

NOVEL TRANSFER LEARNING NEURAL TECHNIQUE FOR QUALITY ASSESSMENT OF POTATOES FROM THERMAL IMAGES

Submitted in partial fulfillment of the requirements for the award of Bachelor of
Engineering degree in Electronics and Communication Engineering

by

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**DEPARTMENT OF ELECTRONICS AND
COMMUNICATIONENGINEERING**

SCHOOL OF ELECTRICAL AND ELECTRONICS

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

APRIL 2021



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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of
ABHILASH VELUVALI (37130431), V SUBBA RAO (37130445) who carried out the
Project entitled "Novel Transfer Learning Neural Technique for Quality Assessment of
Potatoes from Thermal Images" under my supervision from November 2020 to April 2021.

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Submitted for Viva voce Examination held on_____

Internal Examiner

External Examiner

DECLARATION

We **ABHILASH VELUVALI** and **V SUBBA RAO**, hereby declare that the Project Report entitled "**NOVEL TRANSFER LEARNING NEURAL TECHNIQUE FOR QUALITY ASSESSMENT OF POTATOES FROM THERMAL IMAGES**" done by us under the supervision of **Dr.E.Logashanmugam**, is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **ELECTRONICS AND COMMUNICATION ENGINEERING**.

DATE: 16-04-2021

1) ABHILASH VELUVALI

2) V SUBBA RAO

PLACE: CHENNAI

SIGNATURE OF THE CANDIDATE

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We wish to express my thanks to all Teaching and Non-teaching staff members of the Department of Electronics and Communication Engineering who were helpful in many ways for the completion of the project.

ABSTRACT

Quality assessment of potatoes necessitates a computer aided interpretation technique that uses a non-hazardous and non-contact, Non-Destructive Testing technique for image acquisition and a feature extraction technique for extracting and representing the features and a classifier for performing classification/grading of potatoes. In this paper, InfraRed Thermography is used for image acquisition and Convolutional Neural Networks (CNNs) are used for the classification of potatoes. In this work, the thermograms of Normal, Fungus affected potatoes, potatoes with Holes and worst affected potatoes are used. Feasibility of VGGNET, RESNET and modified ALEXNET for classification of potatoes is studied. Performance is measured in terms of sensitivity and accuracy. It is found that RESNET18 outperformed all the other networks in terms of accuracy and it is the only network that classified all the affected potatoes as affected potatoes, i.e. the affected potatoes are not wrongly identified as normal. However in order to improve the performance of the network, a customized convolutional neural network must be developed, pretrained and hence be used for the specific application. The proposed work aims at developing a novel transfer learning network for the quality assessment of potatoes.

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CHAPTER 1

1.1 INTRODUCTION:

Potato is a popular vegetable which is rich in minerals, Vitamins and antioxidants. Potatoes are one of the staple vegetables in India and they play important role in Indian economy. Potato is most popular vegetable that is exported in huge quantities to other countries. Before being exported to foreign countries potatoes are fed for screening test. Computer dependent techniques for quality check are already in use where radio graphs of vegetable are taken and features are collected and given to the networks. Since X-Rays cannot penetrate deep into the tissues of potatoes hence the quality assessment is been limited. Using X-Rays also raise the health issues for the consumers, and the setup is also expensive in nature.

Hence it is necessary to develop a Non-Destructive testing technique (NDT) which is non-contact, non-hazardous in nature to test the potatoes. InfraRed Thermography (IRT) can be used since it is a non-contact and non-hazardous technique in which heat emitted by the object is captured and mapped into Thermogram.

Every object emits heat above Zero Kelvin and the quality and type of the object can be determined by the quantity of heat emitted by the object. Similarly (IRT) concept can be used for quality assessment of potatoes. The temperature of normal tissue is different from the affected one. So heat can be utilized for quality check purposes. If thermogram of the vegetable shows a uniform distribution it is a normal potato, If the thermogram of the potato shows abrupt variation or non-uniform distributions it is of a defective potato.

1.2: LITERATURE SURVEY:

Serial No	Author	Title	Year of Publishing	Objective
1	Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jain Sun	Deep Residual Learning for Image Recognition	2016	Develop residual learning technique framework for efficient image recognition
2	M.S Sangeetha, N.M Nanditha	Improved active counter modelling for isolating different hues in infrared thermograms	2017	Development of efficient color image segmentation technique
3	Nur Azida Muhammad, Alina A Nasir	Evaluation of CNN, AlexNet and GoogleNet for Fruit Recognition	2019	Development of Convolutional Neural network (CNN)[AlexNet and GoogleNet] for classification of different fruits
4	Sankara Sai Sumanth Kota Anthony Rajesh Reddy Yeruva Venubabu Rachapudi	Improved Convolutional Neural Network for Detecting Covid-19 from X ray Images	2020	Development of a CNN network with 4 layers (2 max pooling and drop outs) to detect COVID-19 and differentiate it with lung infections
5	Qing li Weidong Cai Xiaogang Wang Yum Zhou	Medical Image Classification with Convolutional neural network	2015	Development of customized CNN with shallow convolution layer to classify lung images.
6	Mahbub Hussian Jordan J Bird Diego R Faria	A study on CNN Transfer Learning for Image Classification	2018	Development of CNN architecture model to test the accuracy with a new image dataset via transfer learning
7	Manali Shaha Meenakshi Pawar	Transfer Learning for Image Classification	2018	To use Transfer learning for tuning the pre trained network (VGG19) parameters for image Classification tasks
8	Long D Nguyen Dongyu n Lin Jiuwen Cao	Deep CNNs for microscopic image classification by exploiting transfer learning and feature concatenation	2018	Development of novel deep neural network architecture based on transfer learning for microscopic image classification.

1.3: PROBLEM DEFINITION:

The proposed work aims at developing a modified neural network for assessing the quality of potatoes from thermal images. It also at modifying the conventional DENSENET architecture for increasing the sensitivity and specificity.

1.4: OBJECTIVES:

Objectives are detailed as follows:

- To acquire the thermal images of potatoes.
- To preprocess the thermal images.
- To customize the thermal images.
- To implement the pretrained neural network for quality assessment of potatoes.
- To incorporate the new architecture in Deep Learning tool box.
- To Develop quality assessment technique by using the modified DENSENET architecture and measuring its performance in terms of sensitivity and specificity.

1.5: ORGANIZATION OF THE REPORT:

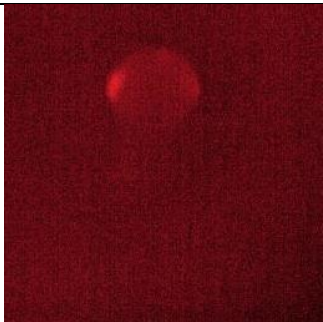
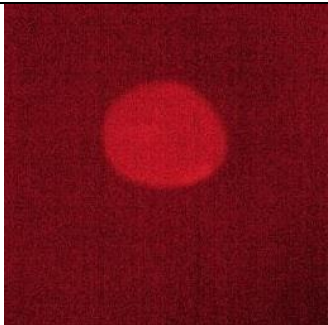
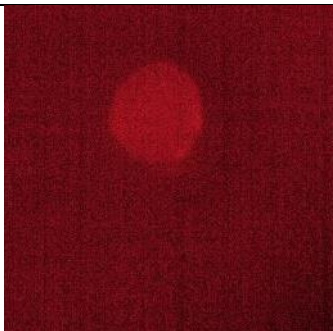
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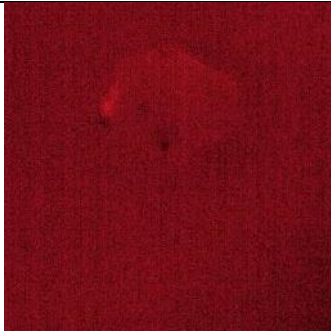
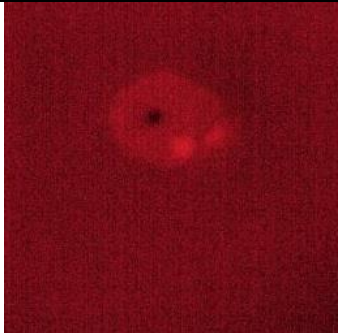
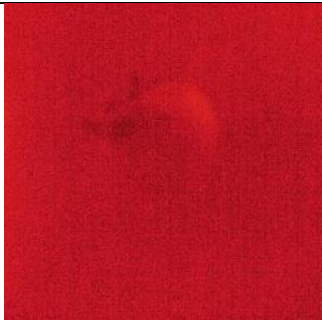
- Chapter 2 is provided with research database.
- Chapter 3 deals with CNN networks developed for classification
- Chapter 4 deals with modified DENSENET architecture for the classification
- Conclusion and future work is provided in chapter 5.

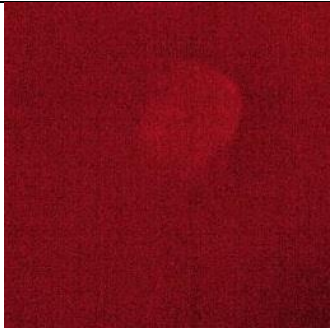
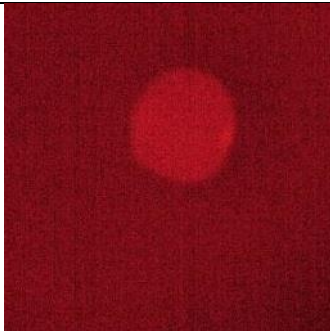
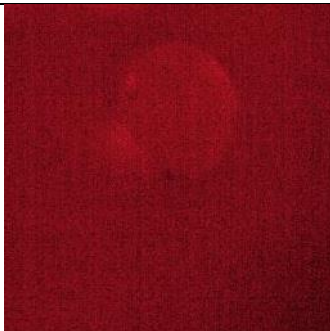
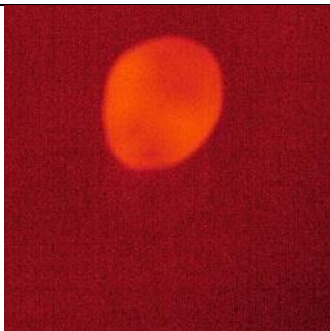
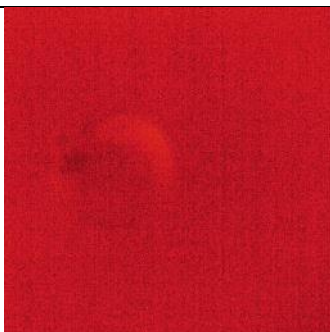
CHAPTER 2

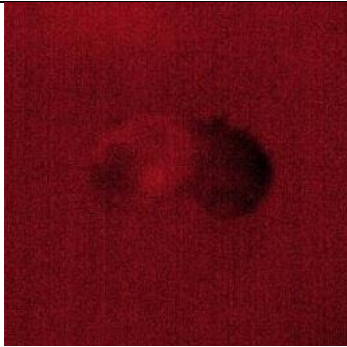
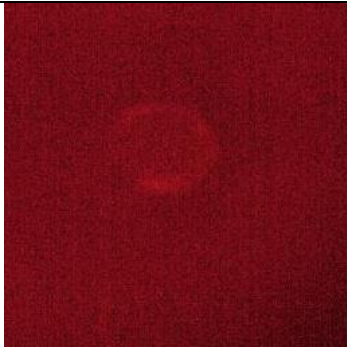
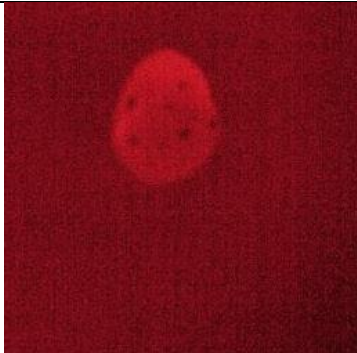
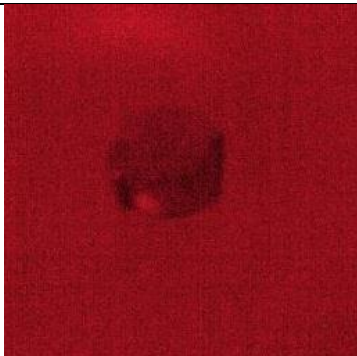
RESEARCH DATABASE

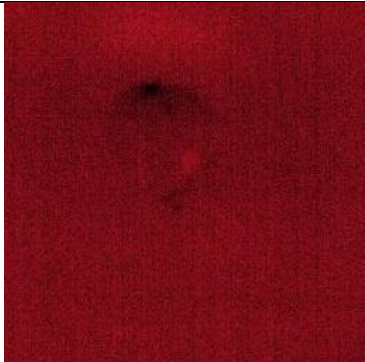
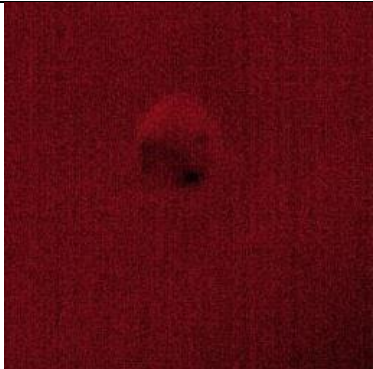
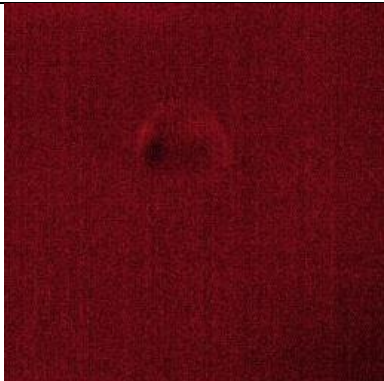
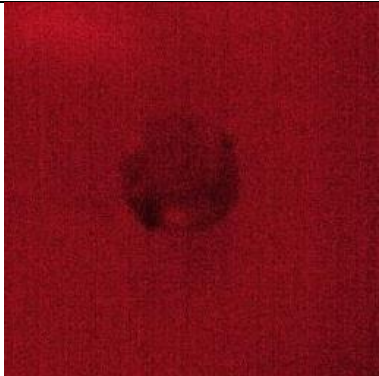
To perform this project, it is necessary to acquire thermal images of potatoes. In this work, using SCT640, a total of 84 thermal images were acquired. Potatoes affected by Fungus, potatoes with Holes, unaffected potatoes and to be rejected potatoes were considered

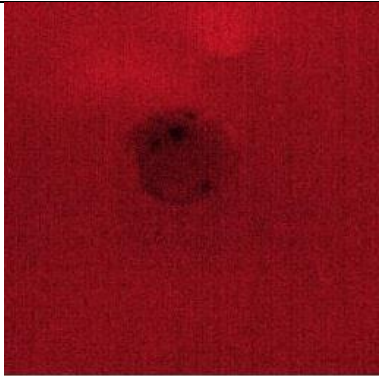
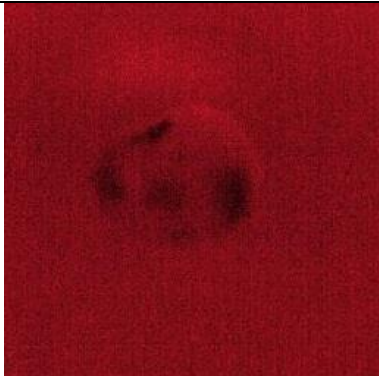
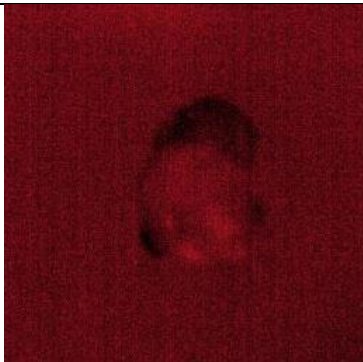
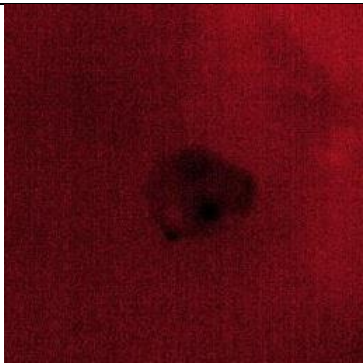
Serial.No	Type of Potato	Thermal Image
1	Normal Potato	
2	Normal Potato	
3	Normal Potato	

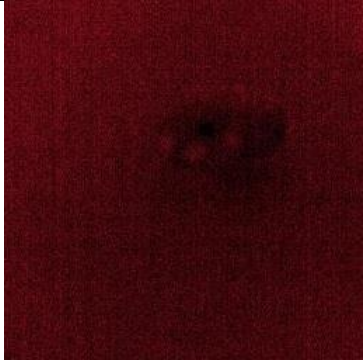
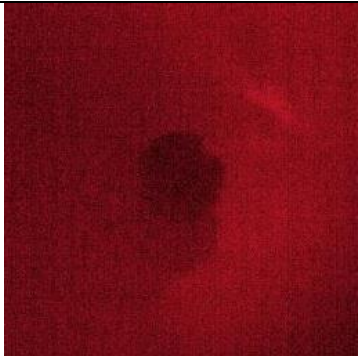
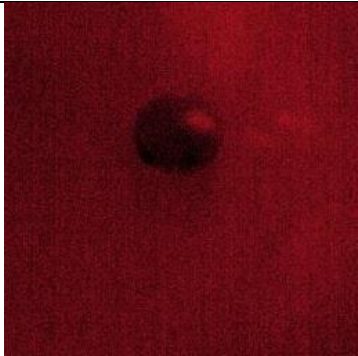
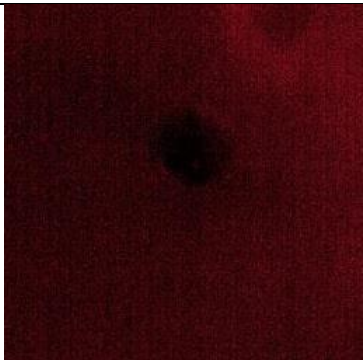
4	Normal Potato	
5	Normal Potato	
6	Normal Potato	
7	Normal Potato	
8	Normal Potato	

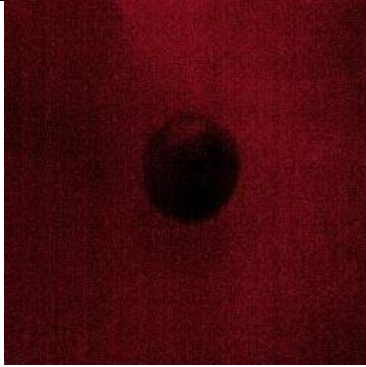
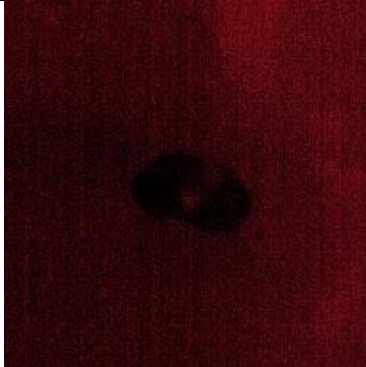
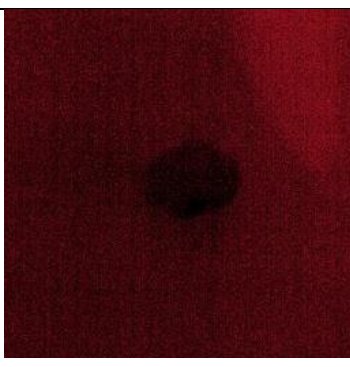
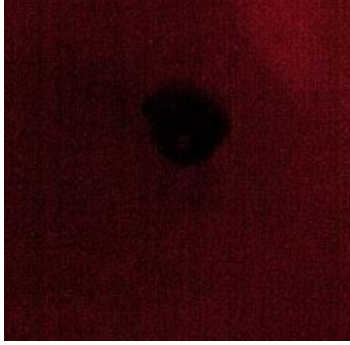
9	Normal Potato	
10	Normal Potato	
11	Normal Potato	
12	Normal Potato	
13	Normal Potato	

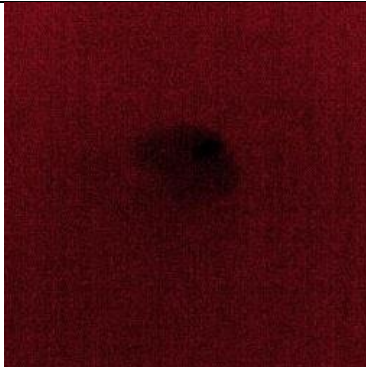
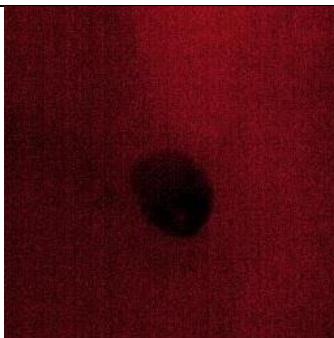
14	Fungus effected Potato	
15	Fungus effected Potato	
16	Fungus effected Potato	
17	Fungus effected Potato	

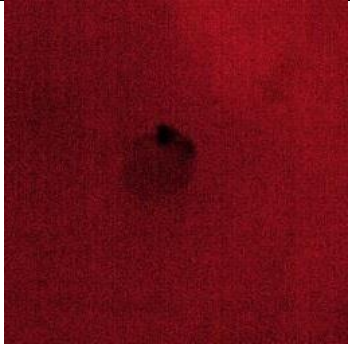
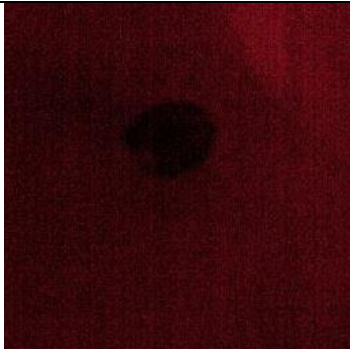
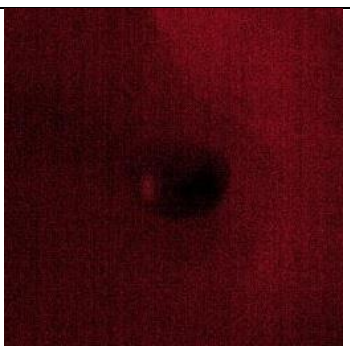
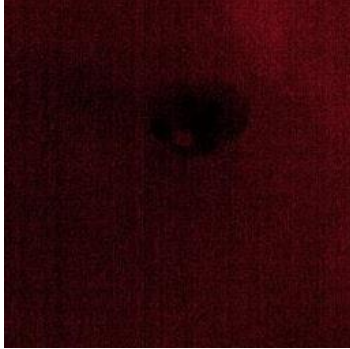
18	Fungus effected Potato	
19	Fungus effected Potato	
20	Fungus effected Potato	
21	Fungus effected Potato	

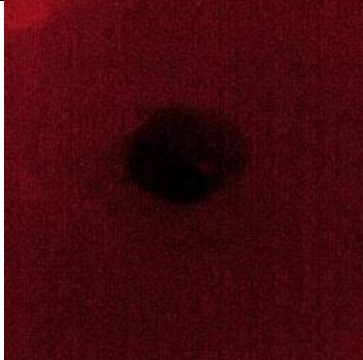
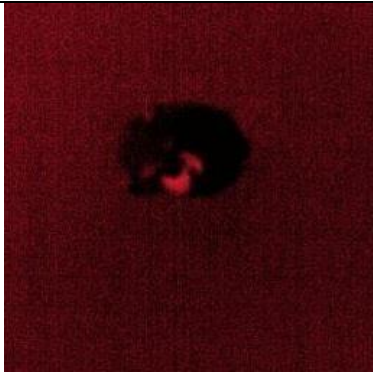
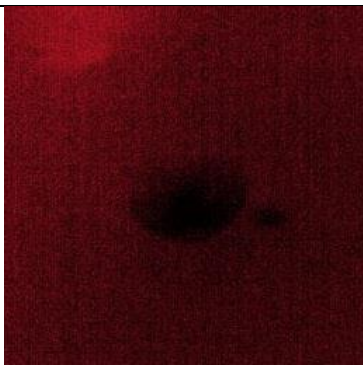
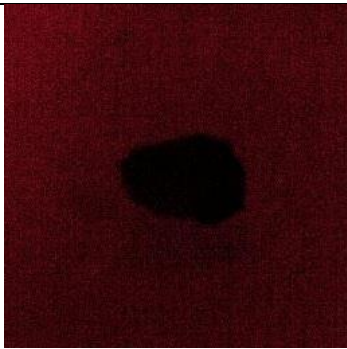
22	Fungus effected Potato	
23	Fungus effected Potato	
24	Fungus effected Potato	
25	Worst Potato	

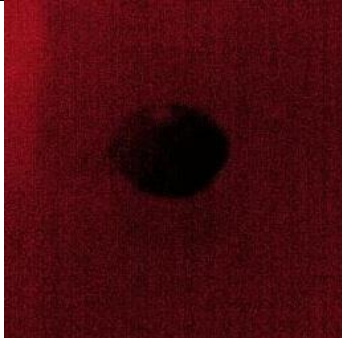
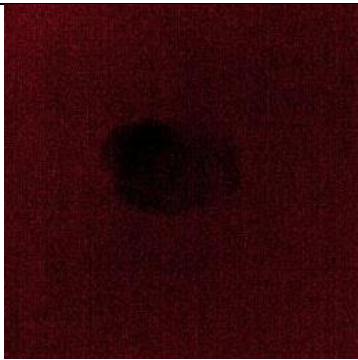
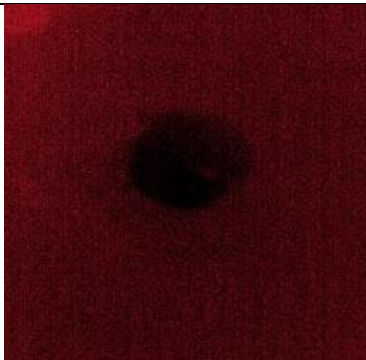
26	Worst Potato	
27	Worst Potato	
28	Worst Potato	
29	Worst Potato	

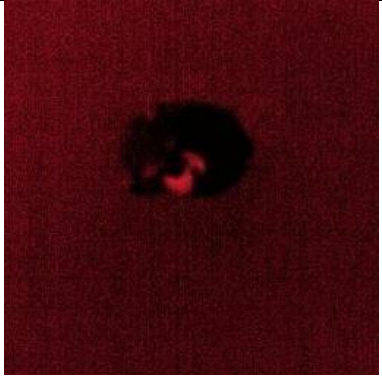
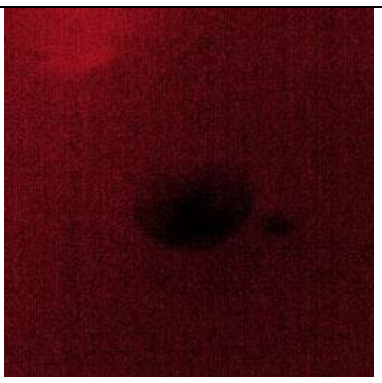
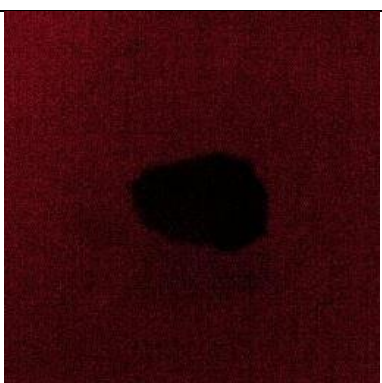
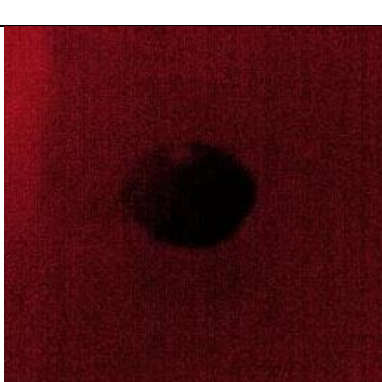
30	Worst Potato	
31	Worst Potato	
32	Worst Potato	
33	Worst Potato	

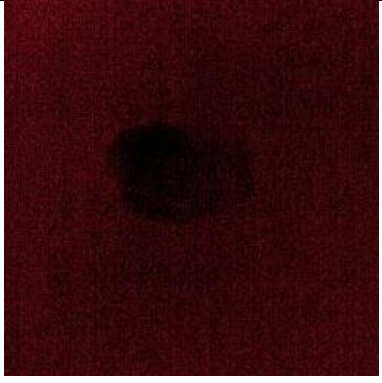
34	Worst Potato	
35	Worst Potato	
36	Worst Potato	
37	Worst Potato	

38	Worst Potato	
39	Worst Potato	
40	Worst Potato	
41	Worst Potato	

42	Potato with Hole	
43	Potato with Hole	
44	Potato with Hole	
45	Potato with Hole	

46	Potato with Hole	
47	Potato with Hole	
48	Potato with Hole	
49	Potato with Hole	

50	Potato with Hole	
51	Potato with Hole	
52	Potato with Hole	
53	Potato with Hole	

54	Potato with Hole	
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CHAPTER 3

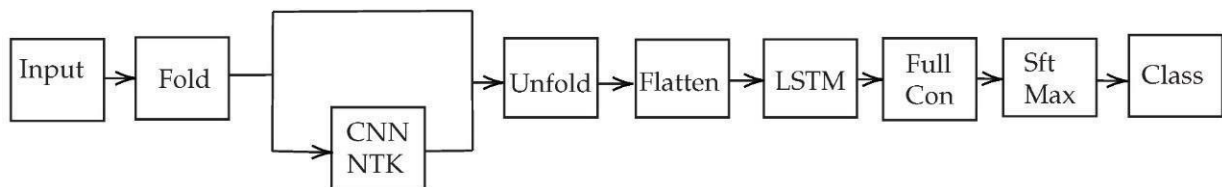
QUALITY ASSESSMENT WITH EXISTING ARCHITECTURES OF CNN

Convolutional Neural Network is a class of Deep Neural Networks that can perceive and characterize specific highlights from pictures and are generally utilized for dissecting visual pictures. Their applications goes from picture and video acknowledgment, picture order, clinical picture examination, computer vision and characteristic language preparing.

The expression "Convolution" in CNN indicates the numerical capacity of convolution which is an exceptional sort of straight activity wherein two capacities are increased to deliver a third capacity which communicates how the state of one capacity is adjusted by the other. In basic terms, two pictures which can be addressed as grids are increased to give a yield that is utilized to extricate highlights from the picture.

There are two principle parts to a CNN engineering:

A convolution instrument that isolates and distinguishes the different highlights of the picture for examination in a cycle called as Feature Extraction A completely associated layer that uses the yield from the convolution interaction and predicts the class of the picture dependent on the highlights removed in past stages. There are three sorts of layers that make up the CNN which are the convolutional layers, pooling layers, and completely associated (FC) layers.



3.1 :Architecture of Convolutional Neural Network

3.1.1 Convolved Layer:

This layer is the main layer that is utilized to separate the different highlights from the info pictures. In this layer, the numerical activity of convolution is performed between the information picture and a channel of a specific size $M \times M$. By sliding the channel over the information picture, the spot item is taken between the channel and the pieces of the info picture regarding the size of the channel ($M \times M$).

The yield is named as the Feature map which gives us data about the picture like the corners and edges. Afterward, this component map is taken care of to different layers to gain proficiency with a few different highlights of the info picture.

3.1.2 Strides:

Strides helps in moving the channel framework over the pixels in the component network. Assuming the step size is 1, we can move the channel to 1 pixel at a time. On the off chance that the info network measurement is $n \times n$, channel measurement is $f \times f$ and step size $= s$ then the yield size will be equivalent to $((n-f/s) + 1) * ((n-f/s) + 1)$. In the event that we increment the step size to a higher worth, there is no yield so we can utilize cushioning for it.

3.1.3 Padding:

Padding helps in making the output and input size equal.

Padding is used for:

To avoid shrinking of output image if we increase the number of convolution layers. To make use of the outer edge along with the inner edge of the input image while doing convolution. If padding $p=1$ then it adds two rows and two columns for the input matrix. Mostly we use zero padding. In zero padding we assign zeros to the newly formed rows and columns.

Types of Padding:

Valid padding: In valid padding there is no padding involved. So, the dimensions of input and output are different.

Same padding: Same padding helps in making the dimensions of convolution output dimension and input dimension equal.

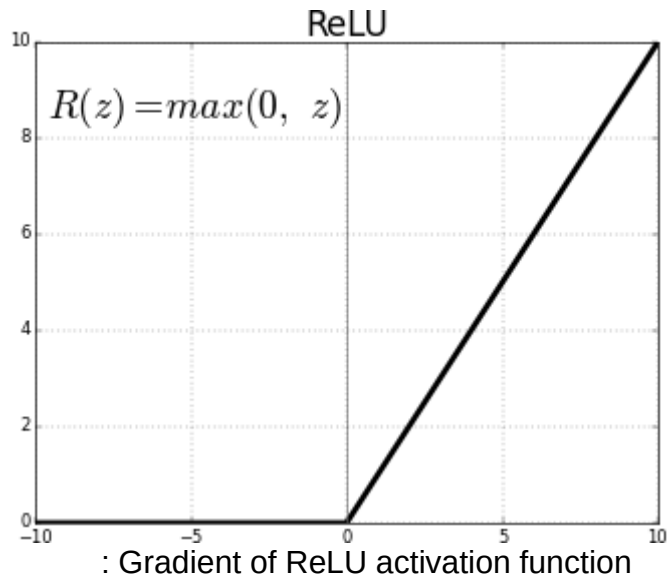
3.1.4 : Pooling Layer:

Convolutional layers are trailed by the Pooling layer. The essential point of this layer is to diminish the size of the convolved include guide to lessen the computational expenses. This is performed by diminishing the associations among layers and freely works on each component map. Contingent on strategy utilized, there are a few sorts of Pooling activities.

In Max Pooling, the biggest component is taken from highlight map. Normal Pooling computes the normal of the components in a predefined estimated Image area. The absolute amount of the components in the predefined area is figured in Sum Pooling. The Pooling Layer generally fills in as a scaffold between the Convolutional Layer and the FC Layer.

3.1.5 : Activation Function:

Activation Function is a numerical condition which decides the field of neural organization. It helps in normalizing the field of neuron to be in the range of [1 and 0] (or) in between [1 and -1]. ReLU is the most generally utilized actuation work in any neural organization. In basic words, it chooses which data of the model should fire the forward way and which ones ought not toward the finish of the organization.



3.2

3.1.6 : SOFTMAX:

SoftMax gives us the final probability for each label and assigns decimal probabilities to each class in a problem with multiple classes. It is also an activation function. Input values can be negative, zero, positive or greater than one but the output values will be between 0 and 1, so they can be interpreted as probabilities.

3.1.7 : Flattering:

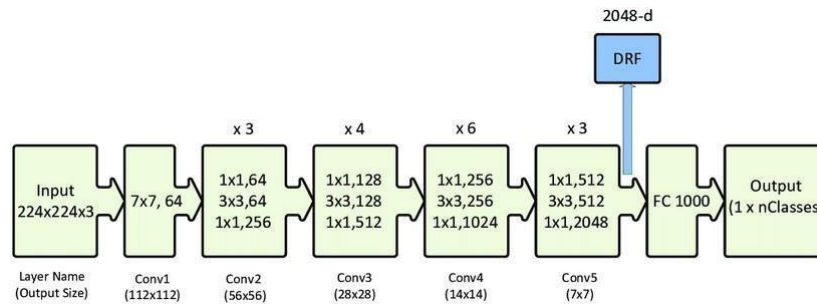
Flattering is a process of converting the output of previous layer into a vector/1-dimensional array to send it to the next layer as input. Flattening is the main advantage of CNN over Feed- Forward Neural Nets.

3.1.8 : Full Connected Layer(FC):

The Full connected (FC) layer comprises of loads and predispositions alongsidethe neurons and is utilized to interface the neurons between two distinct layers. These layers are normally positioned before the yield layer and structure the last couple of layers of a CNN Architecture.

3.1: ASSESSMENT OF POTATOES USING RESNET50:

RESNET50 is pre-trained Deep learning network model for image recognition and classification. It has a class of deep neural networks and it is mostly used to analyze visual images. RESNET50 is a network with 50 layers deep which is trained with 100,000 images of more than 1000 categories from the database called ImageNet.



3.3: RESNET50 Architecture

In this work, the existing architecture of RESNET50 is used for assessing the quality of potatoes. Of a total of 84 images, 50% is used for training and another 50% is used for testing.

Table 3.2.1: Probability of detection (RESNET50)

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	4	1	0	0
Type-Normal	1	5	0	0
Type-Worst	2	0	2	4
Type-Hole	1	0	0	6

Table 3.2.2: Sensitivity of different classes of potatoes.

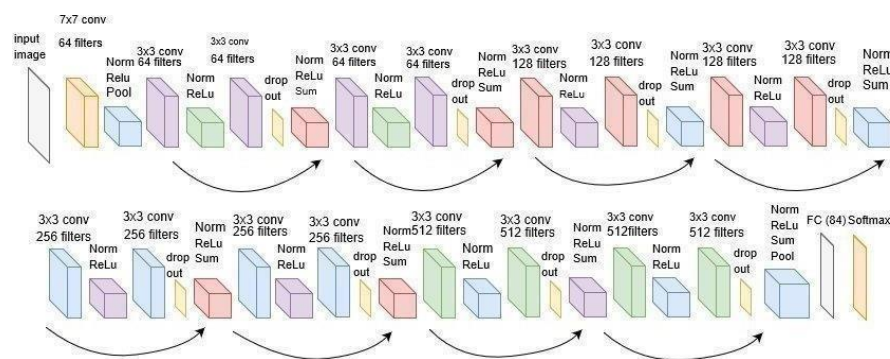
	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Sensitivity	80%	83.33%	25%	85.71%

In order to understand the performance of RESNET50, probability of detection is determined and shown in table 3.2.2. It is observed that this network classifies well for Type-Hole, Type-Fungus, Type-Normal. To increase the sensitivity of Type-Cpotatoes RSNET18 is used.

3.3: QUALITY ASSESMNET OF POTATOES USING RESNET18:

RESNET18 is a CNN network that is developed with the help of 1,000,000 pictures from ImageNet database. This network consists of 18 layers and can group pictures into 1000 article classes.

In this work the existing architecture of RESNET18 is used for assessing the quality of potatoes. Of total 84 images, 50% is used for training and another 50% is used for testing.



3.4: Architecture of RESNET18

Table 3.3.1: Probability of detection (RESNET18)

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	6	0	0	0
Type-Normal	3	3	0	0
Type-Worst	2	0	5	1
Type-Hole	3	0	1	3

Table 3.3.1: Sensitivity of detection (RESNET18)

Sensitivity	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
	100%	50%	62.5%	42.8%

In order to understand the performance of RESNET-18, probability of detection is determined and is shown in the above table. From the Table 3.3.2 we can see that above network works well in classifying Type-Fungus, and Type-Worst potatoes. In order to improve the sensitivity of Type-Normal and Type-Hole conventional Darknetis used.

3.3: QUALITY ASSESSMENT OF POTATOES USING CONVENTIONAL DARKNET

DARKNET is open source neural network used for classification and image detection. Existing DARKNET53 is used for assessing the quality of potatoes. Of a total of 84 images, 50% is used for training and another 50% is used for testing.

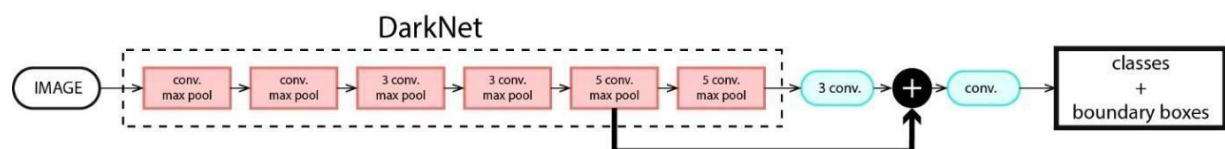


Fig 3.4: Architecture of DarkNet

Table 3.4.1: Probability of detection (DARKNET53)

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	1	1	4	0
Type-Normal	2	1	2	2
Type-Worst	0	5	1	0
Type-Hole	0	2	6	0

Table 3.4.2: Sensitivity of different classes of potatoes.

	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Sensitivity	16%	57.14%	83%	75%

CHAPTER 4

MODIFIED DENSENET ARCHITECTURE

In convolutional Modified DENSENET architecture, some modifications are done for improving the efficiency and high sensitivity. A modified DENSENET architecture is obtained by removing a set of convolutional layers. Instead of 64 layers, 58 layers are used. The description of the layers are given in the table below.

Table 4.1: Layers of Modified DENSENET

S.NO	Name	Type	Activation	Learnables
1	Input	Image Input	256x256x3	
2	Conv1	Convolution	256x256x32	Weights 3x3x3x32 Bias 1x1x32
3	Batchnorm1	Batch Normalization	256x256x32	Offset Scale 1x1x32 1x1x32
4	Leaky 1	Leaky ReLU	256x256x32	-
5	Pool1	Max Pooling	128x128x32	-
6	Conv2	Convolution	128x128x64	Weights

				Bias 3x3x32x64 1x1x64
7	Batchnorm	Batch normalization	128x128x64	Offset Scale 1x1x64 1x1x64
8	Leaky 2	Leaky ReLU	128x128x64	-
9	Pool2	Max Pooling	64x64x64	-
10	Conv 3	Convolution	64x64x128	Weights Bias 3x3x64x128 1x1x128
11	Batchnorm 3	Batch Normalization	64x64x128	Offset Scale 1x1x128 1x1x128
12	Leaky 13	Leaky ReLU	64x64x128	-
13	Conv 4	Convolution	64x64x64	Weights Bias 1x1x128x64 1x1x64
14	Batchnorm	Batch normalization	64x64x64	Offset Scale 1x1x64 1x1x64
15	Leaky 4	Leaky ReLU	64x64x64	-
16	Conv 5	Convolution	64x64x128	Weight Bias 3x3x64x128 1x1xx158

17	Batchnorm 5	Batch Normalization	64x64x128	Scale Offset 1x1x128 1x1x128
18	Leaky 5	Leaky ReLU	64x64x128	-
19	Pool3	Max Pooling	32x32x256	-
20	Conv 6	Convolution	32x32x256	Weights Bias 3x3x128x256 1x1x256
21	Batchnorm 6	Batch Normalization	32x32x256	Offset Scale 1x1x256 1x1x256
22	Leaky 6	Leaky ReLU	32x32x256	-
23	Conv 7	Convolution	32x32x128	Weights Bias 1x1x256x128 1x1x128
24	Batchnorm 7	Batch Normalization	32x32x128	Offset Scale 1x1x128 1x1x128
25	Leaky 7	Leaky ReLU	32x32x128	-
26	Conv 8	Convolution	32x32x256	Weights Bias 3x3x128x256 1x1x256
27	Batchnorm 9	Batch Normalization	32x32x256	Offset Scale

				1x1x256 1x1x256
28	Leaky 8	Leaky ReLU	32x32x256	-
29	Pool 4	Max Pooling	16x16x256	-
30	Conv 9	Convolution	16x16x512	Weights 3x3x256x512 1x1x512
31	Batchnorm 9	Batch normalization	16x16x512	Offset Scale 1x1x512 1x1x512
32	Leaky 9	Leaky ReLU	16x16x512	-
33	Conv 10	Convolution	16x16x256	Weights Bias 1x1x512x256 1x1x256
34	Batchnorm 10	Batch Normalization	16x16x256	Offset Scale 1x1x256 1x1x256
35	Leaky 10	Leaky ReLU	16x16x256	-
36	Conv 11	Convolution	16x16x512	Weights Bias 3x3x256x512 1x1x512
37	Batchnorm 11	Batch Normalization	16x16x512	Offset Scale 1x1x512 1x1x512

38	Leaky 11	Leaky ReLU	16x16x512	-
39	Conv 12	Convolution	16x16x256	Weights Bias 1x1x512x256 1x1x256
40	Batchnorm 12	Batch Normalization	16x16x256	Offset Scale 1x1x256 1x1x256
41	Leaky 12	Leaky ReLU	16x16x256	-
42	Conv 13	Convolution	16x16x512	Weights Bias 3x3x256x512 1x1x512
43	Batchnorm 13	Batch Normalization	16x16x512	Offset Scale 1x1x512 1x1x512
44	Leaky 13	Leaky ReLU	16xx16x512	-
45	Pool 5	Max Pooling	8x8x512	-
46	Conv 14	Convolution	8x8x1024	Weights Bias 3x3x512x1024 1x1x1024
47	Batchnorm 14	Batch normalization	8x8x1024	Offset Scale 1x1x1024 1x1x1024
48	Leaky 14	Leaky ReLU	8x8x1024	-

49	Conv 17	Convolution	8x8x512	Weights Bias 1x1x1024x512 1x1x512
50	Batchnorm 17	Batch normalization	8x8x512	Offset Scale 1x1x512 1x1x512
51	Leaky 17	Leaky ReLU	8x8x512	-
52	Conv 18	Convolution	8x8x1024	Weights Bias 3x3x512x1024 1x1x1024
53	Batchnorm 18	Batch normalization	8x8x1024	Offset Scale 1x1x1024 1x1x1024
54	Leaky 18	Leaky ReLU	8x8x1024	-
55	Conv 19	Convolution	8x8x1000	Weights Bias 1x1x1024x1000 1x1x1000
57	Avg1	Global Average Pooling	1x1x1000	-
57	Softmax	Softmax	1x1x1000	-
58	Output	Classification output	-	-

In this work, architecture of MODIFIED DENSENET is used for assessing the quality. Of a total of 84 images, 50% is used for training and another 50% is used for testing.

Table 4.1: Probability of detection (MODIFIED DENSENET).

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	5	0	1	0
Type-Normal	0	0	2	5
Type-Worst	4	2	0	0
Type-Hole	3	0	4	1

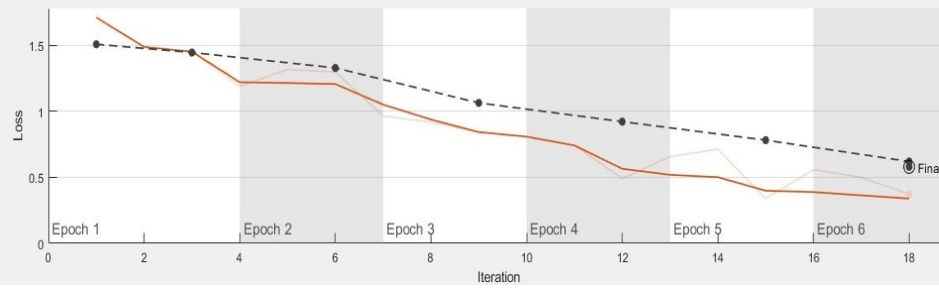
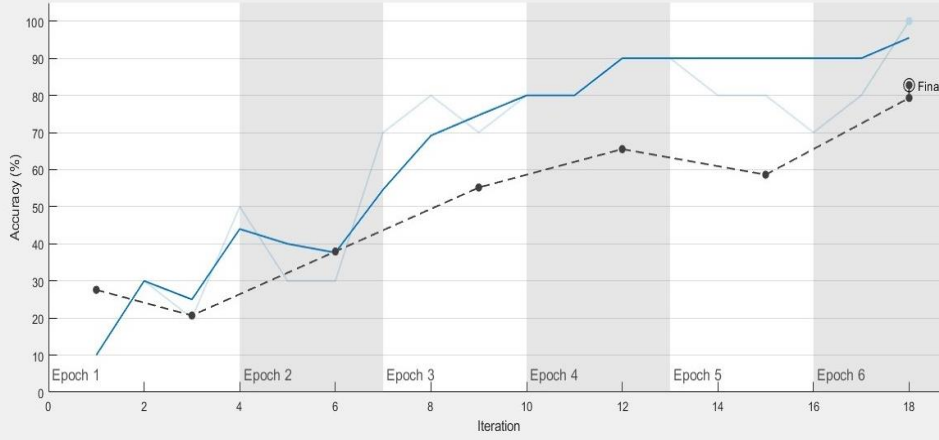
In order to understand the performance of DENSENET, sensitivity of different classes is given below.

Table 4.2: Sensitivity of different classes of potatoes.

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Sensitivity	83.3%	33.3%	50%	71.4%

From above table we can see that developed network classifies Type-Fungus and Type-Normal potatoes well.

MODIFIED OUTPUT



Results

Validation accuracy: 82.76%

Training finished: Reached final iteration

Training Time

Start time: 02-Feb-2021 22:56:17

Elapsed time: 3 min 52 sec

Training Cycle

Epoch: 6 of 6

Iteration: 18 of 18

Iterations per epoch: 3

Maximum iterations: 18

Validation

Frequency: 3 iterations

Other Information

Hardware resource: Single CPU

Learning rate schedule: Constant

Learning rate: 0.0003

[Learn more](#)

Accuracy

- Training (smoothed)
- Training
- Validation

Loss

- Training (smoothed)
- Training
- Validation

CHAPTER 5

CONCLUSION

Research database has been created with 84 thermal images of Type-Fungus, Type-Normal, Type-Worst and Type-Hole using SCT640, FLIR IR Camera. Preprocessing of these images is done. Feasibility of existing architecture of RESNET50, RESNET18, Conventional DARKNET for classification of potatoes using the images is studied. Performance is noted along with probability of detection and sensitivity. RESNET50 has classified Type-Normal potatoes successfully but it could not classify Type-Worst potatoes.

On the other hand RESNET 18 has classified Type-Fungus but could not classify Type-Normal potatoes. Sensitivity of potatoes with holes is 25% and it provides 100% sensitivity for fungus affected potatoes.

Conventional DARKNET provides 83.3% sensitivity for fungus affected potatoes, but it failed in detecting normal potatoes with sensitivity 33.3% on the other hand sensitivity of hole potatoes is 71%. Darknet classifies fungus potatoes with high sensitivity.

Based on accuracy, DENSENET gives better accuracy with 82.76% This project is stopped at simulation level, hardware implementation of this work can be done in future as well. Feasibility of the other neural networks for quality assessments of potatoes can be done.

Batch67_Report AN

by Plagiarism Checker

Submission date: 16-Apr-2021 03:34AM (UTC-0400)

Submission ID: 1507889468

File name: Batch67_Report_1.docx (1.01M)

Word count: 3089

Character count: 16556

CHAPTER 1

1.1 INTRODUCTION:

Potato is a popular vegetable which is rich in minerals, Vitamins and antioxidants. Potatoes are one of the staple vegetables in India and they play important role in Indian economy. Potato is most popular vegetable that is exported in huge quantities to other countries. Before being exported to foreign countries potatoes are fed for screening test. Computer dependent techniques for quality check are already in use where radio graphs of vegetable are taken and features are collected and given to the networks. Since X-Rays cannot penetrate deep into the tissues of potatoes hence the quality assessment is been limited. Using X-Rays also raise the health issues for the consumers, and the setup is also expensive in nature.

Hence it is necessary to develop a Non-Destructive testing technique (NDT) which is non-contact, non-hazardous in nature to test the potatoes. InfraRed Thermography (IRT) can be used since it is a non-contact and non-hazardous technique in which heat emitted by the object is captured and mapped into Thermogram.

Every object emits heat above Zero Kelvin and the quality and type of the object can be determined by the quantity of heat emitted by the object. Similarly (IRT) concept can be used for quality assessment of potatoes. The temperature of normal tissue is different from the affected one. So heat can be utilized for quality check purposes. If thermogram of the vegetable shows a uniform distribution it is a normal potato, If the thermogram of the potato shows abrupt variation or non-uniform distributions it is of a defective potato.

1.2: LITERATURE SURVEY:

Serial No	Author	Title	Year of Publishing	Objective
1	Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jain Sun	Deep Residual Learning for Image Recognition	2016	Develop residual learning technique framework for efficient image recognition
2	M.S Sangeetha, N.M Nanditha	Improved active counter modelling for isolating different hues in infrared thermograms	2017	Development of efficient color image segmentation technique
3	Nur Azida Muhammad, Alina A Nasir	Evaluation of CNN, AlexNet and GoogleNet for Fruit Recognition	2019	Development of Convolutional Neural network (CNN)[AlexNet and GoogleNet] for classification of different fruits
4	Sankara Sai Sumanth Kota Anthony Rajesh Reddy Yeruva Venubabu Rachapudi	Improved Convolutional Neural Network for Detecting Covid-19 from X ray Images	2020	Development of a CNN network with 4 layers (2 max pooling and drop outs) to detect COVID-19 and differentiate it with lung infections
5	Qing li Weidong Cai Xiaogang Wang Yum Zhou	Medical Image Classification with Convolutional neural network	2015	Development of customized CNN with shallow convolution layer to classify lung images.
6	Mahbub Hussian Jordan J Bird Diego R Faria	A study on CNN Transfer Learning for Image Classification	2018	Development of CNN architecture model to test the accuracy with a new image dataset via transfer learning
7	Manali Shaha Meenakshi Pawar	Transfer Learning for Image Classification	2018	To use Transfer learning for tuning the pre trained network (VGG19) parameters for image Classification tasks
8	Long D Nguyen Dongyu n Lin Jiuwen Cao	Deep CNNs for microscopic image classification by exploiting transfer learning and feature concatenation	2018	Development of novel deep neural network architecture based on transfer learning for microscopic image classification.

1.3: PROBLEM DEFINITION:

The proposed work aims at developing a modified neural network for assessing the quality of potatoes from thermal images. It also at modifying the conventional DENSENET architecture for increasing the sensitivity and specificity.

1.4: OBJECTIVES:

Objectives are detailed as follows:

- To acquire the thermal images of potatoes.
- To preprocess the thermal images.
- To customize the thermal images.
- To implement the pretrained neural network for quality assessment of potatoes.
- To incorporate the new architecture in Deep Learning tool box.
- To Develop quality assessment technique by using the modified DENSENET architecture and measuring its performance in terms of sensitivity and specificity.

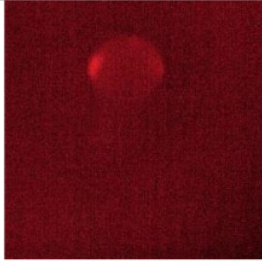
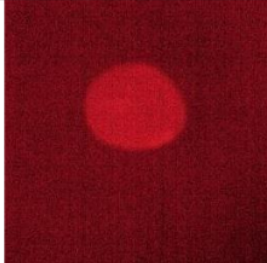
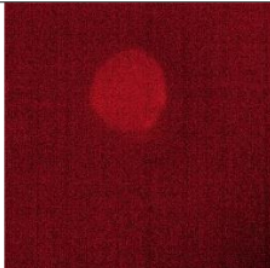
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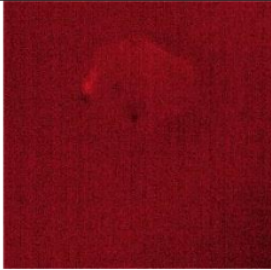
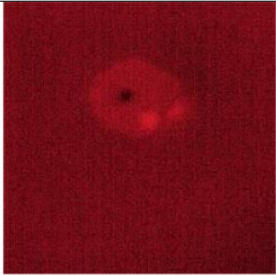
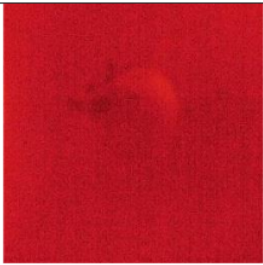
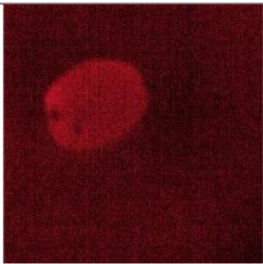
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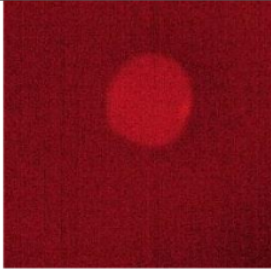
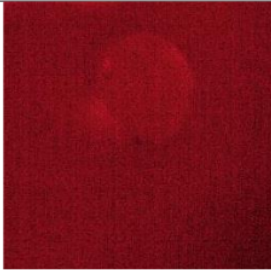
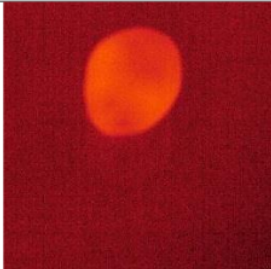
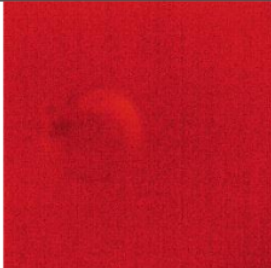
- Chapter 2 is provided with research database.
- Chapter 3 deals with CNN networks developed for classification
- Chapter 4 deals with modified DENSENET architecture for the classification
- Conclusion and future work is provided in chapter 5.

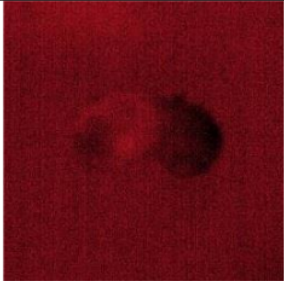
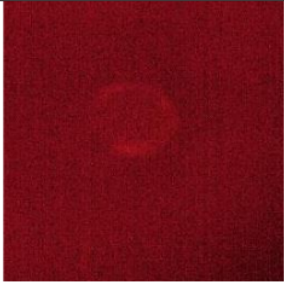
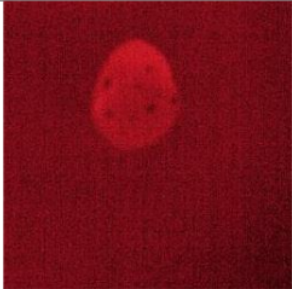
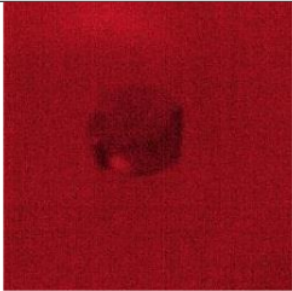
CHAPTER 2 RESEARCH DATABASE

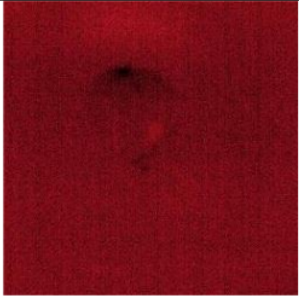
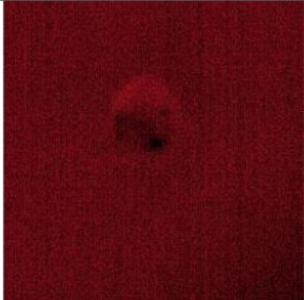
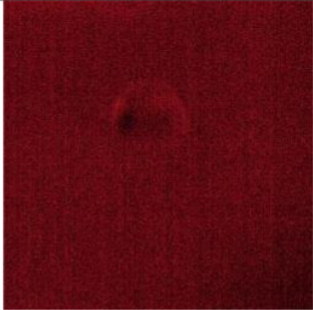
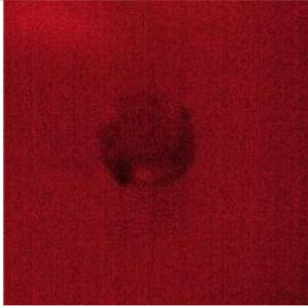
To perform this project, it is necessary to acquire thermal images of potatoes. In this work, using SCT640, a total of 84 thermal images were acquired. Potatoes affected by Fungus, potatoes with Holes, unaffected potatoes and to be rejected potatoes were considered

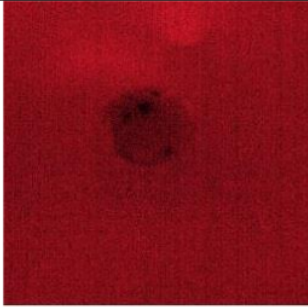
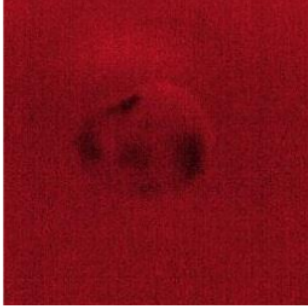
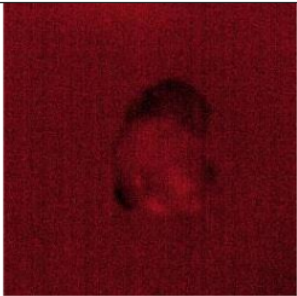
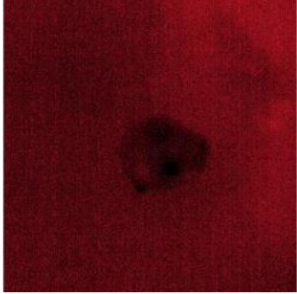
Serial.No	Type of Potato	Thermal Image
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2	Normal Potato	
3	Normal Potato	

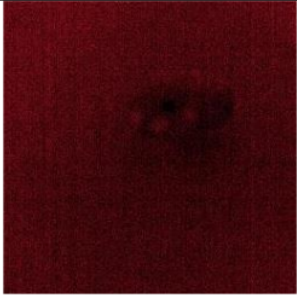
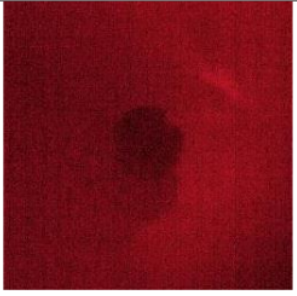
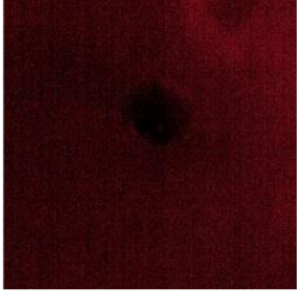
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5	Normal Potato	
6	Normal Potato	
7	Normal Potato	
8	Normal Potato	

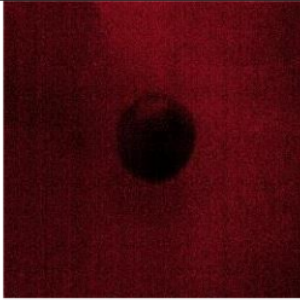
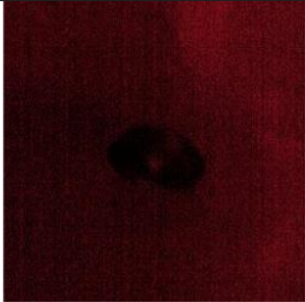
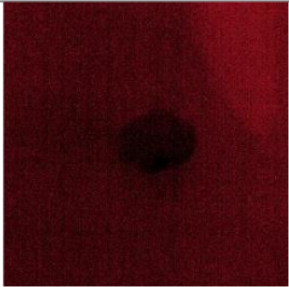
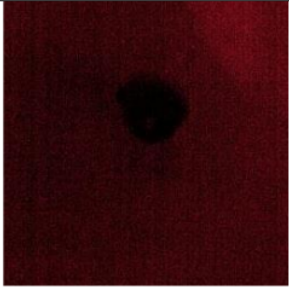
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10	Normal Potato	
11	Normal Potato	
12	Normal Potato	
13	Normal Potato	

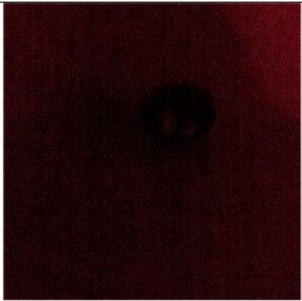
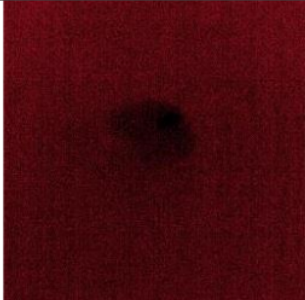
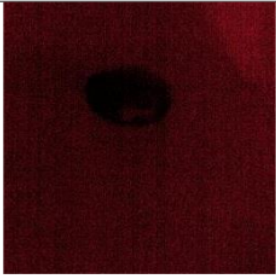
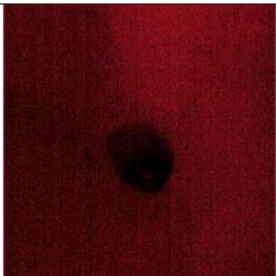
14	Fungus effected Potato	
15	Fungus effected Potato	
16	Fungus effected Potato	
17	Fungus effected Potato	

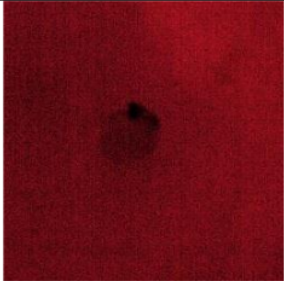
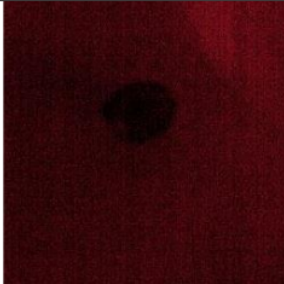
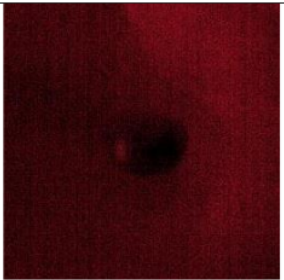
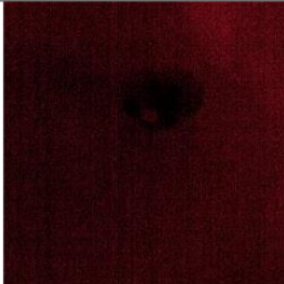
18	Fungus effected Potato	
19	Fungus effected Potato	
20	Fungus effected Potato	
21	Fungus effected Potato	

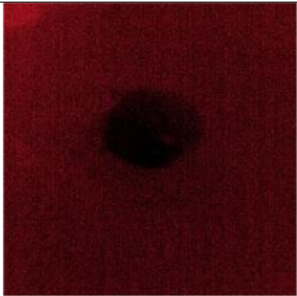
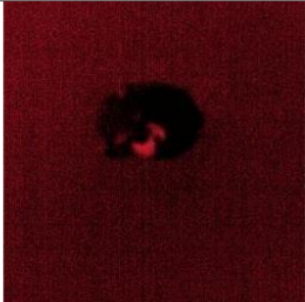
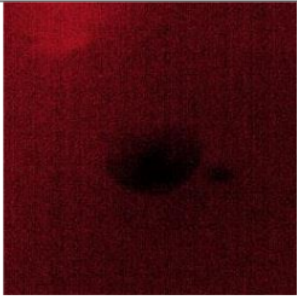
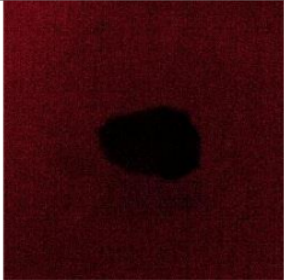
22	Fungus effected Potato	
23	Fungus effected Potato	
24	Fungus effected Potato	
25	Worst Potato	

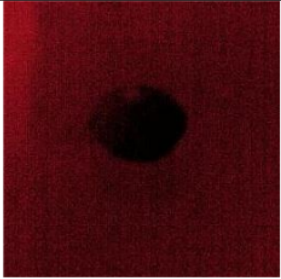
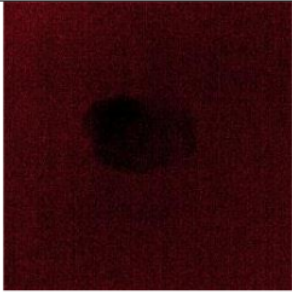
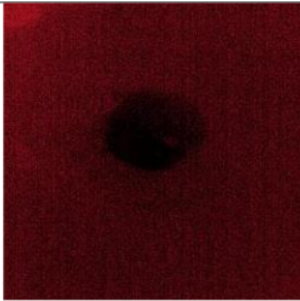
26	Worst Potato	
27	Worst Potato	
28	Worst Potato	
29	Worst Potato	

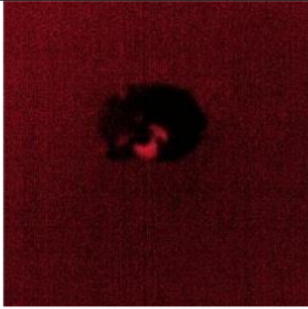
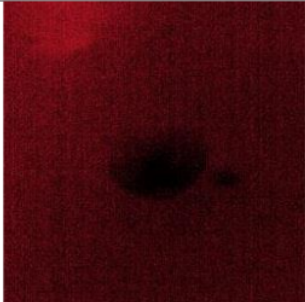
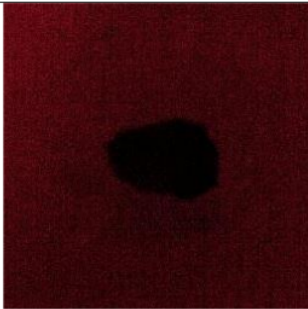
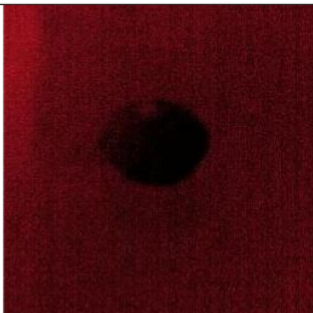
30	Worst Potato	
31	Worst Potato	
32	Worst Potato	
33	Worst Potato	

34	Worst Potato	
35	Worst Potato	
36	Worst Potato	
37	Worst Potato	

38	Worst Potato	
39	Worst Potato	
40	Worst Potato	
41	Worst Potato	

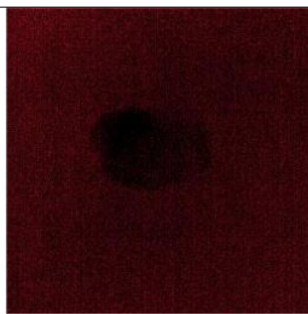
42	Potato with Hole	
43	Potato with Hole	
44	Potato with Hole	
45	Potato with Hole	

46	Potato with Hole	
47	Potato with Hole	
48	Potato with Hole	
49	Potato with Hole	

50	Potato with Hole	
51	Potato with Hole	
52	Potato with Hole	
53	Potato with Hole	

54

Potato with Hole



CHAPTER 3

QUALITY ASSESSMENT WITH EXISTING ARCHITECTURES OF CNN

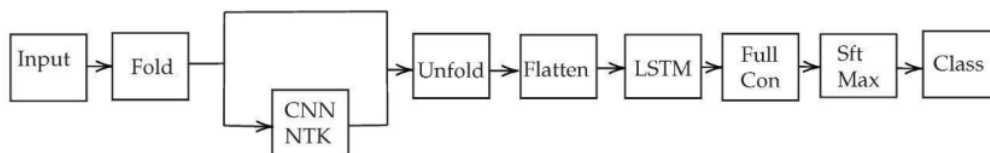
10

Convolutional Neural Network is a class of Deep Neural Networks that can perceive and characterize specific highlights from pictures and are generally utilized for dissecting visual pictures. Their applications goes from picture and video acknowledgment, picture order, clinical picture examination, computer vision and characteristic language preparing.

The expression "Convolution" in CNN indicates the numerical capacity of convolution which is an exceptional sort of straight activity wherein two capacities are increased to deliver a third capacity which communicates how the state of one capacity is adjusted by the other. In basic terms, two pictures which can be addressed as grids are increased to give a yield that is utilized to extricate highlights from the picture.

There are two principle parts to a CNN engineering:

A convolution instrument that isolates and distinguishes the different highlights of the picture for examination in a cycle called as Feature Extraction A completely associated layer that uses the yield from the convolution interaction and predicts the class of the picture dependent on the highlights removed in past stages. There are three sorts of layers that make up the CNN which are the convolutional layers, pooling layers, and completely associated (FC) layers.



3.1 :Architecture of Convolutional Neural Network

3.1.1 Convolved Layer:

This layer is the main layer that is utilized to separate the different highlights from the info pictures. In this layer, the numerical activity of convolution is performed between the information picture and a channel of a specific size $M \times M$. By sliding the channel over the information picture, the spot item is taken between the channel and the pieces of the info picture regarding the size of the channel ($M \times M$).

The yield is named as the Feature map which gives us data about the picture like the corners and edges. Afterward, this component map is taken care of to different layers to gain proficiency with a few different highlights of the info picture.

3.1.2 Strides:

Strides helps in moving the channel framework over the pixels in the component network. Assuming the step size is 1, we can move the channel to 1 pixel at a time. On the off chance that the info network measurement is $n \times n$, channel measurement is $f \times f$ and step size $= s$ then the yield size will be equivalent to $((n-f/s) + 1) * ((n-f/s) + 1)$. In the event that we increment the step size to a higher worth, there is no yield so we can utilize cushioning for it.

3.1.3 Padding:

Padding helps in making the output and input size equal.

Padding is used for:

To avoid shrinking of output image if we increase the number of convolution layers. To make use of the outer edge along with the inner edge of the input image while doing convolution. If padding $p=1$ then it adds two rows and two columns for the input matrix. Mostly we use zero padding. In zero padding we assign zeros to the newly formed rows and columns.

Types of Padding:

Valid padding: In valid padding there is no padding involved. So, the dimensions of input and output are different.

Same padding: Same padding helps in making the dimensions of convolution output dimension and input dimension equal.

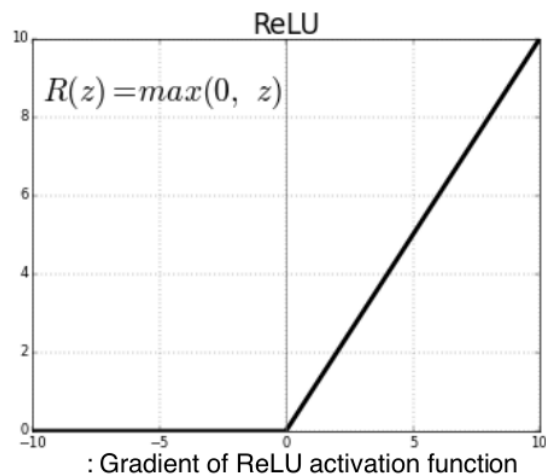
3.1.4 : Pooling Layer:

Convolutional layers are trailed by the Pooling layer. The essential point of this layer is to diminish the size of the convolved include guide to lessen the computational expenses. This is performed by diminishing the associations among layers and freely works on each component map. Contingent on strategy utilized, there are a few sorts of Pooling activities.

In Max Pooling, the biggest component is taken from highlight map. Normal Pooling computes the normal of the components in a predefined estimated Image area. The absolute amount of the components in the predefined area is figured in Sum Pooling. The Pooling Layer generally fills in as a scaffold between the Convolutional Layer and the FC Layer.

3.1.5 : Activation Function:

Activation Function is a numerical condition which decides the field of neural organization. It helps in normalizing the field of neuron to be in the range of [1 and 0] (or) in between [1 and -1]. ReLU is the most generally utilized actuation work in any neural organization. In basic words, it chooses which data of the model should fire the forward way and which ones ought not toward the finish of the organization.



3.2

3.1.6 : SOFTMAX:

SoftMax gives us the final probability for each label and assigns decimal probabilities to each class in a problem with multiple classes. It is also an activation function. Input values can be negative, zero, positive or greater than one but the output values will be between 0 and 1, so they can be interpreted as probabilities.

3.1.7 : Flattering:

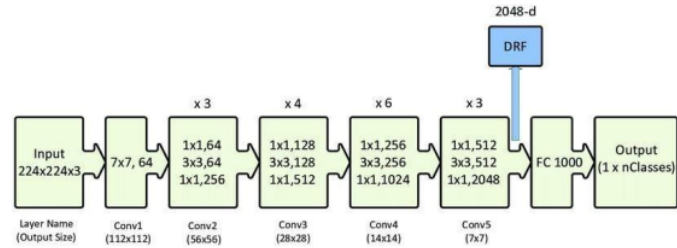
Flattering is a process of converting the output of previous layer into a vector/1-dimensional array to send it to the next layer as input. Flattening is the main advantage of CNN over Feed- Forward Neural Nets.

3.1.8 : Full Connected Layer(FC):

The Full connected (FC) layer comprises of loads and predispositions alongsidethe neurons and is utilized to interface the neurons between two distinct layers. These layers are normally positioned before the yield layer and structure the last couple of layers of a CNN Architecture.

3.1: ASSESSMENT OF POTATOES USING RESNET50:

RESNET50 is pre-trained Deep learning network model for image recognition and classification. It has a class of deep neural networks and it is mostly used to analyze visual images. RESNET50 is a network with 50 layers deep which is trained with 100,000 images of more than 1000 categories from the database called ImageNet.



3.3: RESNET50 Architecture

In this work, the existing architecture of RESNET50 is used for assessing the quality of potatoes. Of a total of 84 images, 50% is used for training and another 50% is used for testing.

Table 3.2.1: Probability of detection (RESNET50)

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	4	1	0	0
Type-Normal	1	5	0	0
Type-Worst	2	0	2	4
Type-Hole	1	0	0	6

Table 3.2.2: Sensitivity of different classes of potatoes.

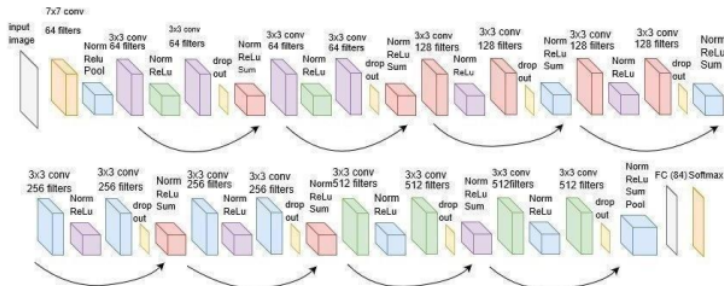
Sensitivity	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
	80%	83.33%	25%	85.71%

In order to understand the performance of RESNET50, probability of detection is determined and shown in table 3.2.2. It is observed that this network classifies well for Type-Hole, Type-Fungus, Type-Normal. To increase the sensitivity of Type-Cpotatoes RSNET18 is used.

3.3 : QUALITY ASSESMNET OF POTATOES USING RESNET18:

RESNET18 is a CNN network that is developed with the help of 1,000,000 pictures from ImageNet database. This network consists of 18 layers and can group pictures into 1000 article classes.

In this work the existing architecture of RESNET18 is used for assessing the quality of potatoes. Of total 84 images, 50% is used for training and another 50% is used for testing.



3.4 : Architecture of RESNET18

Table 3.3.1: Probability of detection (RESNET18)

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	6	0	0	0
Type-Normal	3	3	0	0
Type-Worst	2	0	5	1
Type-Hole	3	0	1	3

Table 3.3.1: Sensitivity of detection (RESNET18)

	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Sensitivity	100%	50%	62.5%	42.8%

In order to understand the performance of RESNET-18, probability of detection is determined and is shown in the above table. From the Table 3.3.2 we can see that above network works well in classifying Type-Fungus, and Type-Worst potatoes. In order to improve the sensitivity of Type-Normal and Type-Hole conventional Darknet is used.

3.3 : QUALITY ASSESSMENT OF POTATOES USING CONVENTIONAL DARKNET

DARKNET is open source neural network used for classification and image detection. Existing DARKNET53 is used for assessing the quality of potatoes. Of a total of 84 images, 50% is used for training and another 50% is used for testing.

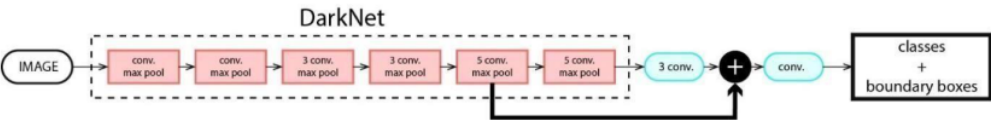


Fig 3.4: Architecture of DarkNet

Table 3.4.1: Probability of detection (DARKNET53)

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	1	1	4	0
Type-Normal	2	1	2	2
Type-Worst	0	5	1	0
Type-Hole	0	2	6	0

Table 3.4.2: Sensitivity of different classes of potatoes.

	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Sensitivity	16%	57.14%	83%	75%

CHAPTER 4

MODIFIED DENSENET ARCHITECTURE

In convolutional Modified DENSENET architecture, some modifications are done for improving the efficiency and high sensitivity. A modified DENSENET architecture is obtained by removing a set of convolutional layers. Instead of 64 layers, 58 layers are used. The description of the layers are given in the table below.

Table 4.1: Layers of Modified DENSENET

S.NO	Name	Type	Activation	Learnables
1	Input	Image Input	256x256x3	
2	Conv1	Convolution	256x256x32	Weights 3x3x3x32 Bias 1x1x32
3	Batchnorm1	Batch Normalization	256x256x32	Offset Scale 1x1x32 1x1x32
4	Leaky 1	Leaky ReLU	256x256x32	-
5	Pool1	Max Pooling	128x128x32	-
6	Conv2	Convolution	128x128x64	Weights

				Bias 3x3x32x64 1x1x64
7	Batchnorm	Batch normalization	128x128x64	Offset Scale 1x1x64 1x1x64
8	Leaky 2	Leaky ReLU	128x128x64	-
9	Pool2	Max Pooling	64x64x64	-
10	Conv 3	Convolution	64x64x128	Weights Bias 3x3x64x128 1x1x128
11	Batchnorm 3	Batch Normalization	64x64x128	Offset Scale 1x1x128 1x1x128
12	Leaky 13	Leaky ReLU	64x64x128	-
13	Conv 4	Convolution	64x64x64	Weights Bias 1x1x128x64 1x1x64
14	Batchnorm	Batch normalization	64x64x64	Offset Scale 1x1x64 1x1x64
15	Leaky 4	Leaky ReLU	64x64x64	-
16	Conv 5	Convolution	64x64x128	Weight Bias 3x3x64x128 1x1xx158

17	Batchnorm 5	Batch Normalization	64x64x128	Scale Offset 1x1x128 1x1x128
18	Leaky 5	Leaky ReLU	64x64x128	-
19	Pool3	Max Pooling	32x32x256	-
20	Conv 6	Convolution	32x32x256	Weights Bias 3x3x128x256 1x1x256
21	Batchnorm 6	Batch Normalization	32x32x256	Offset Scale 1x1x256 1x1x256
22	Leaky 6	Leaky ReLU	32x32x256	-
23	Conv 7	Convolution	32x32x128	Weights Bias 1x1x256x128 1x1x128
24	Batchnorm 7	Batch Normalization	32x32x128	Offset Scale 1x1x128 1x1x128
25	Leaky 7	Leaky ReLU	32x32x128	-
26	Conv 8	Convolution	32x32x256	Weights Bias 3x3x128x256 1x1x256
27	Batchnorm 9	Batch Normalization	32x32x256	Offset Scale

				1x1x256 1x1x256
28	Leaky 8	Leaky ReLU	32x32x256	-
29	Pool 4	Max Pooling	16x16x256	-
30	Conv 9	Convolution	16x16x512	Weights 3x3x256x512 1x1x512
31	Batchnorm 9	Batch normalization	16x16x512	Offset Scale 1x1x512 1x1x512
32	Leaky 9	Leaky ReLU	16x16x512	-
33	Conv 10	Convolution	16x16x256	Weights Bias 1x1x512x256 1x1x256
34	Batchnorm 10	Batch Normalization	16x16x256	Offset Scale 1x1x256 1x1x256
35	Leaky 10	Leaky ReLU	16x16x256	-
36	Conv 11	Convolution	16x16x512	Weights Bias 3x3x256x512 1x1x512
37	Batchnorm 11	Batch Normalization	16x16x512	Offset Scale 1x1x512 1x1x512

38	Leaky 11	Leaky ReLU	16x16x512	-
39	Conv 12	Convolution	16x16x256	Weights Bias 1x1x512x256 1x1x256
40	Batchnorm 12	Batch Normalization	16x16x256	Offset Scale 1x1x256 1x1x256
41	Leaky 12	Leaky ReLU	16x16x256	-
42	Conv 13	Convolution	16x16x512	Weights Bias 3x3x256x512 1x1x512
43	Batchnorm 13	Batch Normalization	16x16x512	Offset Scale 1x1x512 1x1x512
44	Leaky 13	Leaky ReLU	16x16x512	-
45	Pool 5	Max Pooling	8x8x512	-
46	Conv 14	Convolution	8x8x1024	Weights Bias 3x3x512x1024 1x1x1024
47	Batchnorm 14	Batch normalization	8x8x1024	Offset Scale 1x1x1024 1x1x1024
48	Leaky 14	Leaky ReLU	8x8x1024	-

49	Conv 17	Convolution	8x8x512	Weights Bias 1x1x1024x512 1x1x512
50	Batchnorm 17	Batch normalization	8x8x512	Offset Scale 1x1x512 1x1x512
51	Leaky 17	Leaky ReLU	8x8x512	-
52	Conv 18	Convolution	8x8x1024	Weights Bias 3x3x512x1024 1x1x1024
53	Batchnorm 18	Batch normalization	8x8x1024	Offset Scale 1x1x1024 1x1x1024
54	Leaky 18	Leaky ReLU	8x8x1024	-
55	Conv 19	Convolution	8x8x1000	Weights Bias 1x1x1024x1000 1x1x1000
57	Avg1	Global Average Pooling	1x1x1000	-
57	Softmax	Softmax	1x1x1000	-
58	Output	Classification output	-	-

In this work, architecture of MODIFIED DENSENET is used for assessing the quality. Of a total of 84 images, 50% is used for training and another 50% is used for testing.

Table 4.1: Probability of detection (MODIFIED DENSENET).

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Type-Fungus	5	0	1	0
Type-Normal	0	0	2	5
Type-Worst	4	2	0	0
Type-Hole	3	0	4	1

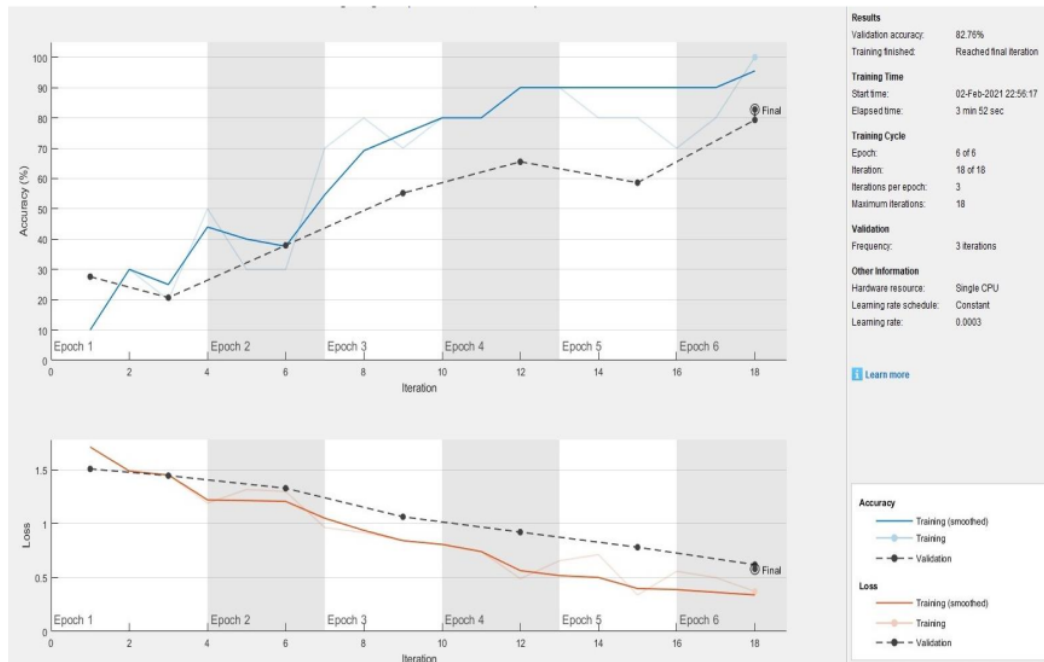
In order to understand the performance of DENSENET, sensitivity of different classes is given below.

Table 4.2: Sensitivity of different classes of potatoes.

Type	Type-Fungus	Type-Normal	Type-Worst	Type-Hole
Sensitivity	83.3%	33.3%	50%	71.4%

From above table we can see that developed network classifies Type-Fungus and Type-Normal potatoes well.

MODIFIED OUTPUT



CHAPTER 5

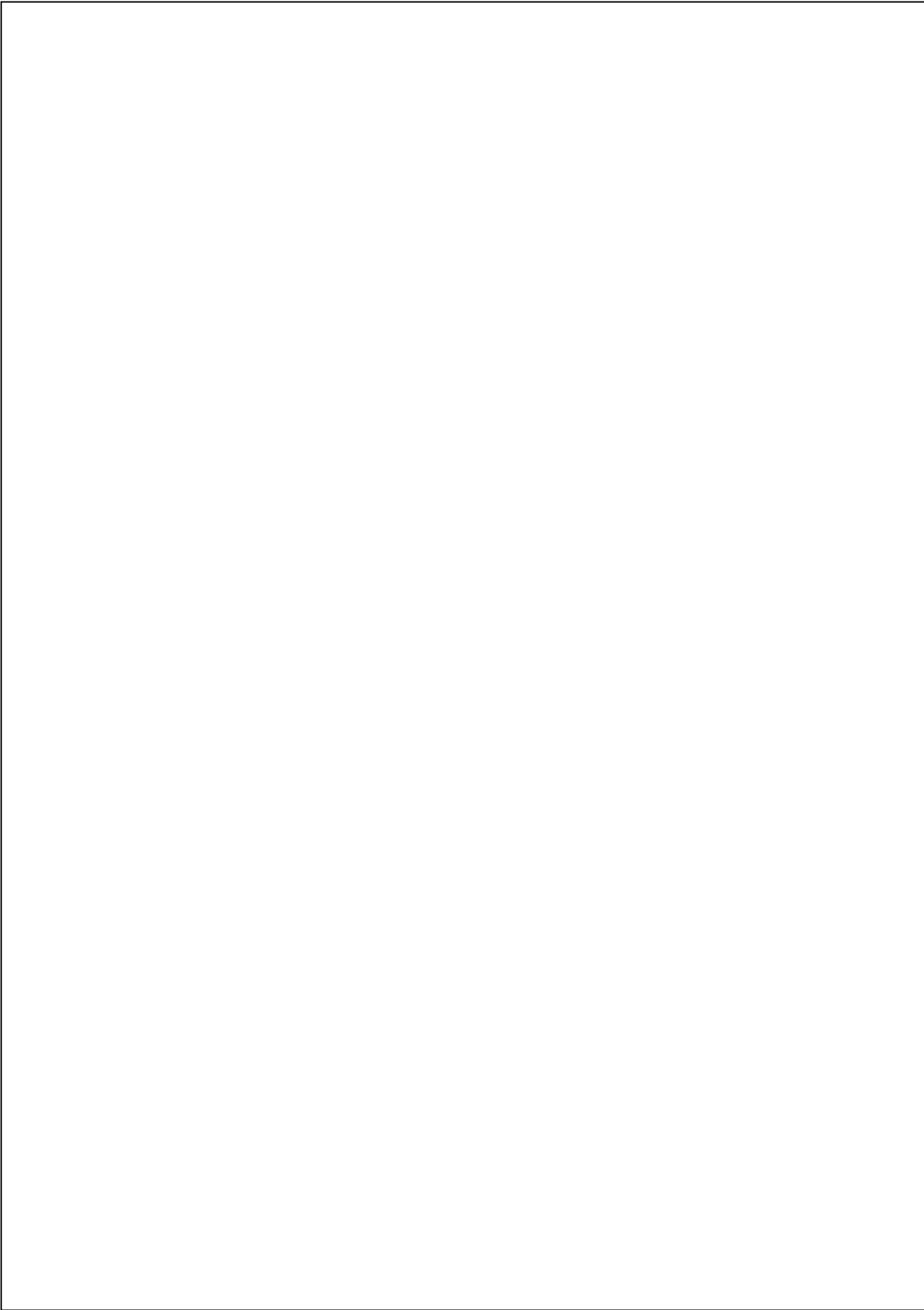
CONCLUSION

Research database has been created with 84 thermal images of Type-Fungus, Type-Normal, Type-Worst and Type-Hole using SCT640, FLIR IR Camera. Preprocessing of these images is done. Feasibility of existing architecture of RESNET50, RESNET18, Conventional DARKNET for classification of potatoes using the images is studied. Performance is noted along with probability of detection and sensitivity. RESNET50 has classified Type-Normal potatoes successfully but it could not classify Type-Worst potatoes.

On the other hand RESNET 18 has classified Type-Fungus but could not classify Type-Normal potatoes. Sensitivity of potatoes with holes is 25% and it provides 100% sensitivity for fungus affected potatoes.

Conventional DARKNET provides 83.3% sensitivity for fungus affected potatoes, but it failed in detecting normal potatoes with sensitivity 33.3% on the other hand sensitivity of hole potatoes is 71%. Darknet classifies fungus potatoes with high sensitivity.

Based on accuracy, DENSENET gives better accuracy with 82.76%. This project is stopped at simulation level, hardware implementation of this work can be done in future as well. Feasibility of the other neural networks for quality assessments of potatoes can be done.



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