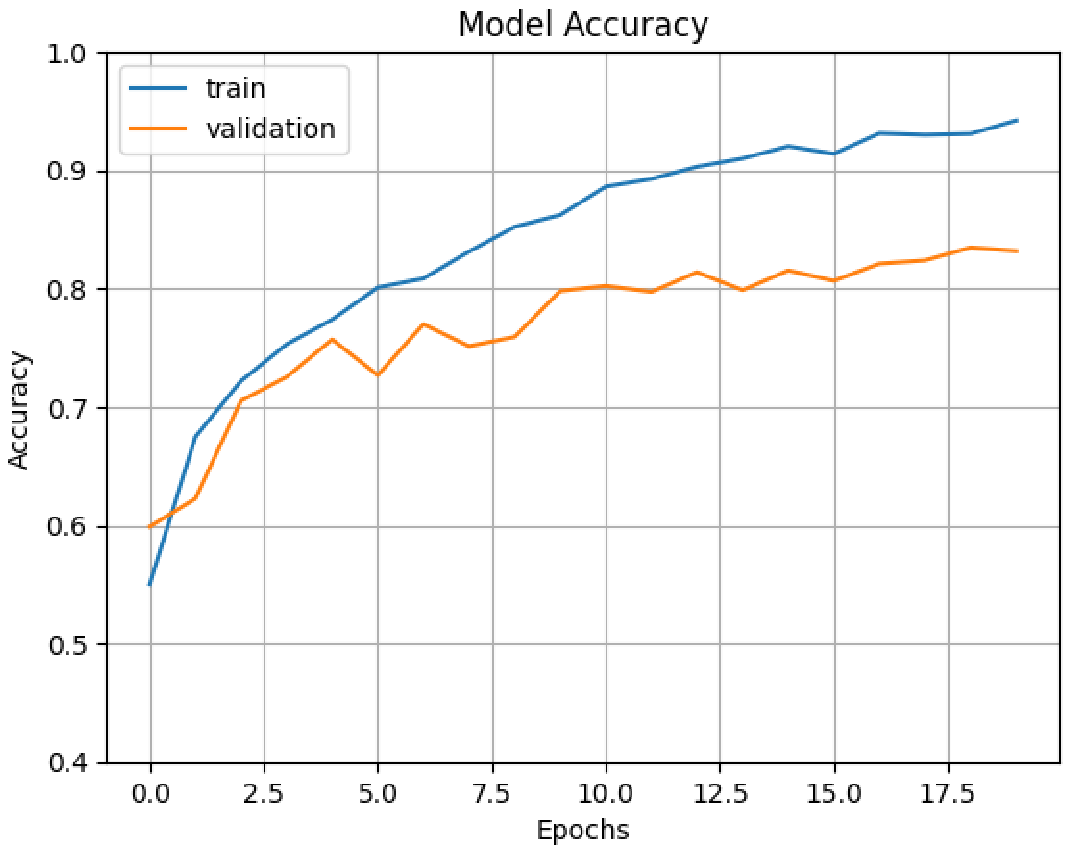
CONFUSION MATRIX

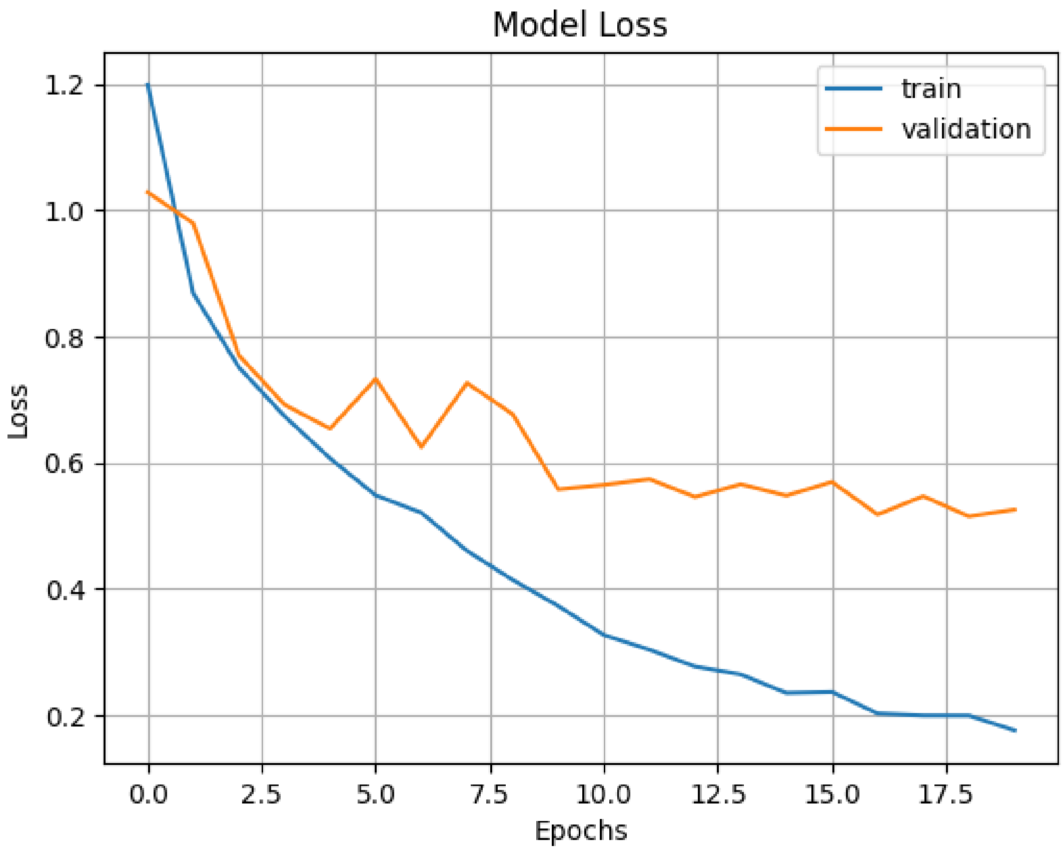


	precision	recall	F1-score	support
Iodine	0.81	0.86	0.84	238
Vitamin B12	0.86	0.71	0.78	248
Vitamin D	0.91	0.82	0.87	239
Zinc	0.79	0.82	0.80	195
Healthy	0.71	0.91	0.80	244
Iron	0.94	0.87	0.90	238
accuracy			0.83	1402

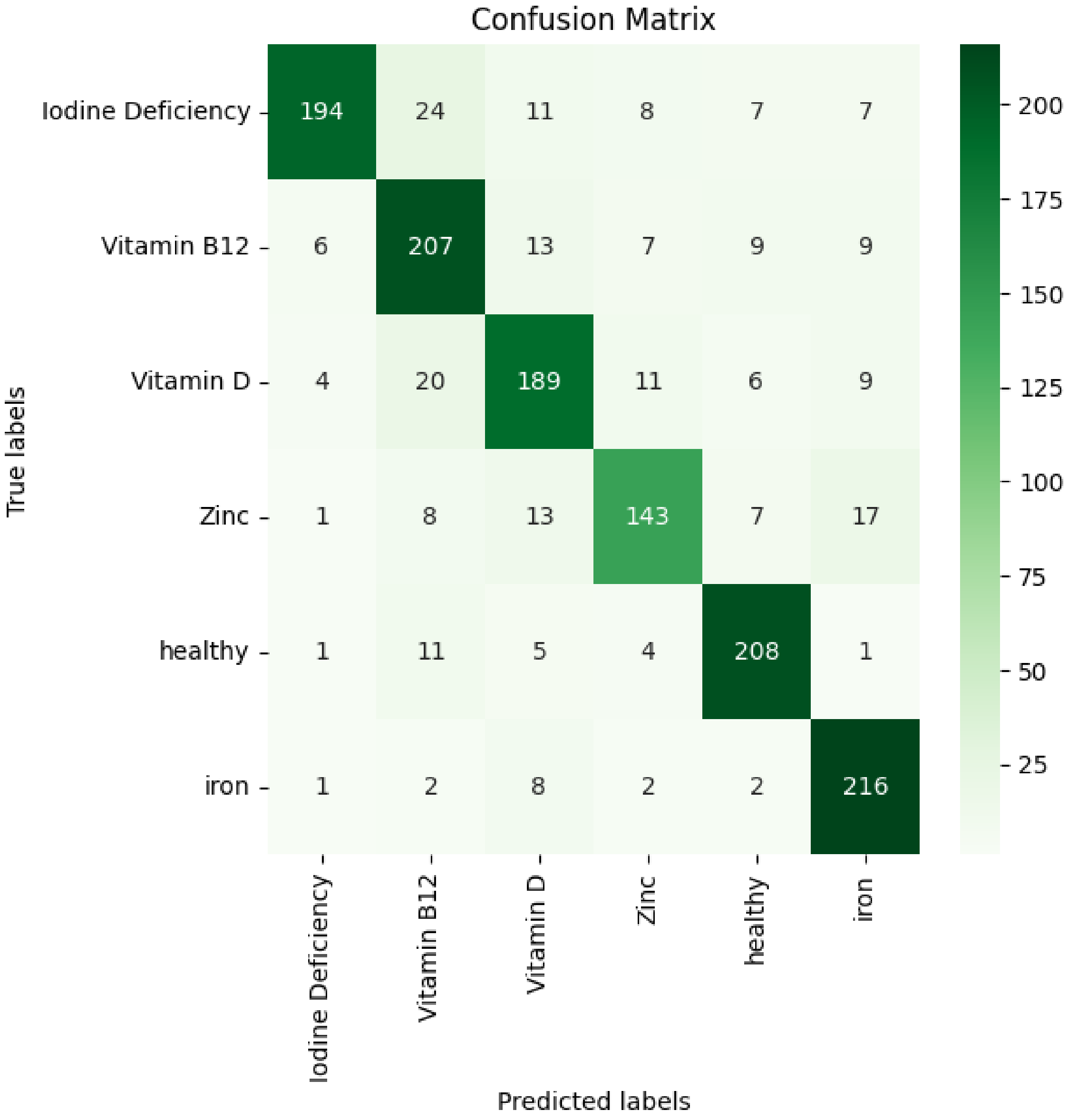
MOBILE NET

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20





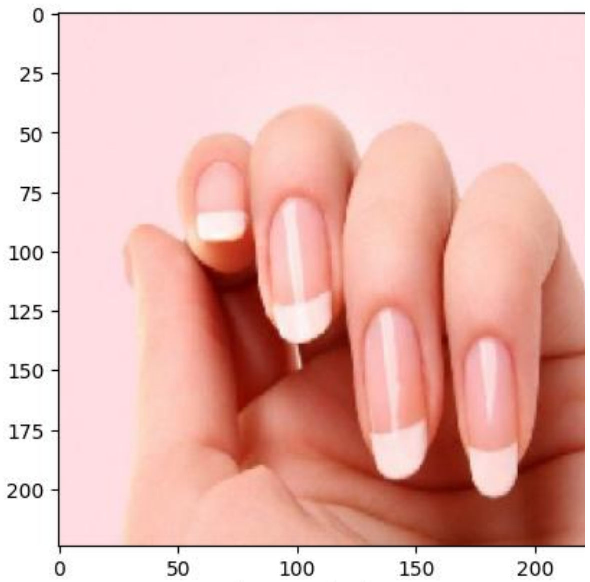
CONFUSION MATRIX



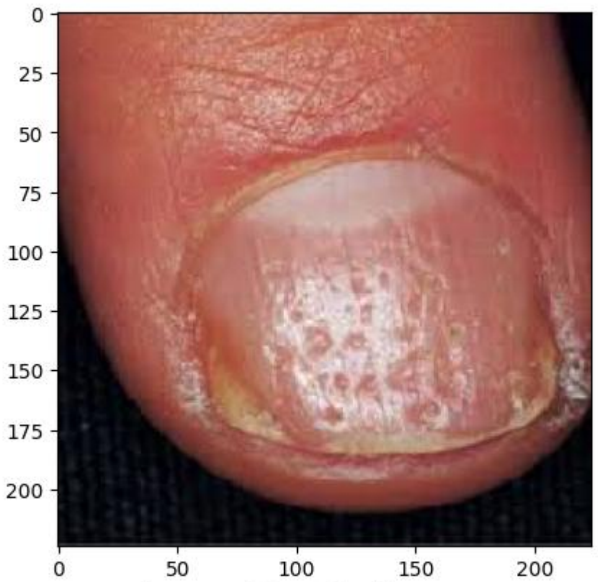
	Precision	recall	F1-score	support
Iodine	0.94	0.77	0.85	238
Vitamin B12	0.79	0.82	0.79	248
Vitamin D	0.79	0.79	0.79	239
Zinc	0.82	0.76	0.79	195
Healthy	0.87	0.90	0.89	244
Iron	0.83	0.94	0.88	238
accuracy			0.83	1402

IMAGE PREDICTION

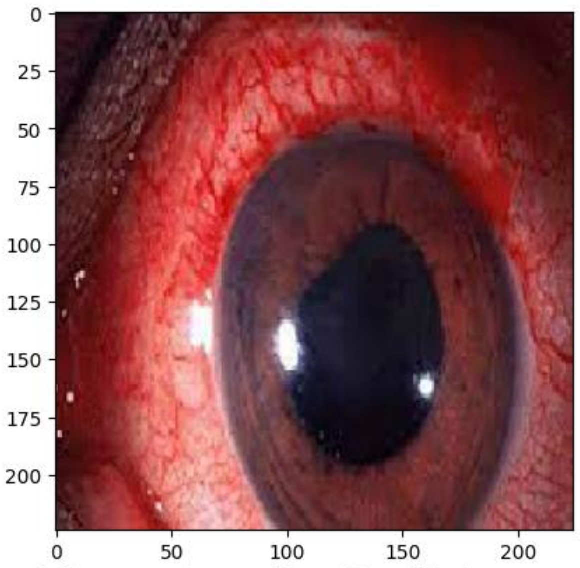
Images are selected in random manner and predicted using the built models



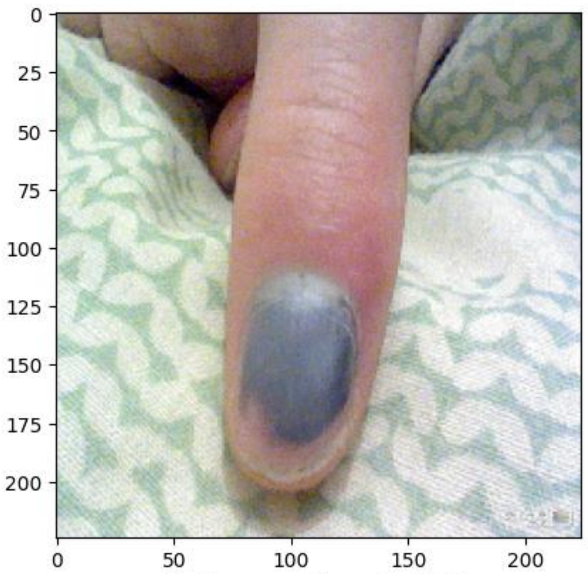
healthy



Iron Deficiency



Vitamin - D Deficiency



Vitamin B12

MODEL BUILDING

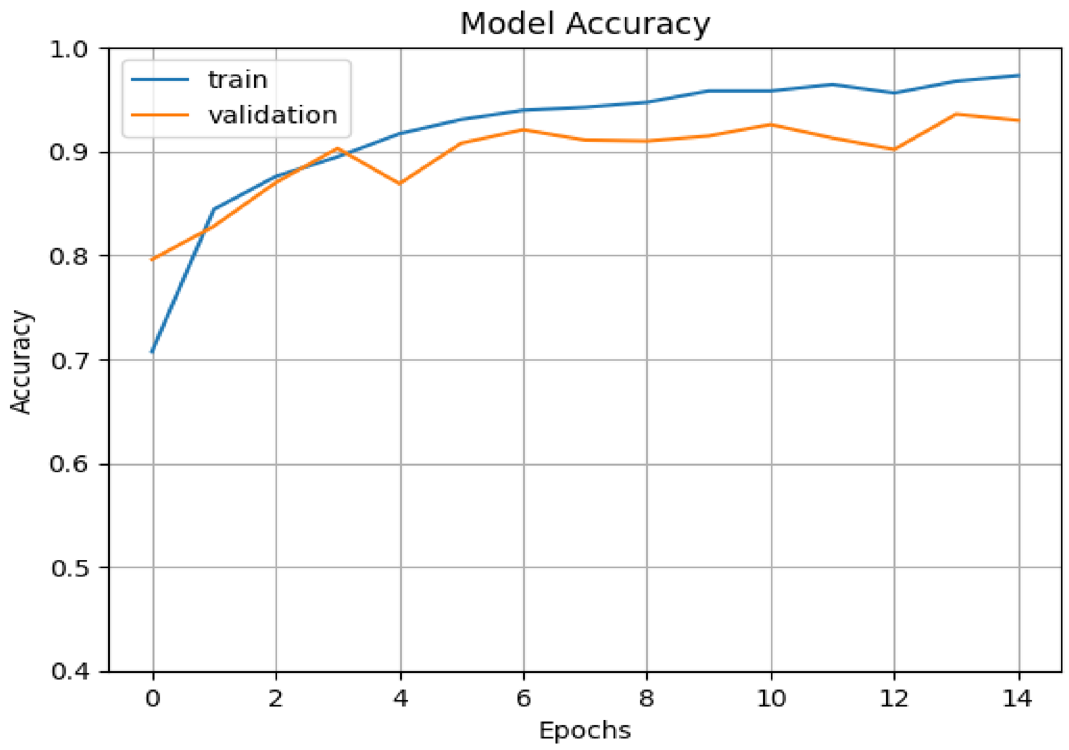
The CNN model we used for model building of leaf dataset are

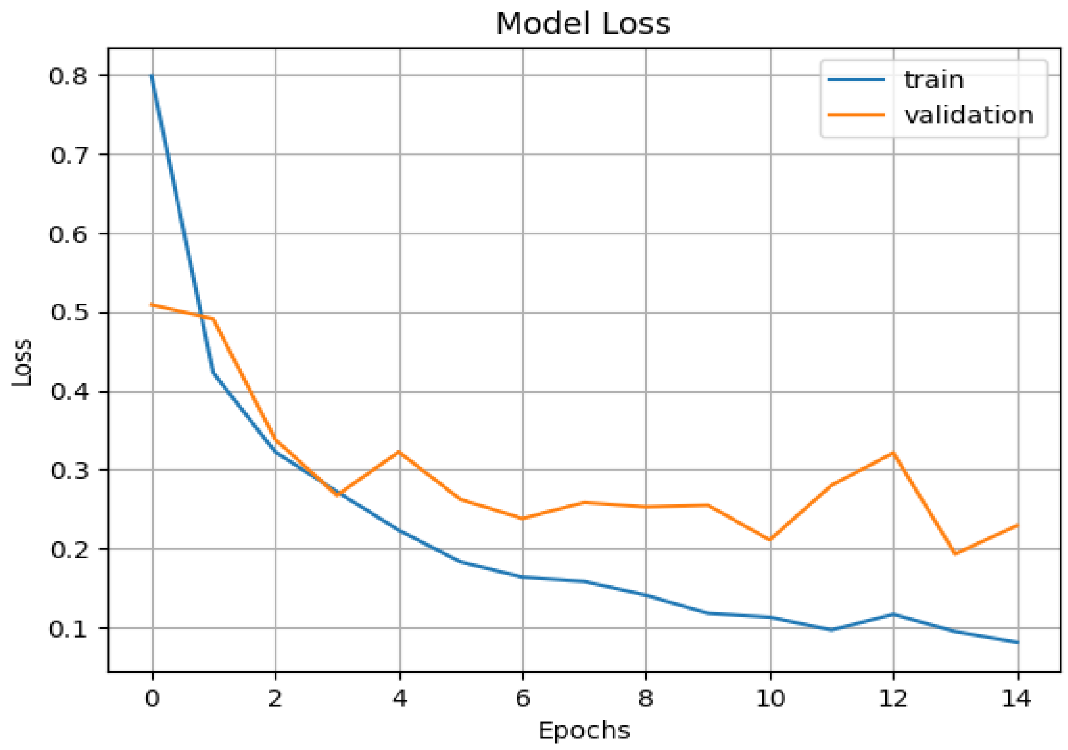
- Inception V3
- Resnet152V2
- CNN model
- Xception
- Mobile net

Resnet152V3	InceptionV3	CNN model	Mobile net	Xception
Trainaccuracy-97.31%	Trainaccuracy-96.80%	Trainaccuracy-83.00%	Train accuracy-97.20%	Train accuracy-96.57%
Test accuracy-93.00%	Test accuracy-90.40%	Test accuracy-80.60%	Test accuracy-92.30%	Test accuracy-91.40%

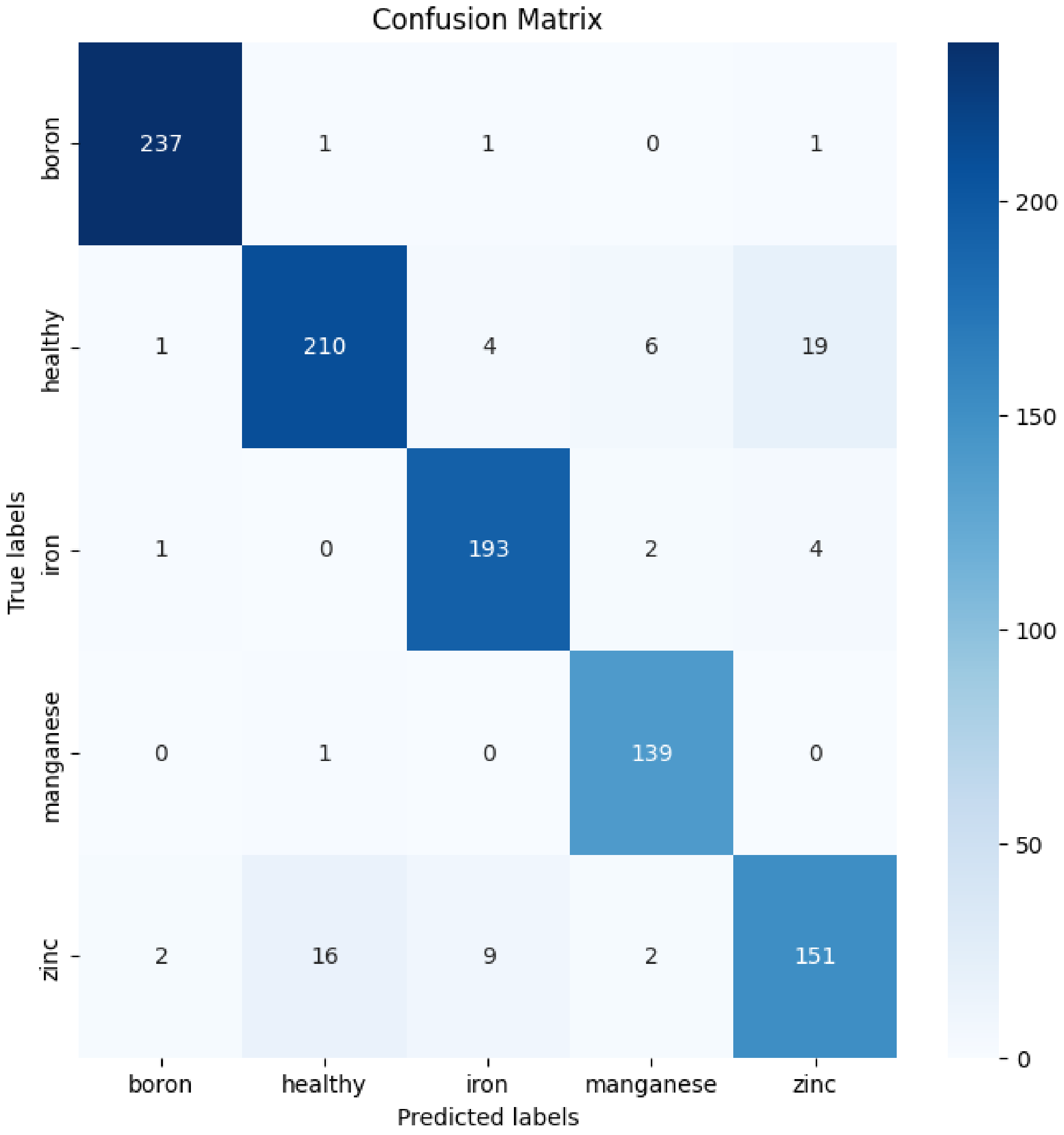
RESNET 152 V2

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-15





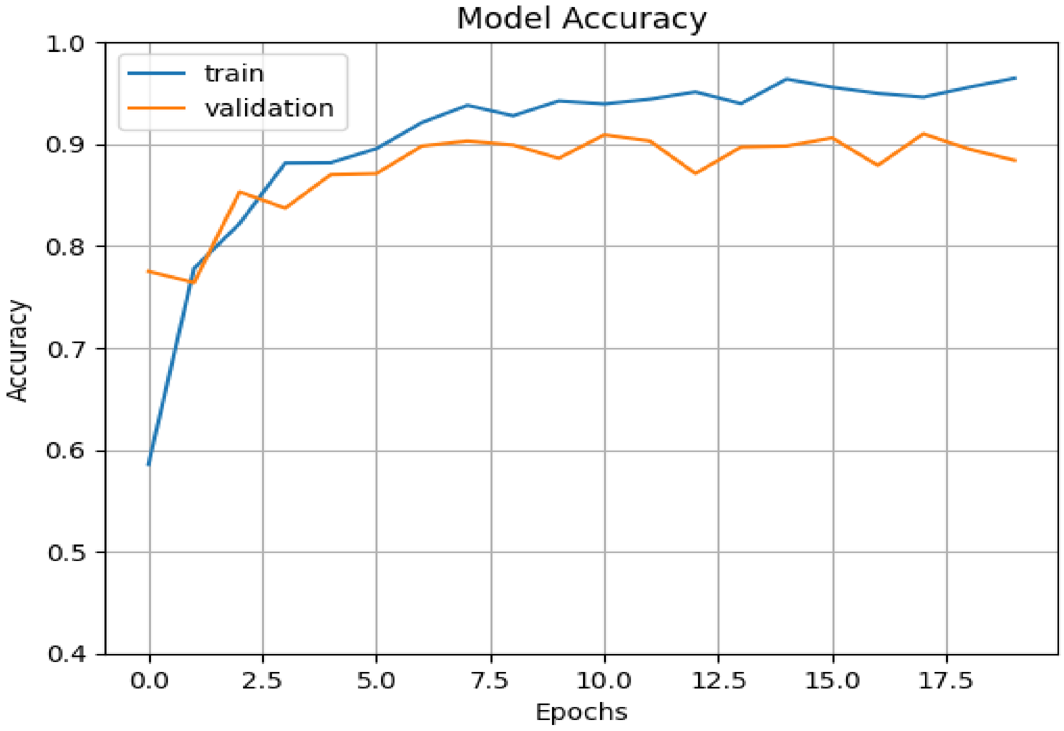
CONFUSION MATRIX

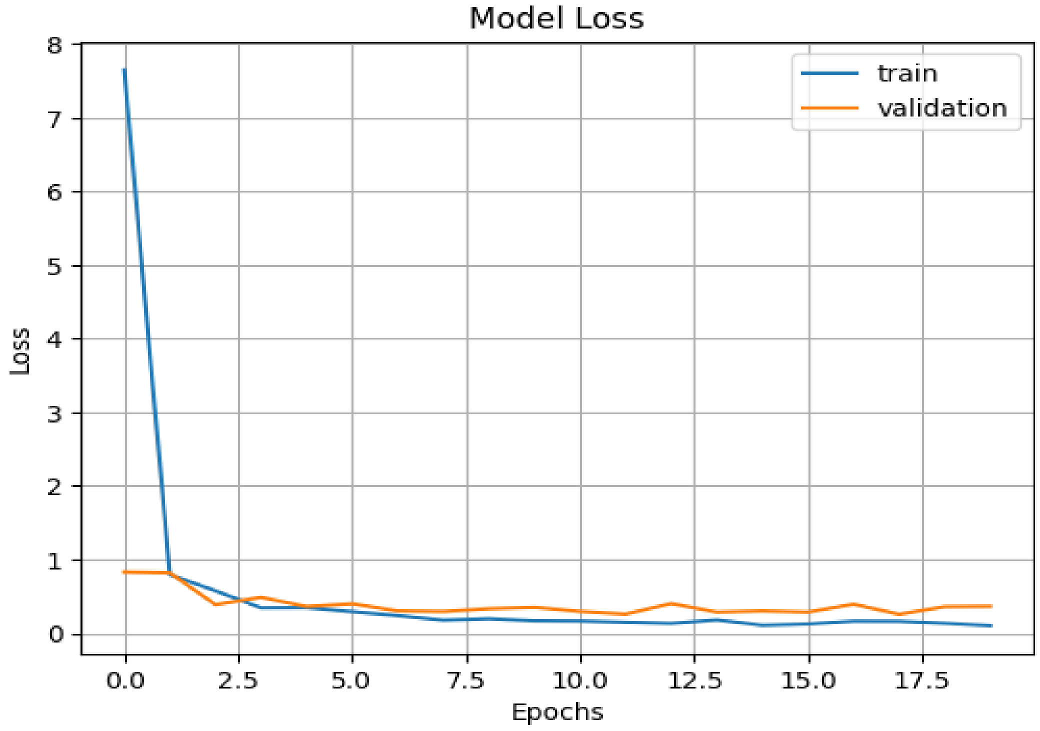


	precision	recall	f1-score	support
boron	0.98	0.99	0.99	240
healthy	0.92	0.88	0.90	240
iron	0.93	0.96	0.95	200
manganese	0.93	0.99	0.96	140
zinc	0.86	0.84	0.85	180
accuracy			0.93	1000

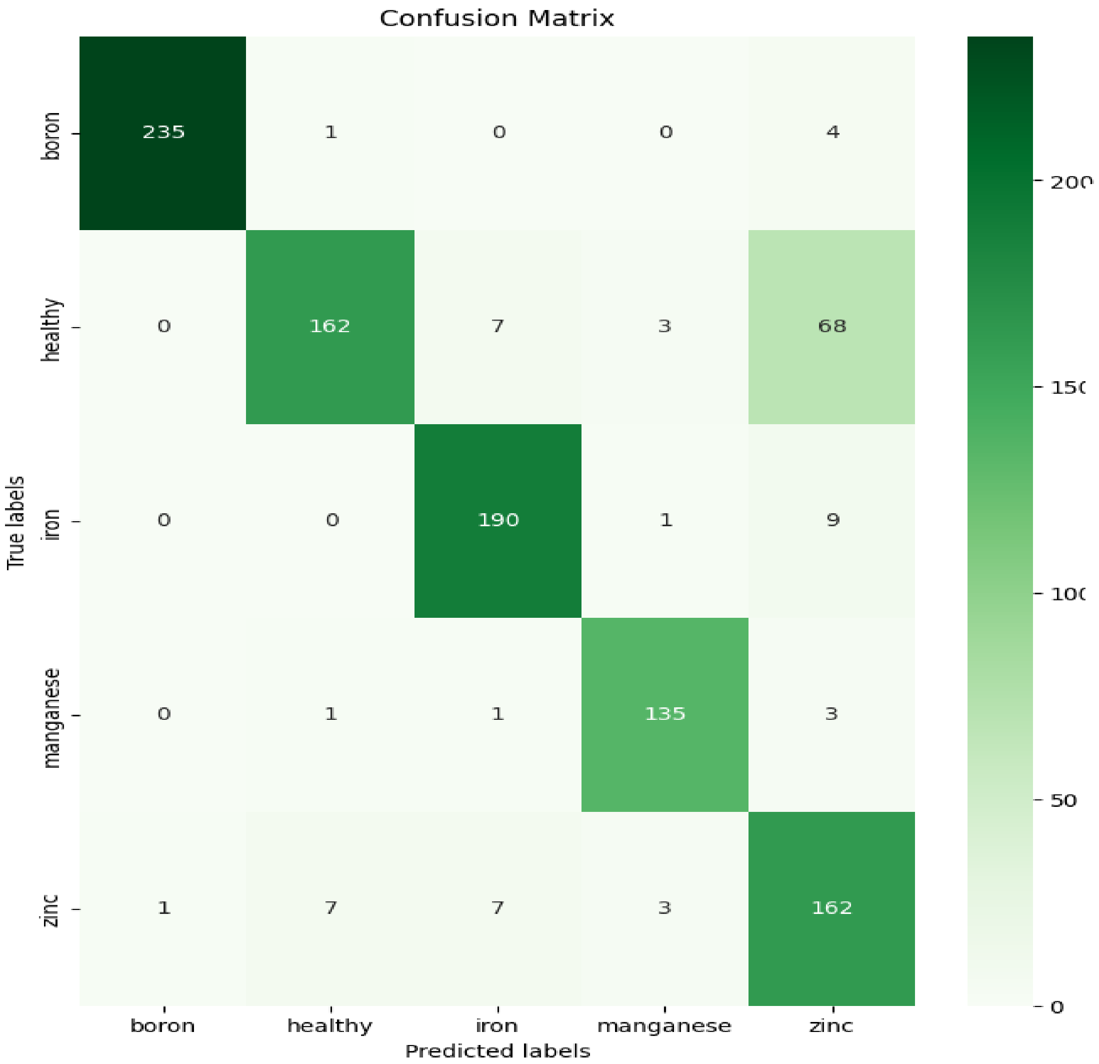
Inception V3

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20





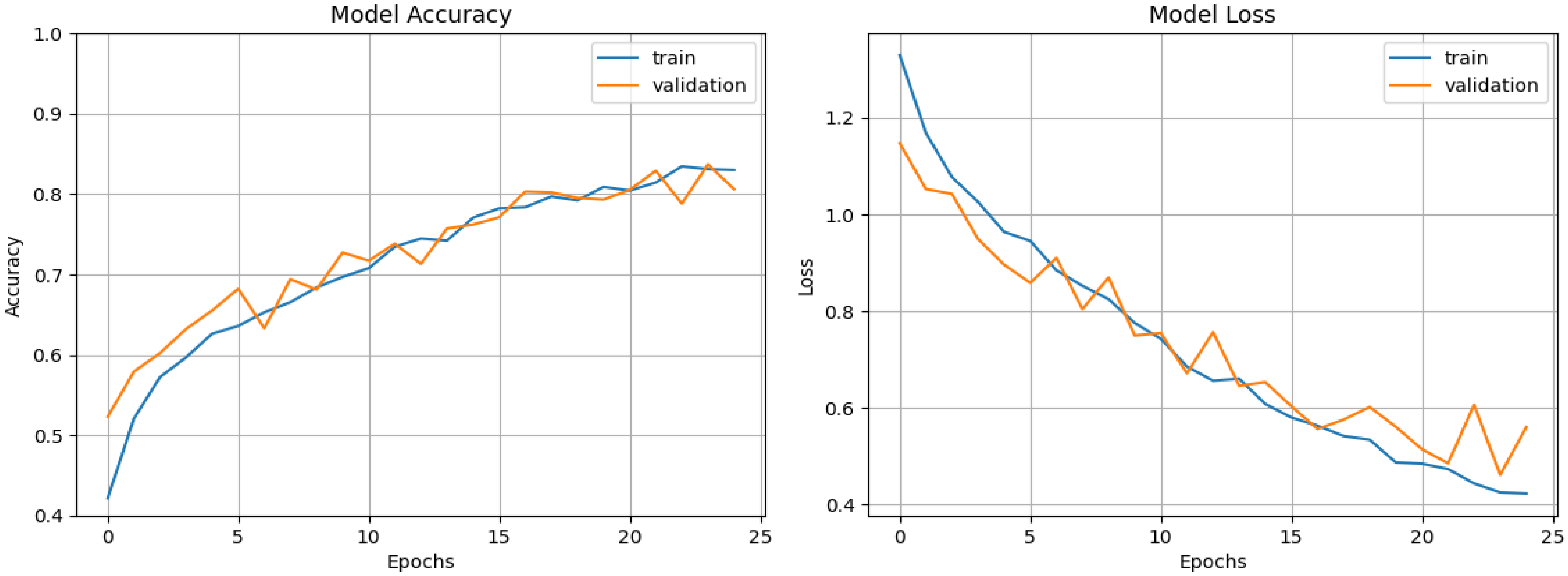
CONFUSION MATRIX



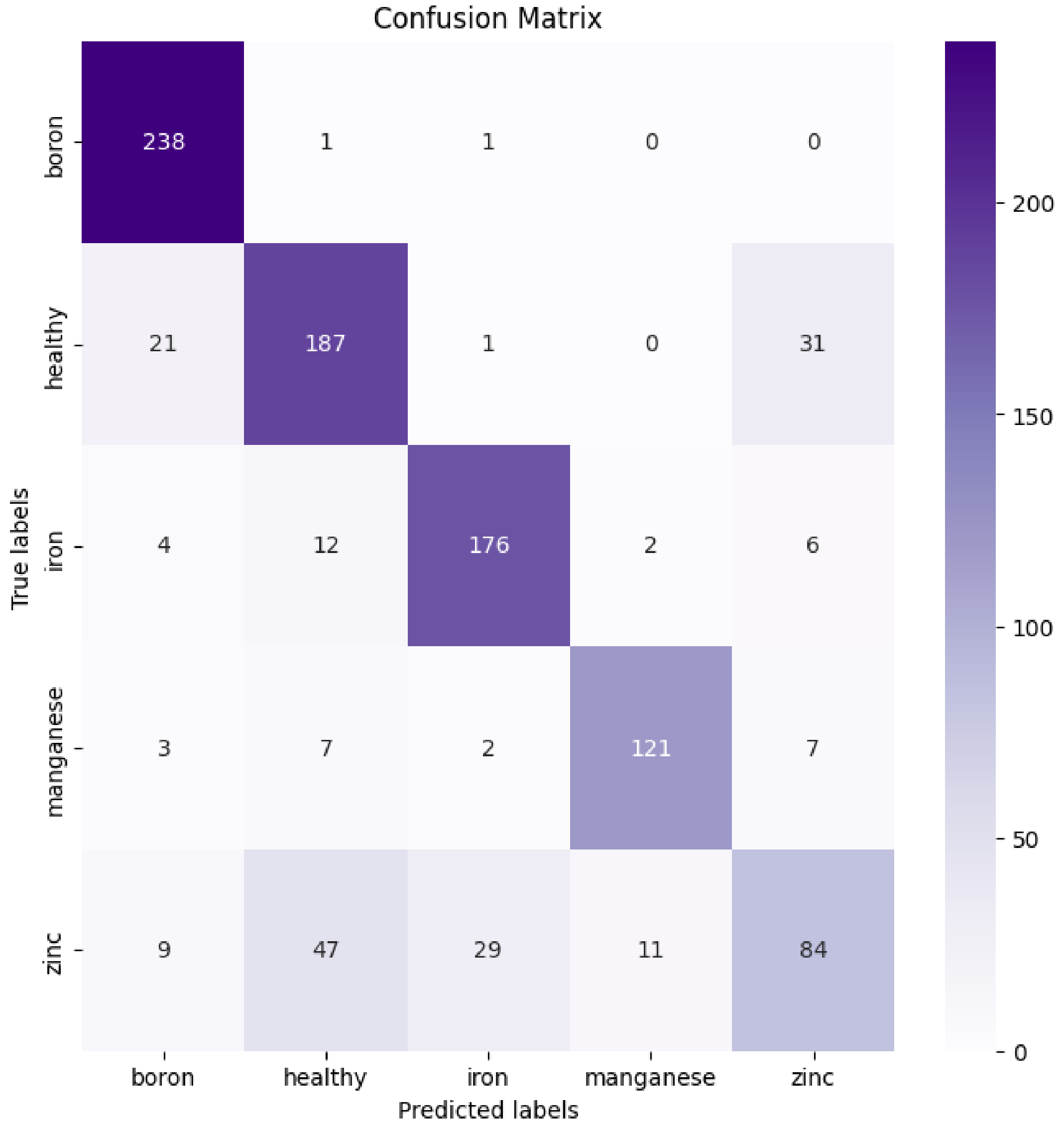
	precision	recall	f1-score	support
boron	1.00	0.98	0.99	240
healthy	0.95	0.68	0.79	240
iron	0.93	0.95	0.94	200
manganese	0.95	0.96	0.96	140
zinc	0.66	0.90	0.76	180
accuracy			0.88	1000

CNN Model

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-25



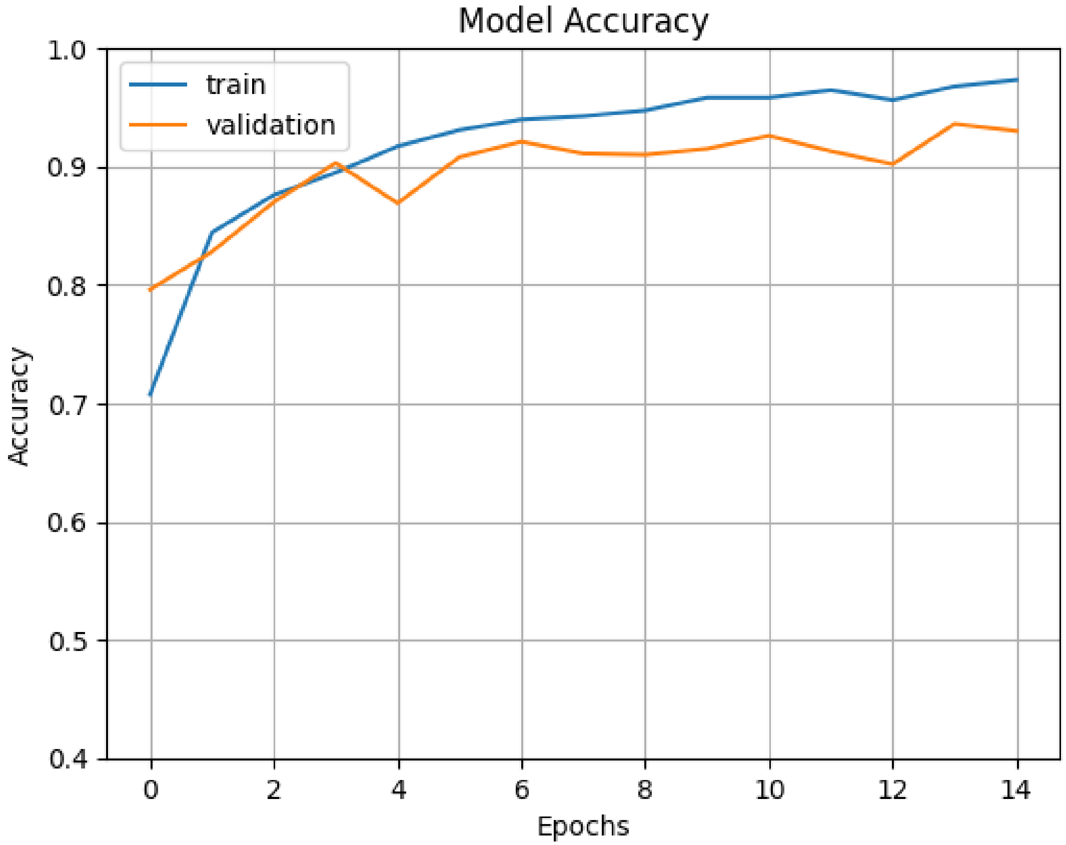
CONFUSION MATRIX

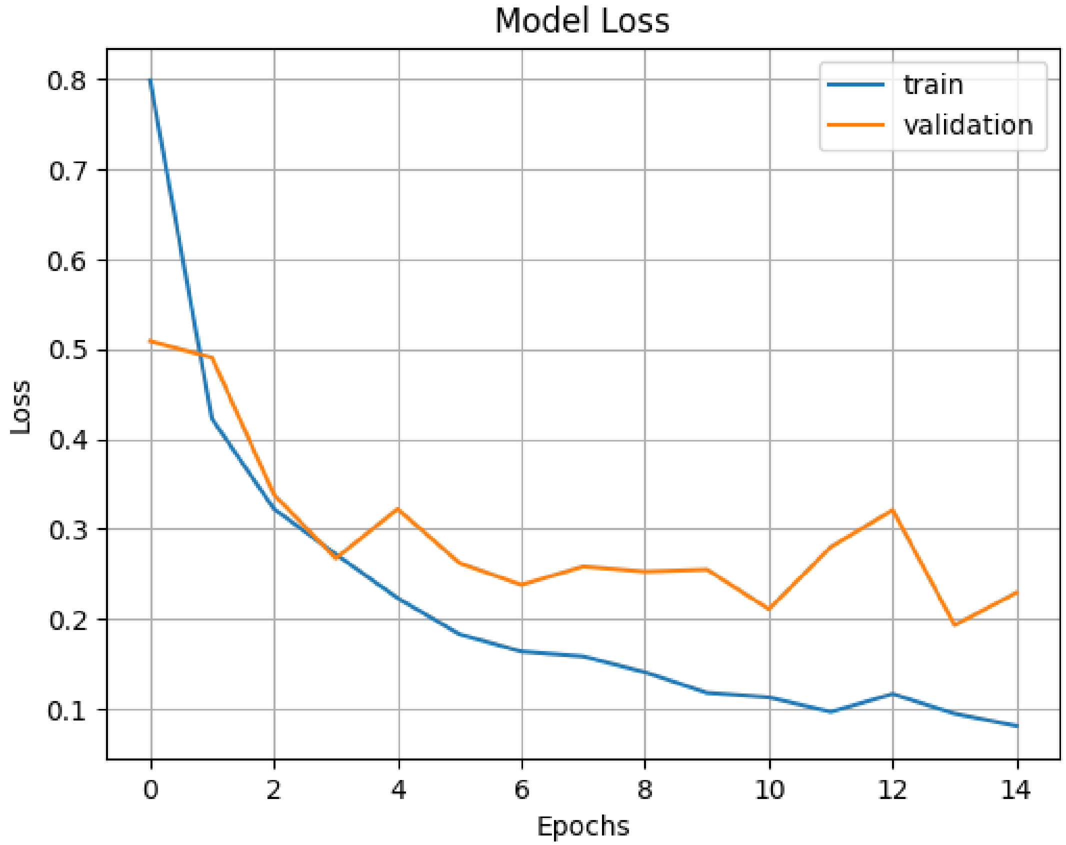


	precision	recall	f1-score	support
boron	0.87	0.99	0.92	240
healthy	0.74	0.78	0.76	240
iron	0.84	0.88	0.86	200
manganese	0.90	0.86	0.88	140
zinc	0.66	0.47	0.55	180
accuracy			0.81	1000

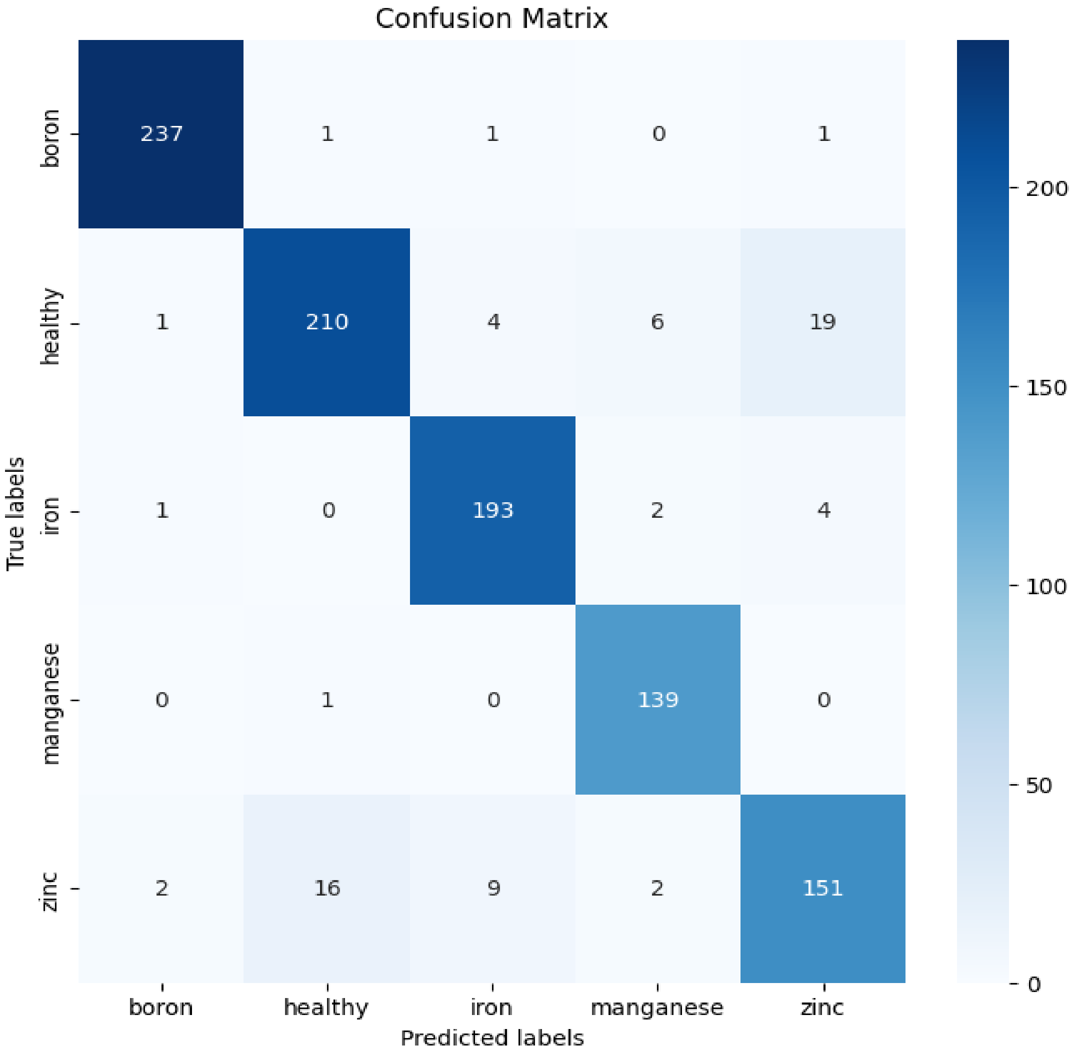
MOBILE NET

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20





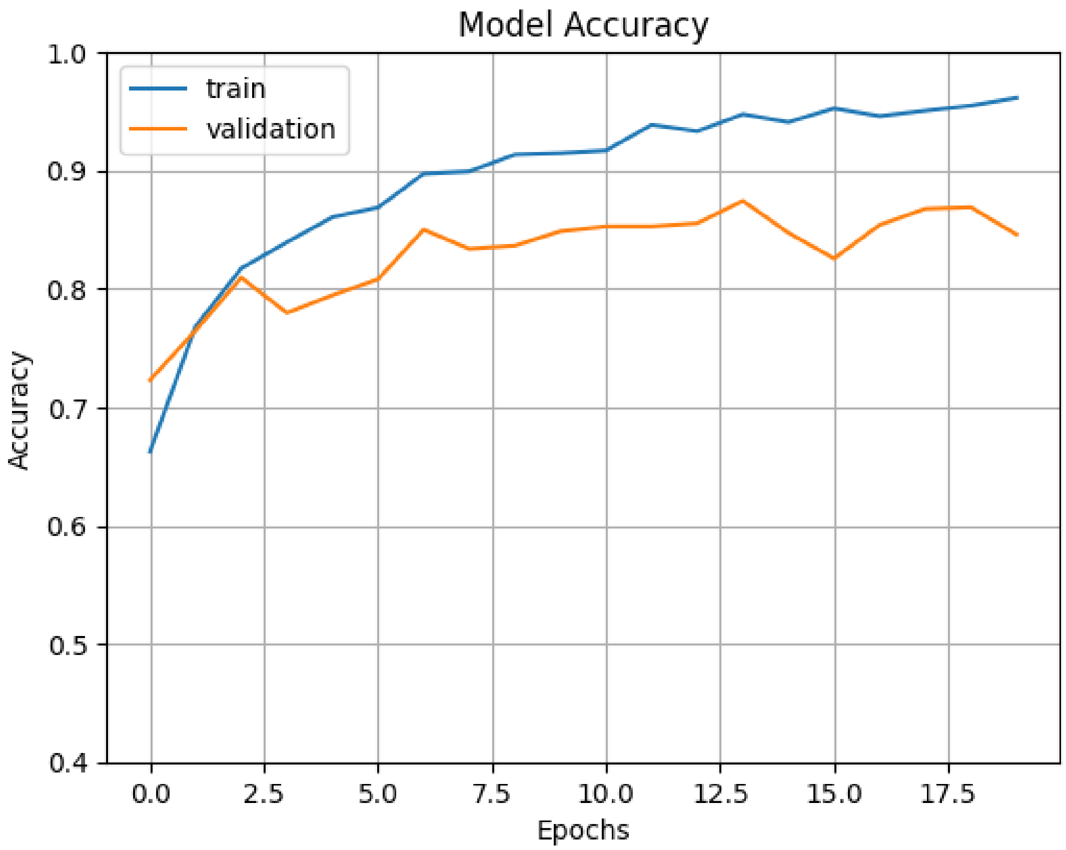
CONFUSION MATRIX

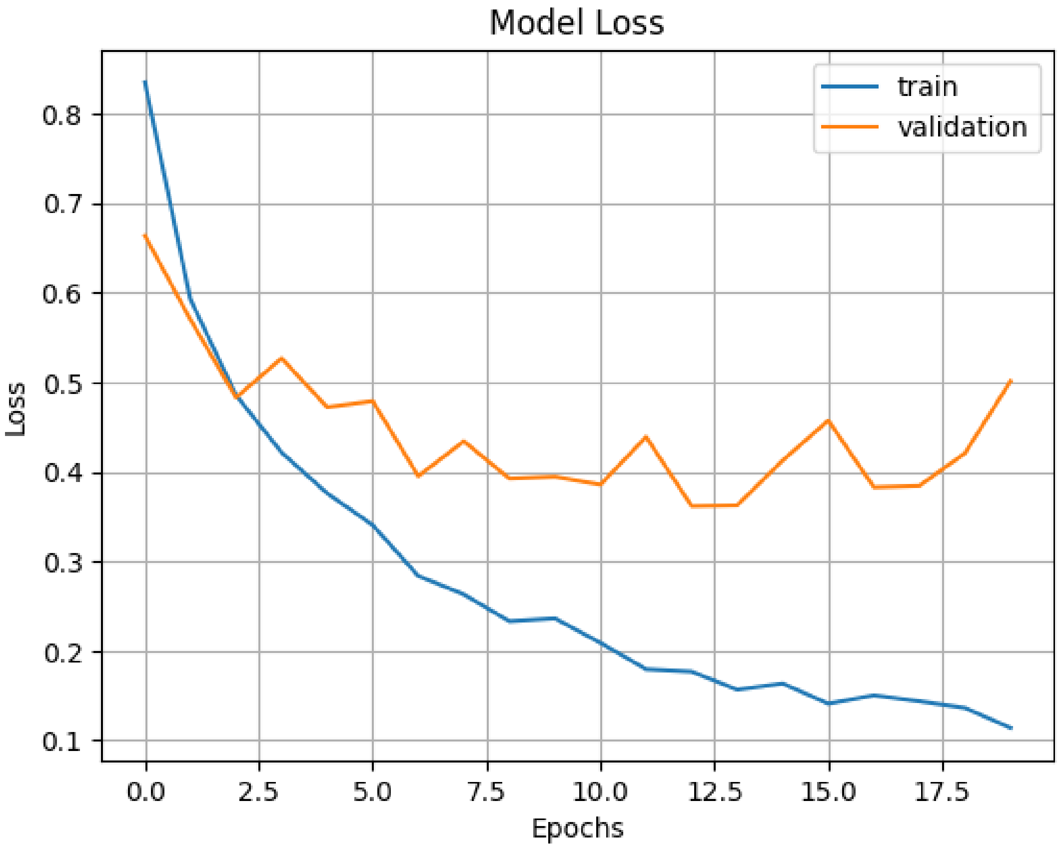


	precision	recall	f1-score	support
boron	0.97	0.99	0.98	240
healthy	0.90	0.85	0.87	240
iron	0.98	0.86	0.92	200
manganese	0.99	0.95	0.97	140
zinc	0.74	0.88	0.81	180
accuracy			0.91	1000

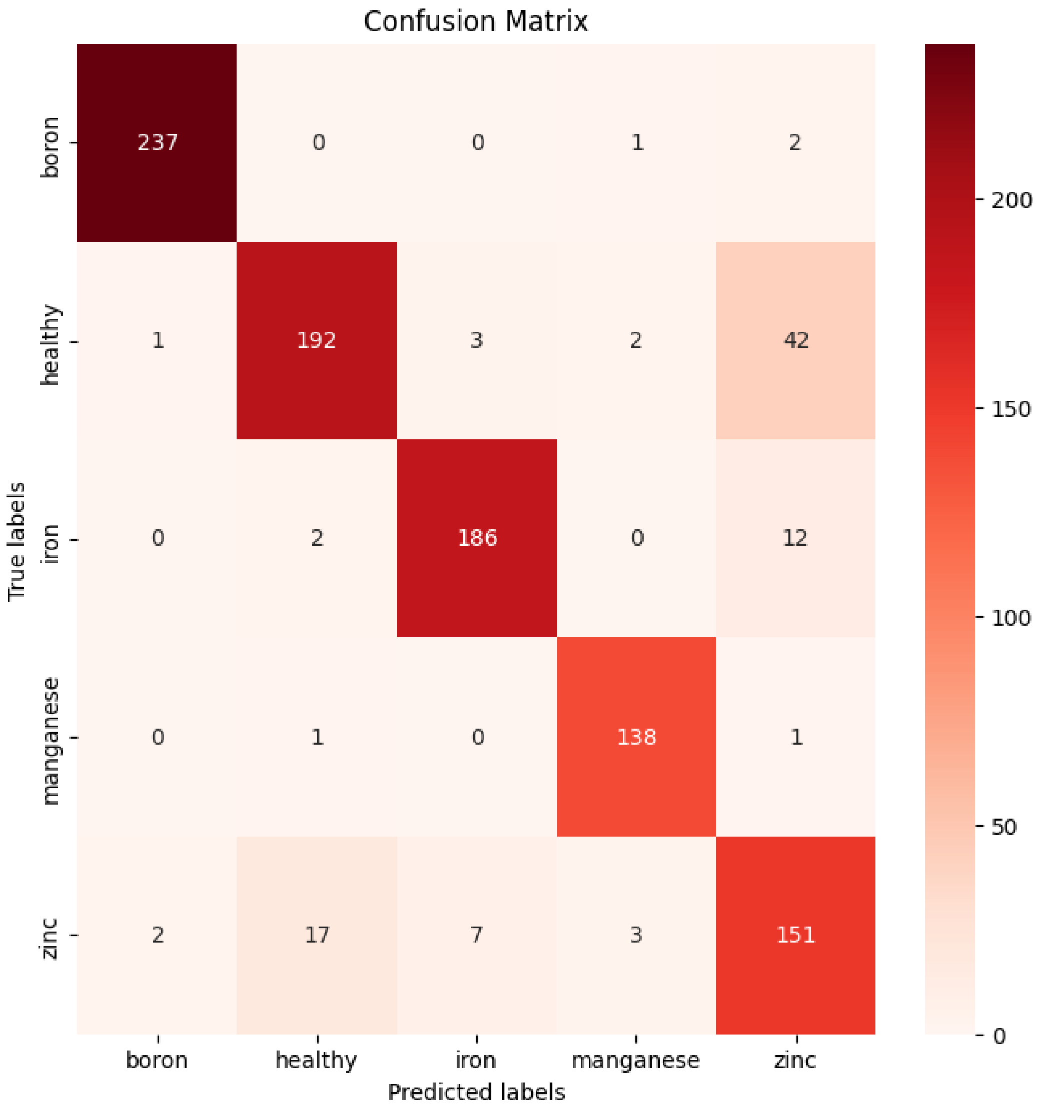
XCEPTION NET

- ✓ Model accuracy and loss plot is shown below
- ✓ No of epochs-20



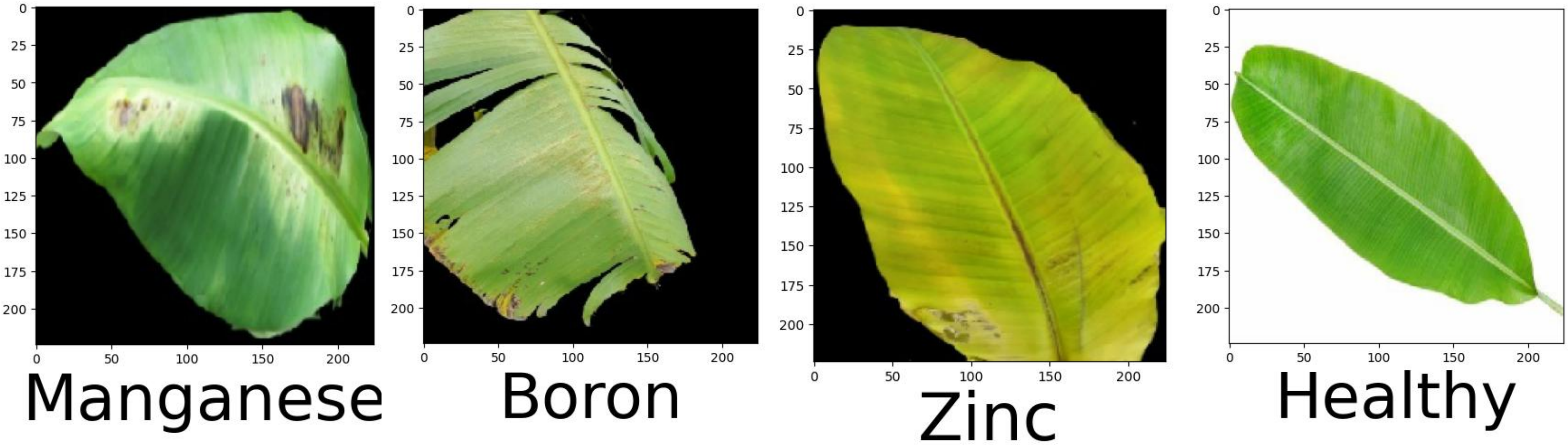


CONFUSION MATRIX



	precision	recall	f1-score	support
boron	0.97	0.99	0.98	240
healthy	0.90	0.85	0.87	240
iron	0.98	0.86	0.92	200
manganese	0.99	0.95	0.97	140
zinc	0.74	0.88	0.81	180
accuracy			0.91	1000

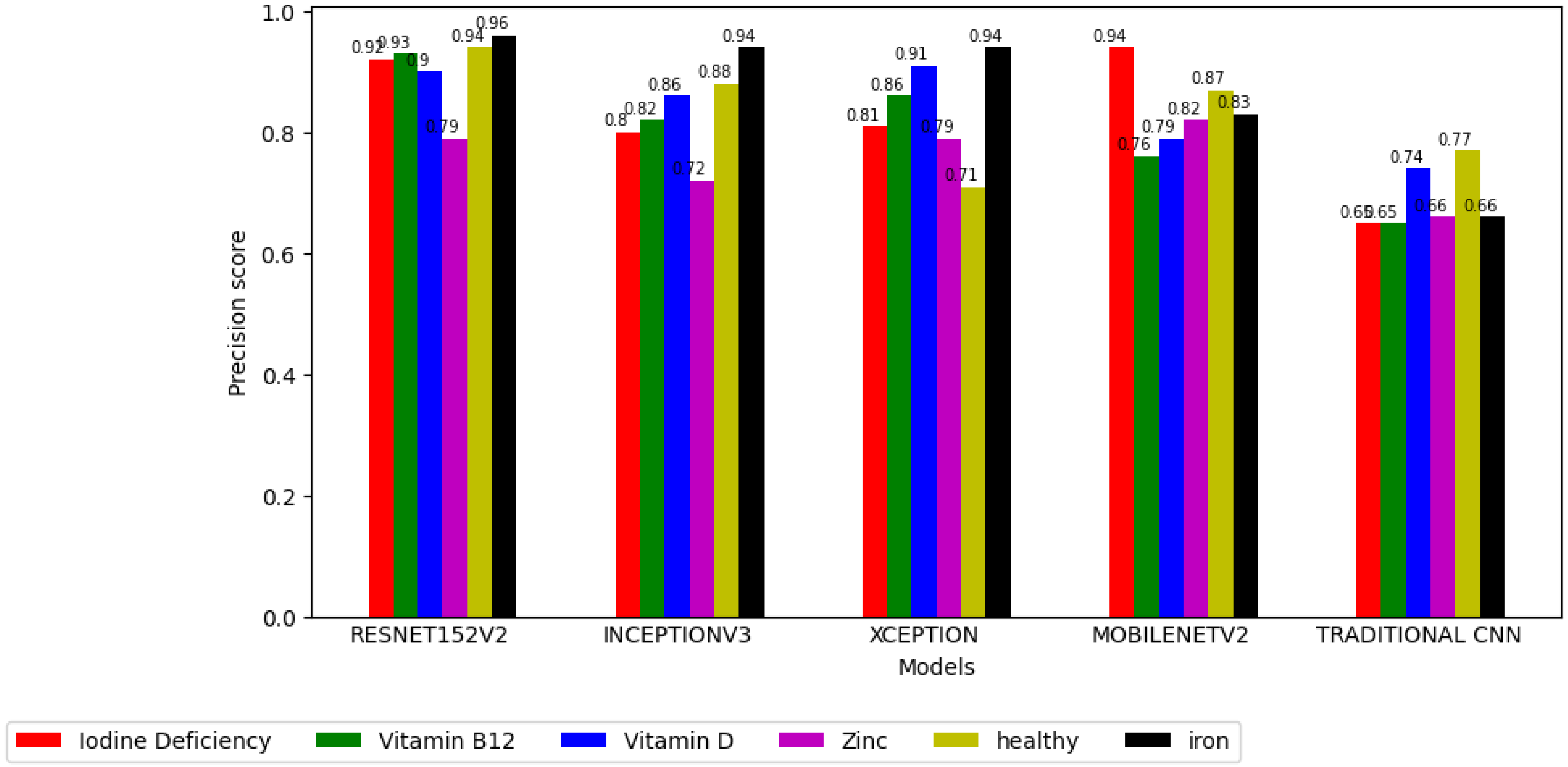
IMAGE PREDICTION



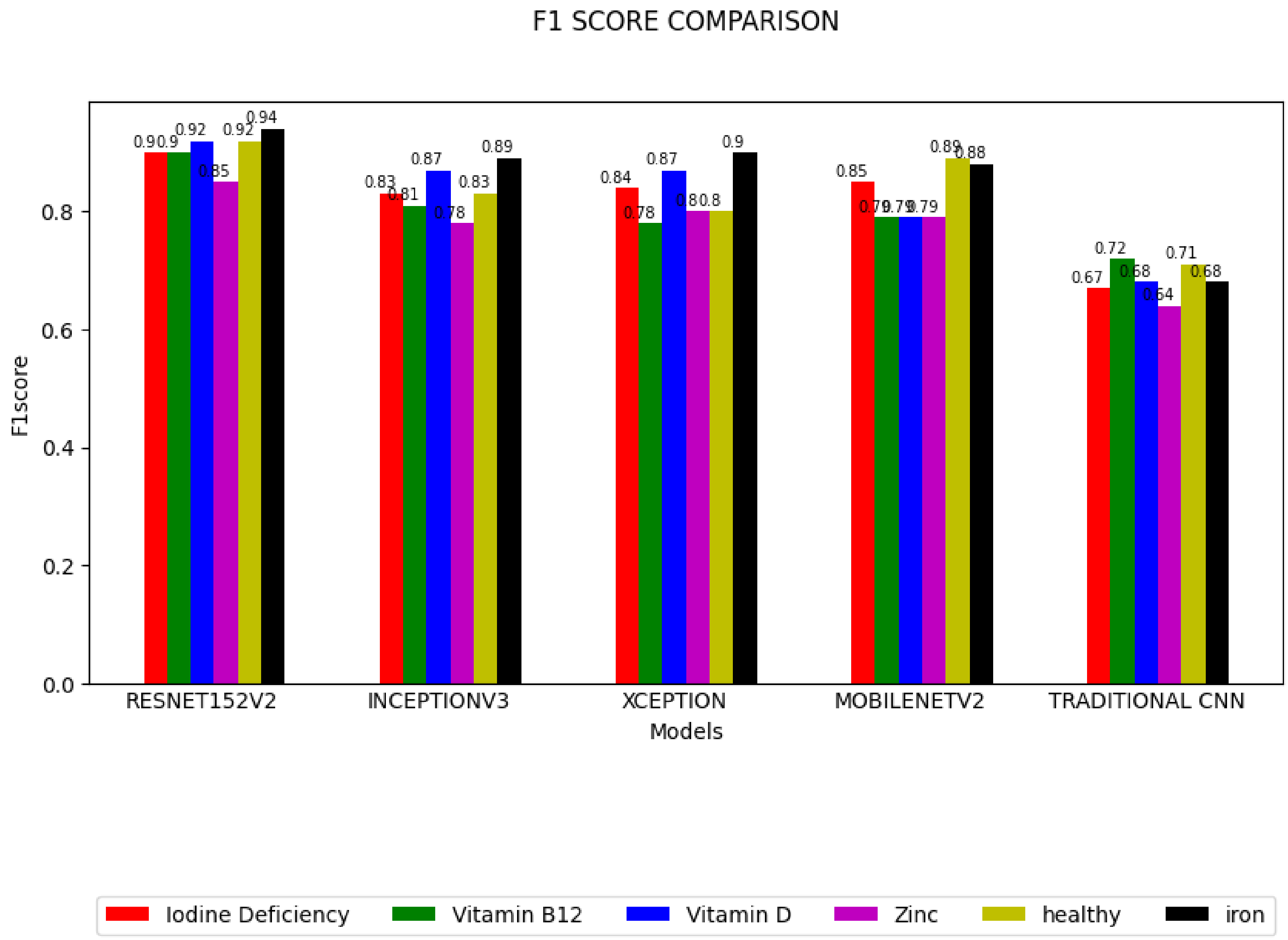
Images are choosen randomly from the test dataset and the browser , it is predicted using the above built cnn models

Performance Measurement Analysis

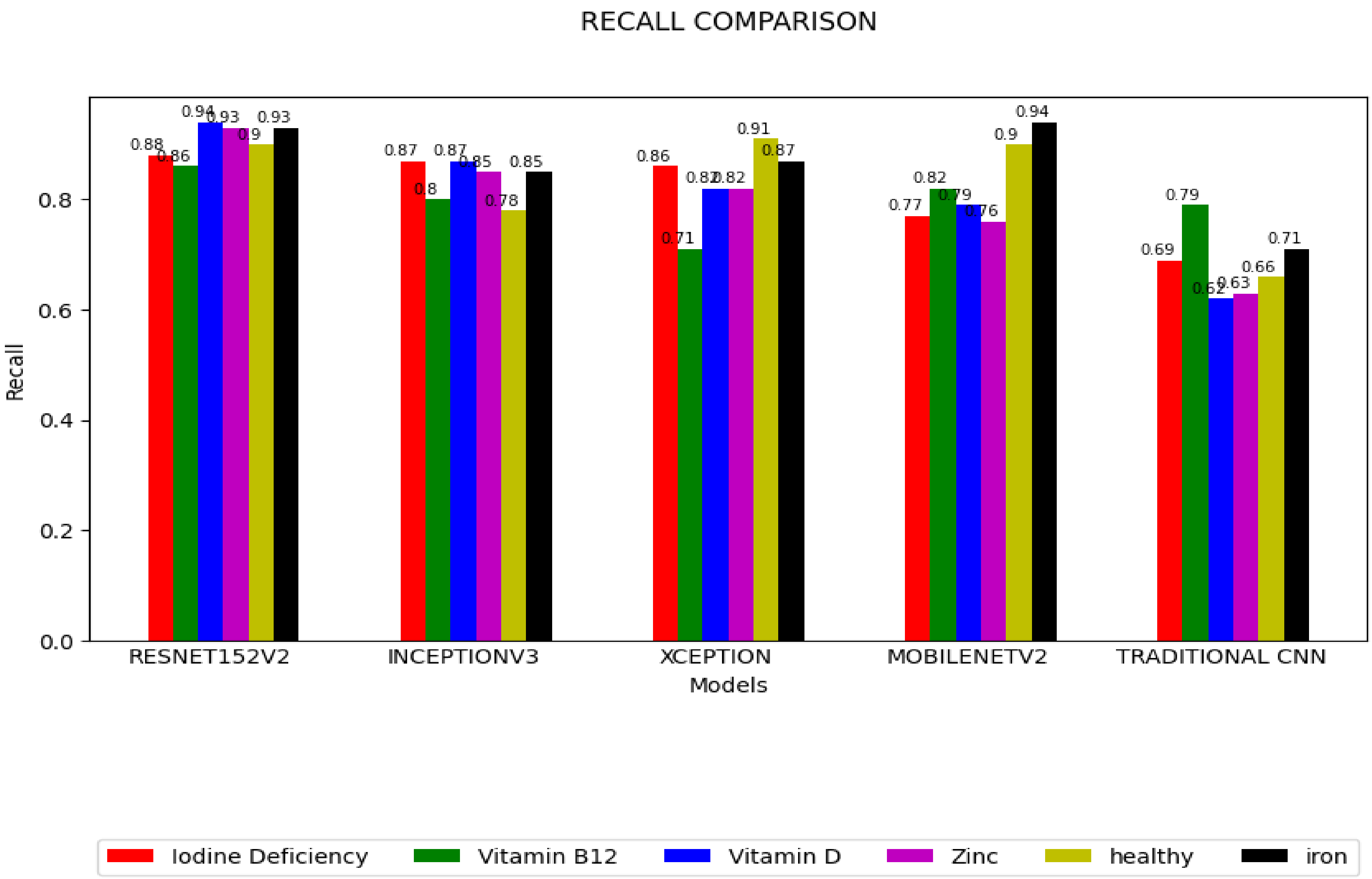
For nail dataset the plot for precision comparison is



The plot for the comparison of f1 score of various models is

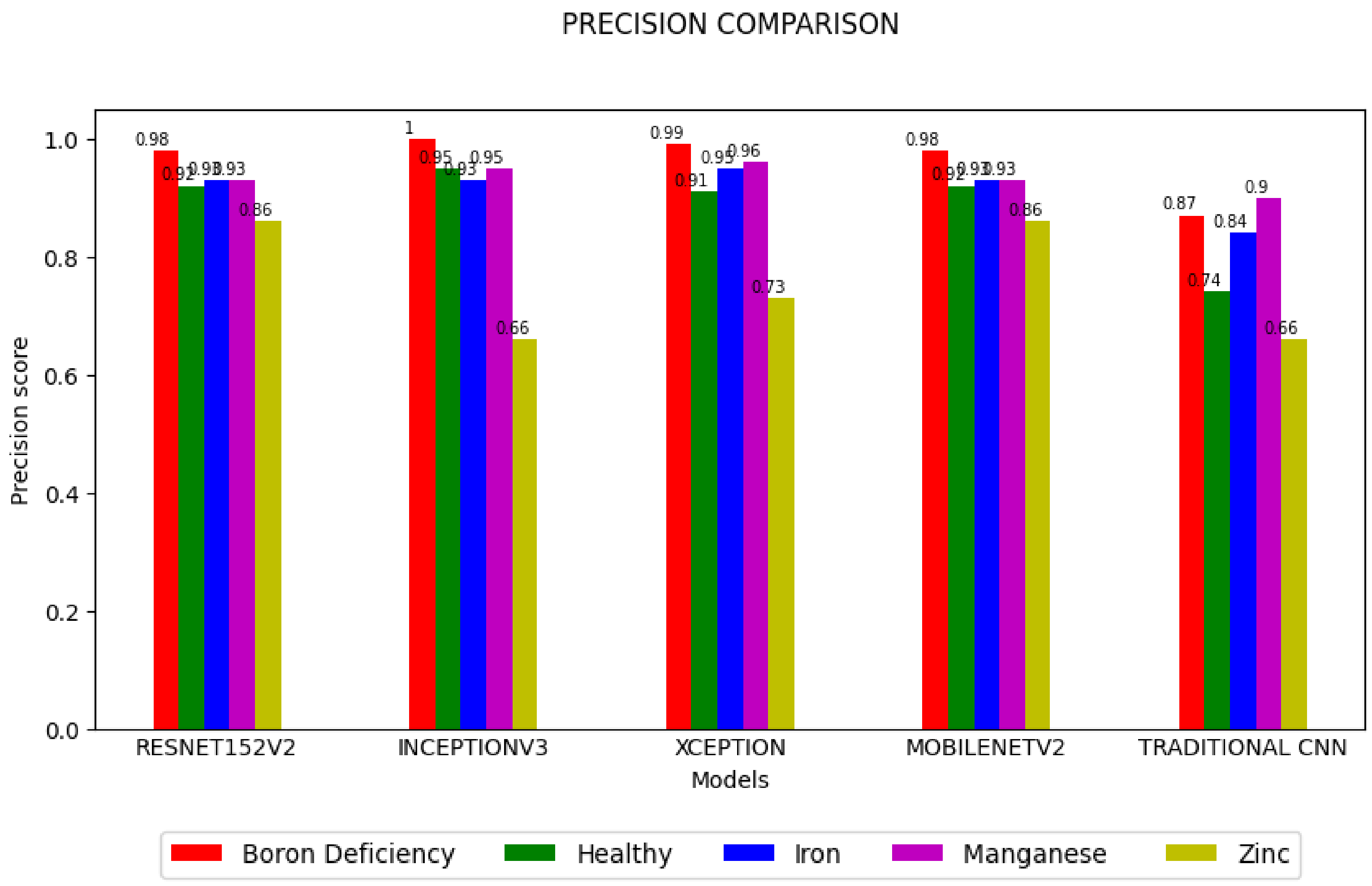


The plot for the comparison of recall of various models is

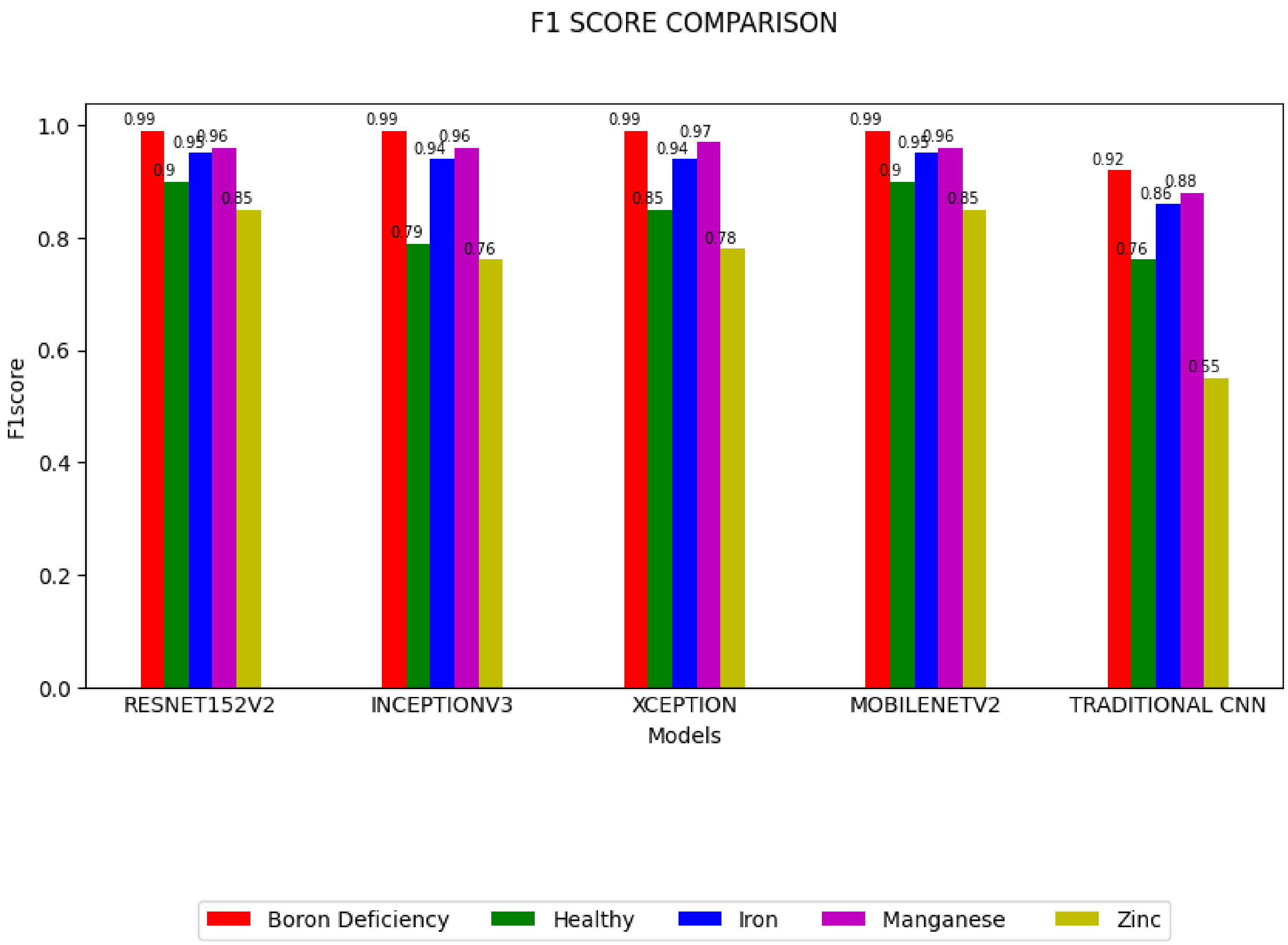


For leaf dataset the performance measurement graph for various model is shown below

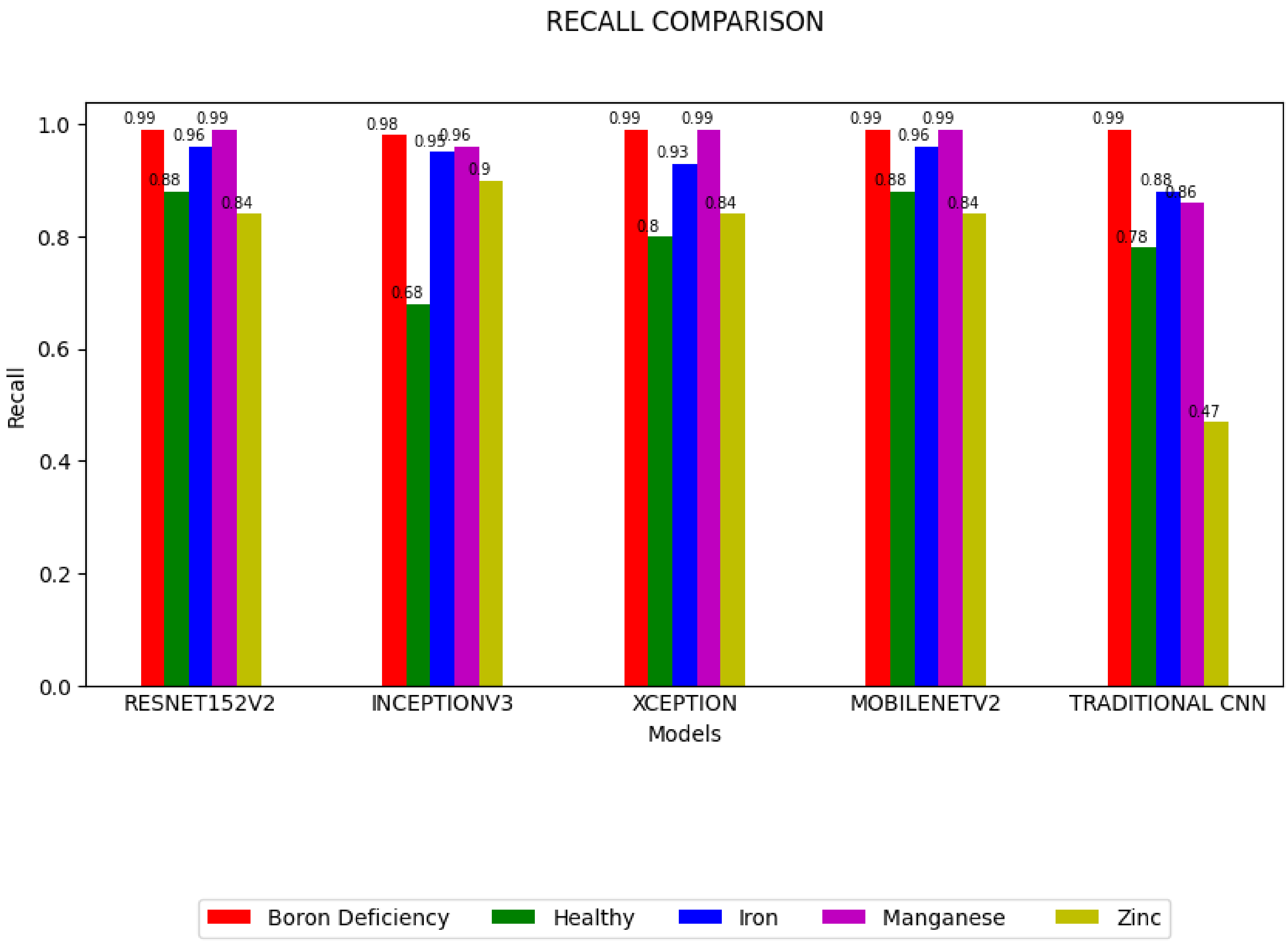
The plot for the comparison of precision of various models is



The plot for the comparison of F1 score of various models is



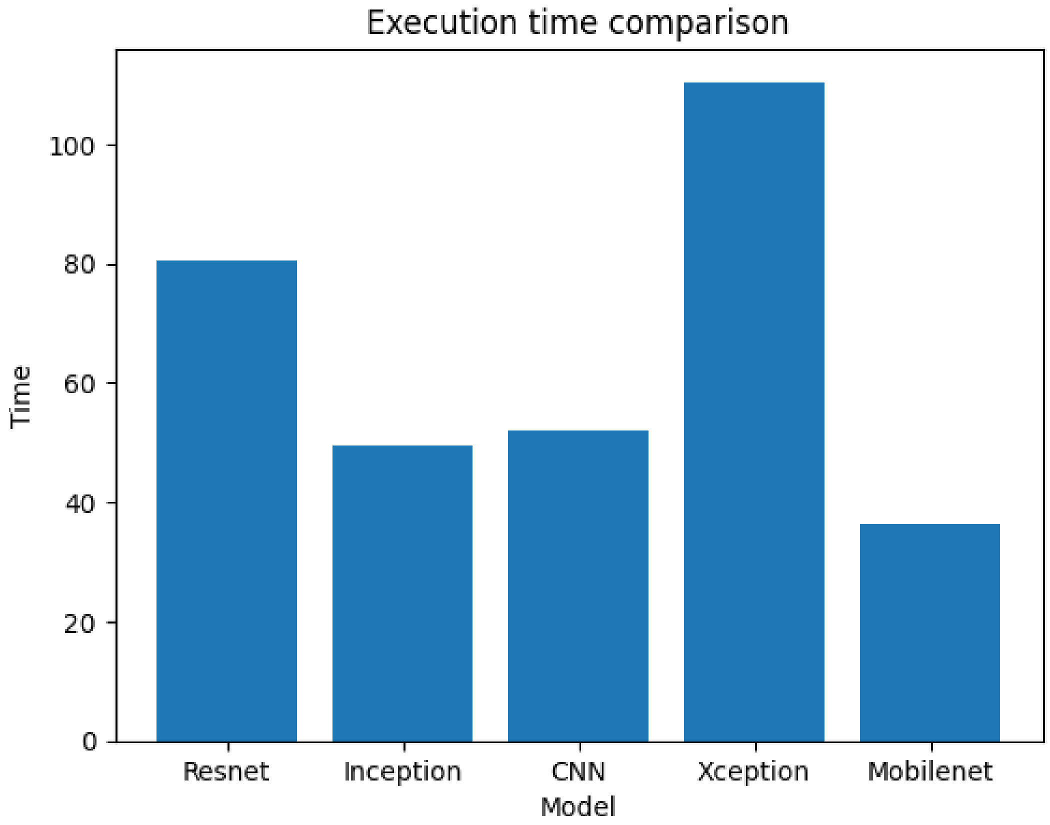
The plot for the comparison of recall of various models is



INFERENCE

- Resnet is considered to be the best as it performs well for all the classes
- CNN model gives comparatively low accuracy, precision & recall in human dataset
- The class zinc has low value in all metrics because its feature is similar to the feature of healthy

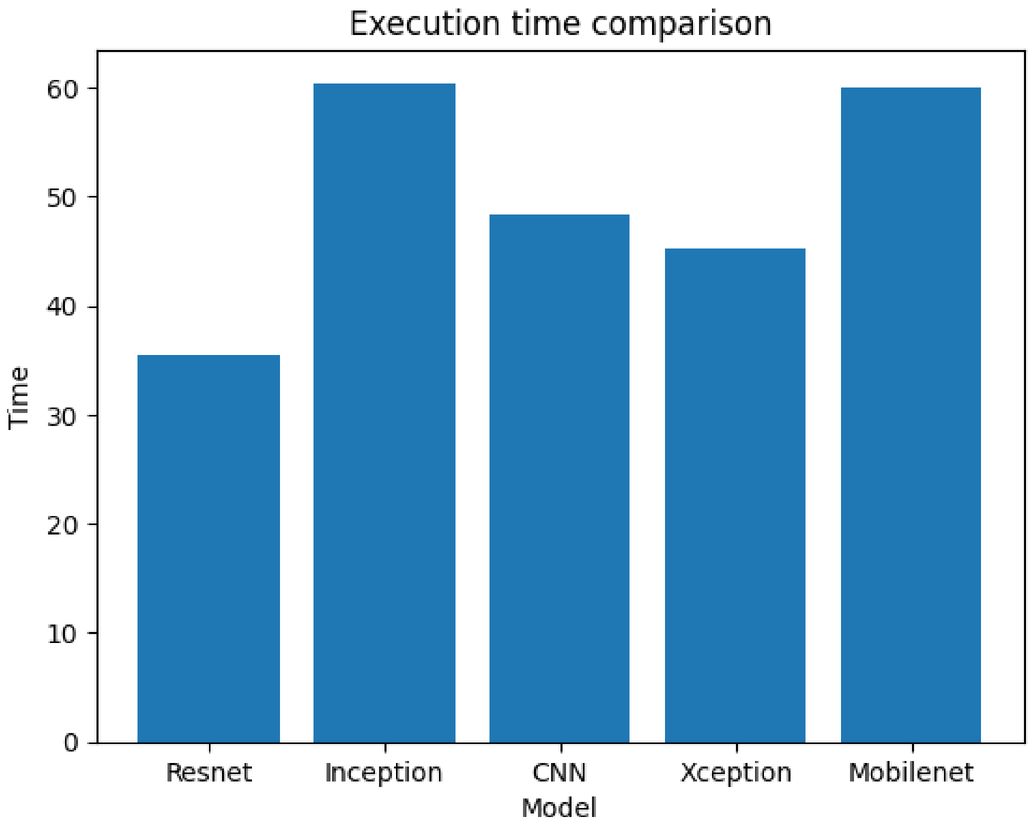
COMPUTATIONAL TIME COMPARISON



Time in Human Dataset

- More time to train –Xception
- Maximum time-110 mins
  Minimum time-36 mins 42 secs
- Resnet - best with comparatively low time and highest accuracy

COMPUTATIONAL TIME COMPARISON



- More time to train –inception and mobilenet
- Maximum time-60 m 2 s
  Minimum time-38m
- Resnet -low time and highest accuracy

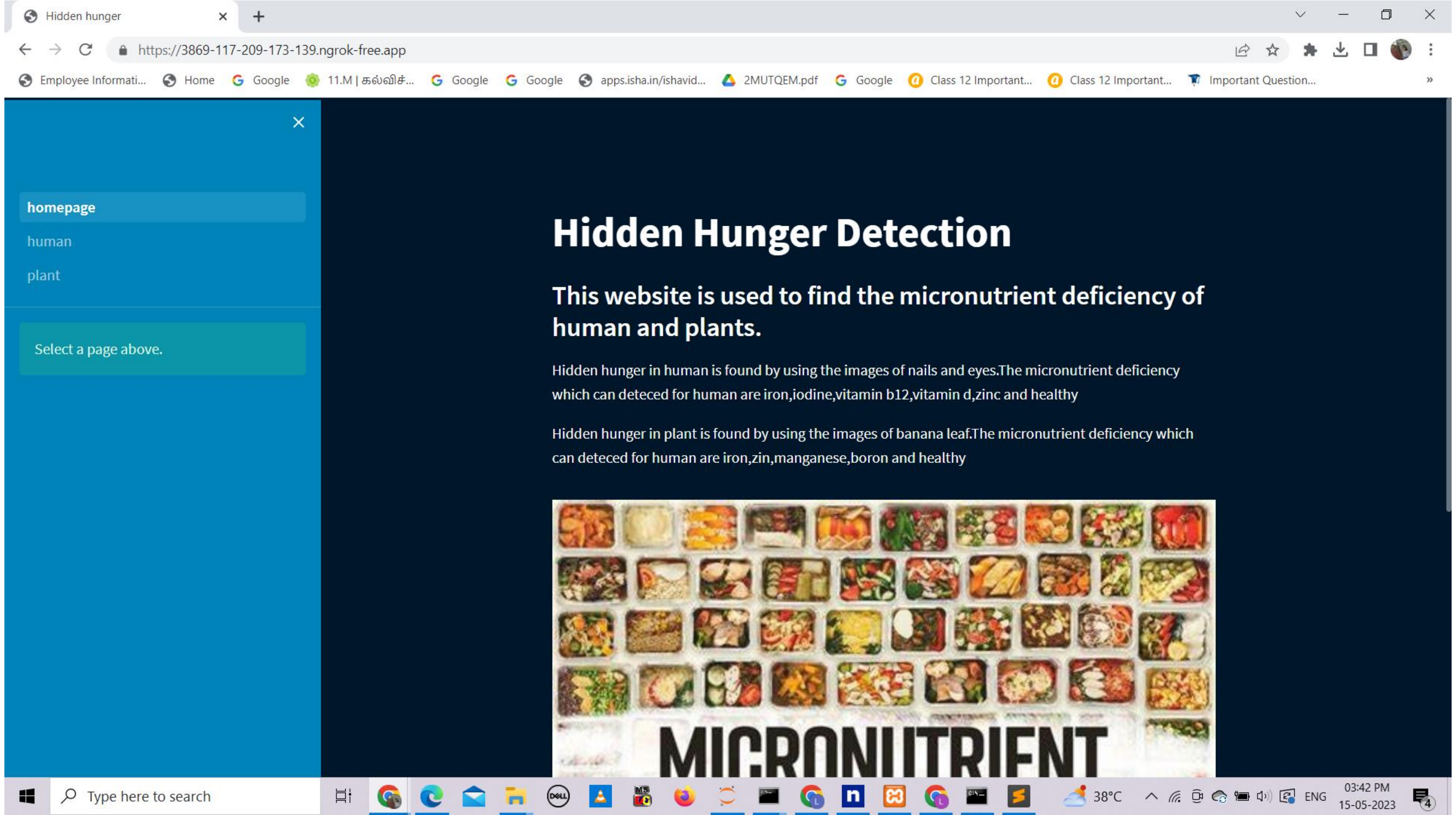
Time in Leaf Dataset

WEBSITE DEVELOPMENT

- Website for the machine learning model can be created using streamlit library
- Streamlit-an open source Python library ,easy to create and share beautiful, custom web apps for machine learning and data science
- Web app runs on local host
- Ngrok is used to share it as public link which can be accessed by everyone

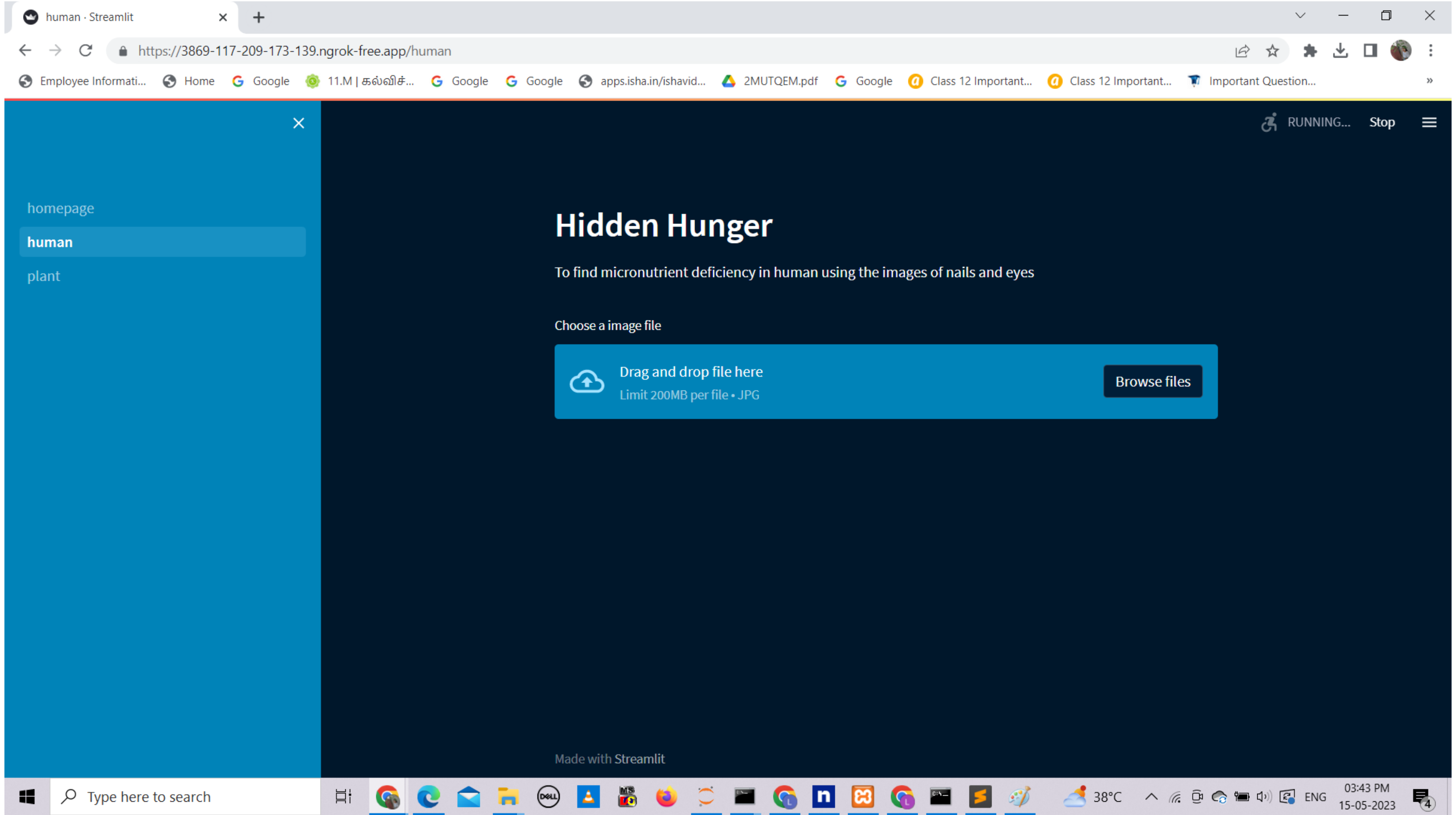
OUTLOOK OF OUR WEBSITE

Link of our website-https://3869-117-209-173-139.ngrok-free.app



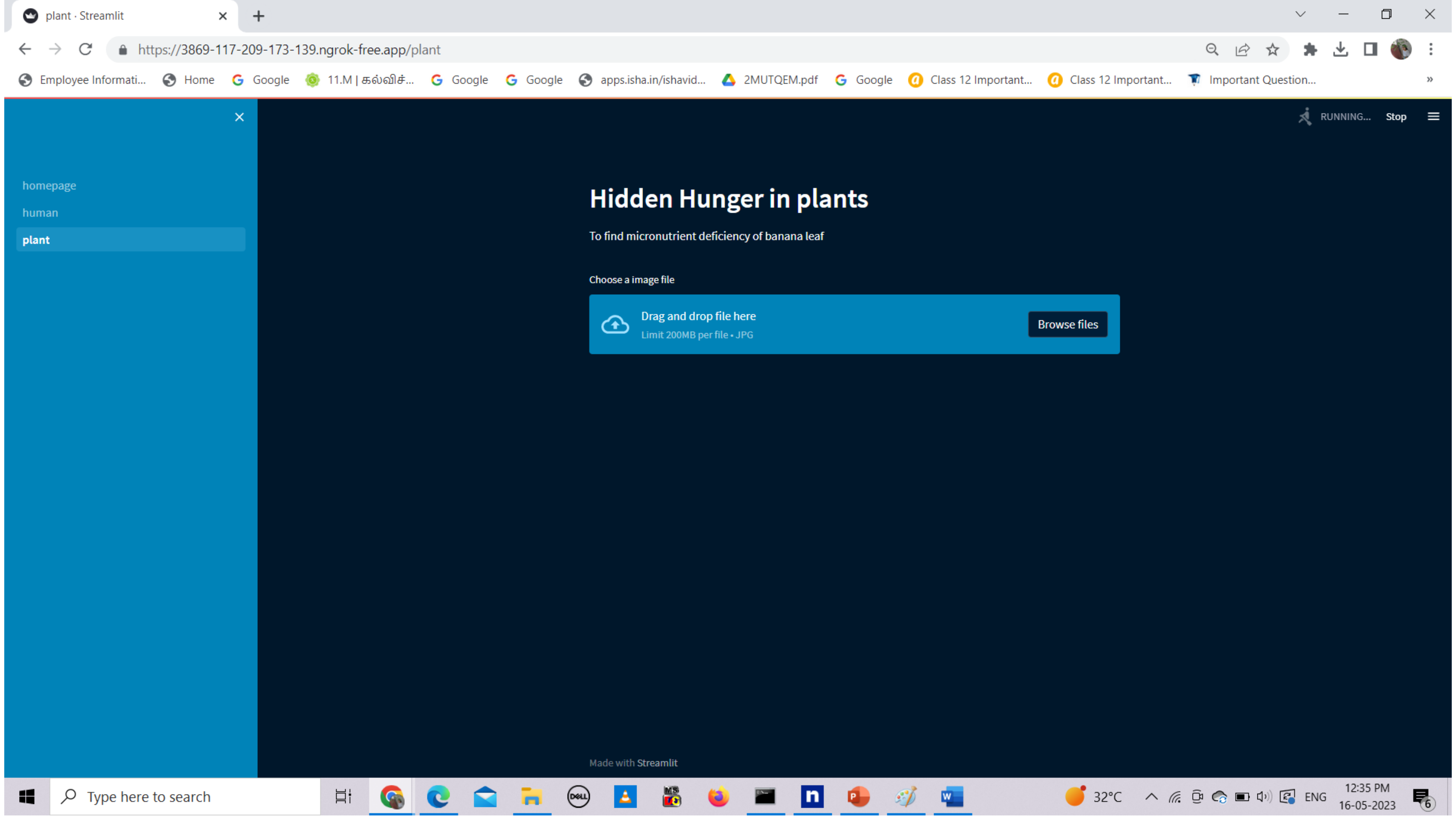
This is our website which has three pages

- Homepage-details of our project
- human-second page where deficiency in human can be identified
- Plant-Third page where deficiency in leaves can be identified

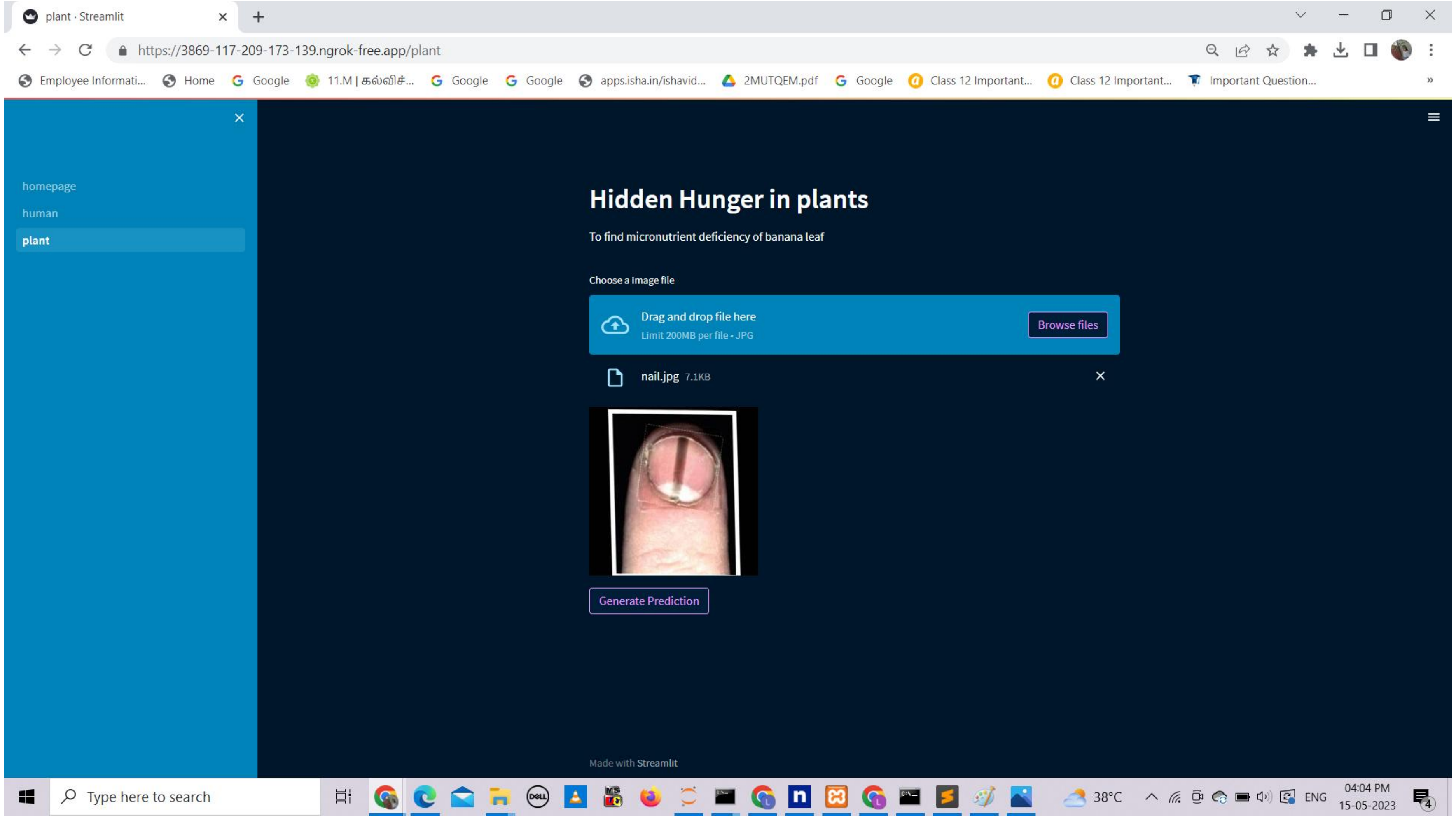


STEPS

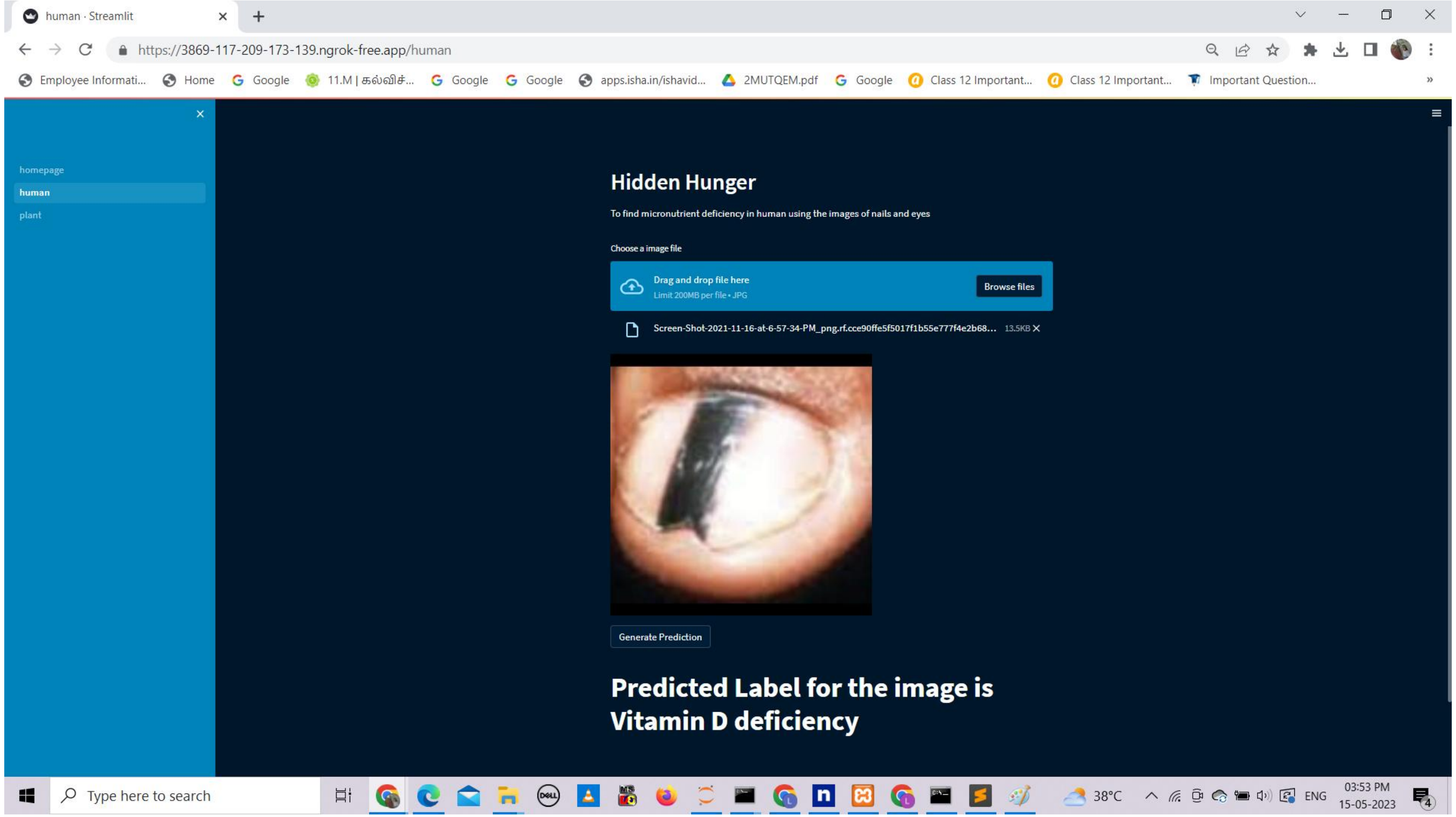
- 1.Click browse file options and select an image

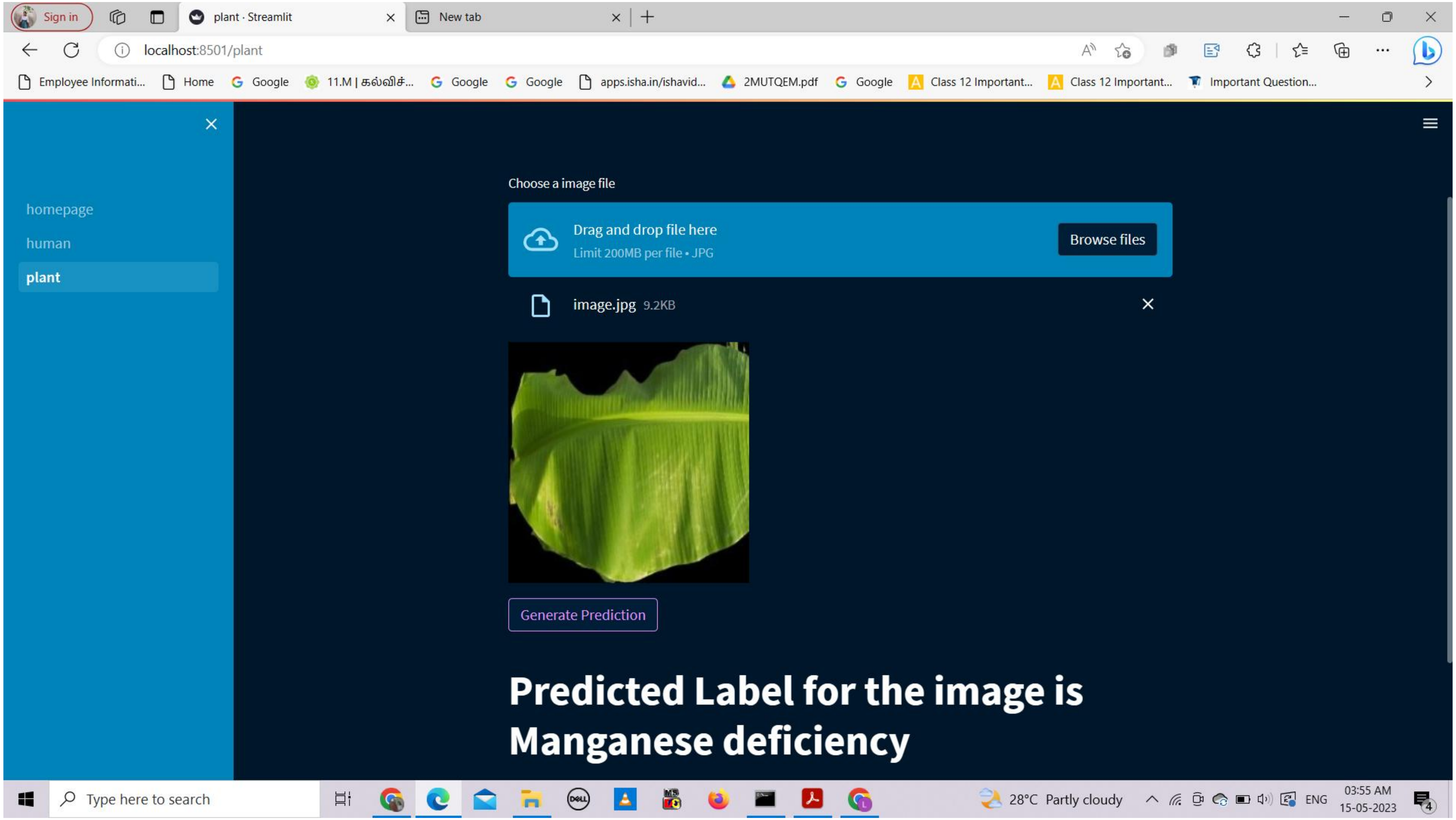


2.After the selected image is loaded , a button to generate prediction will be enabled



3.Upon clicking generate prediction, the predicted class for the given image is displayed




Sign in
plant · Streamlit
New tab
localhost:8501/plant
Employee Informati...
Home
Google
11.M | கல்விச்...
Google
Google
apps.isha.in/ishavid...
2MUTQEM.pdf
Google
Class 12 Important...
Class 12 Important...
Important Question...
homepage
human
plant
Choose a image file
Drag and drop file here
Limit 200MB per file • JPG
Browse files
image.jpg 9.2KB
Generate Prediction
Predicted Label for the image is Manganese deficiency
Type here to search
28°C Partly cloudy
ENG
03:55 AM
15-05-2023

FUTURE SCOPE

- This model can be developed further to predict more number of deficiency classes in both human and plants so that it can be used in the real world
- Micronutrient deficiencies can also be detected in fruits, vegetables and soil
- An app can be developed with more user friendly interface for the real time and easy processing

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- https://github.com/nachi-hebbar/Gradip-FlowerClassification-WebApp

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THANK YOU