

ANCLYOSTOMA DUODENALE DIAGNOSIS FROM CAPSULE ENDOSCOPY IMAGES USING DEEP LEARNING

Submitted in partial fulfilment of the requirements for the award of

Bachelor of Technology degree in Biomedical Engineering

by

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**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **NIVETHA J (38240021)**, **SANTRA E (38240032)** who carried out the project entitled **"ANCYCLOSTOMA DUODENALE DIAGNOSIS FROM CAPSULE ENDOSCOPY IMAGES USING DEEP LEARNING"** under my supervision from **September 2021** to **April 2022**.

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DECLARATION

We, **NIVETHA J (38240021)**, **SANTRA E (38240032)** hereby declare that the Project Report entitled “**ANCYCLOSTOMA DUODENALE DIAGNOSIS FROM CAPSULE ENDOSCOPY IMAGES USING DEEP LEARNING**” done by us under the guidance of Dr. **S. KRISHNAKUMAR**, M.Sc., Ph.D., is submitted in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

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SIGNATURE OF THE CANDIDATES

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ABSTRACT

Wireless Capsule Endoscopy (WCE) has become a widely used diagnostic technique to examine inflammatory bowel diseases and disorders. The most common human helminthes, hookworm is a kind of small tubular structure with a semi-transparent or pinkish body. The main aim of the project is to demonstrate the presence of hookworm in the intestine using capsule endoscopy by deep learning CNN algorithm. A novel deep hookworm detection is done by image processing technique using Conventional Neural Network (CNN) and Guided filter method. The high sensitivity and accuracy of the proposed method in detecting hookworm show its potential for clinical application. Automatic detection of hookworm is a difficult task due to poor image quality, the presence of a foreign substance, the complex structure of the gastrointestinal tract, and various aspects in terms of color and texture. The present study demonstrated that early detection of hookworm in human's intestine and remove from the body by proper treatment. MATLAB software tool is used for the detection of intestinal hookworm by image processing. The image processing techniques are implanted which can automatically to detect the abnormalities. The advantage of this technique is because of its specialized effortlessness and minimal effect.

TABLE OF CONTENTS

CHAPTER NO	TITLE	PAGE NO
	ABSTRACT	v
	LIST OF ABBREVIATION	viii
	LIST OF FIGURES	ix
	LIST OF TABLES	x
1	INTRODUCTION	1
2	LITERATURE SURVEY	4
3	AIM ANDSCOPE	10
3.1	AIM	10
3.2	SCOPE	10
4	MATERIALS AND METHODS	11
4.1	IMAGE ACQUISITION	11
4.1.1	2D IMAGE INPUT	12
4.2	IMAGE PRE-PROCESSING	12
4.2.1	GRAY IMAGE	12
4.2.2	GRAY SCALE AS SINGLE CHANNELS OF MULTICHANNEL COLOR IMAGES	13
4.3	IMAGE ENHANCEMENT	14
4.3.1	GUIDED FILTER	14
4.3.2	WEINER FILTER	15
4.3.3	HISTOGRAM EQUALIZATION	16
4.3.4	ADAPTIVE HISTOGRAM EQUALIZATION	16

4.4	IMAGE SEGMENTATION	17
4.4.1	K - MEANS CLUSTERING	17
4.5	HOOKWORM CLASSIFICATION NETWORK	18
4.5.1	CONVOLUTION NEURAL NETWORK ARCHITECTURE	18
4.5.2	ALEXNET	19
4.5.3	RESNET 50	21
4.5.4	RESNET 101	22
5	RESULT S AND DISCUSSION	23
5.1	RESEARCH DATABASE	23
5.2	RESULTS	24
5.3	FEATURE EXTRACTION PARAMETERS	26
5.4	DISCUSSION	26
5.5	PERFORMANCE ANALYSIS	29
5.5.1	RESNET 50	29
5.5.2	RESNET 101	33
5.5.3	ALEXNET	34
5.6	COMPARISION OF RESNET AND ALEXNET	36
6	SUMMARY AND CONCLUSION	37
6.1	SUMMARY	37
6.2	CONCLUSION	38
	REFERENCES	39

LIST OF ABBREVIATION

ABBREVIATION	EXPANSION
WCE	WIRELESS CAPSULE ENDOSCOPY
GID	GASTRO INTESTINAL DIAGNOSIS
HSV	HUE SATURATION VALUE
CNN	CONVOLUTIONAL NEURAL NETWORK
CAD	COMPUTER AIDED DETECTION
GAN	GENERATIVE ADVERSARIAL NETWORK
RGB	RED GREEN BLUE
LTI	LINEAR TIME INVARIANT
MMSE	MINIMUM MEAN SQUARE ERROR
AHE	ADAPTIVE HISTOGRAM EQUALIZATION
CLAME	CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION
MSE	MEAN SQUARE ERROR
PSNR	PEAK SIGNAL TO NOISE RATIO
AD	AVERAGE DIFFERENCE
MD	MAXIMUM DIFFERENCE
MAE	MEAN ABSOLUTE ERROR
NK	NORMALIZED CROSS CORRELATION
SC	STRUCTURAL CONTENT
PCA	PRINCIPLE COMPONENT ANALYSIS

LIST OF FIGURES

FIGURE NO	NAME OF THE FIGURE	PAGE NO.
4.1	Block Diagram of Hookworm detection	11
4.2	Conversion of RGB to Gray	14
4.3	Guided Filter	15
4.4	CNN Diagram	18
5.1	Output Image 1	24
5.2	Output Image 2	24
5.3	Output Image 3	25
5.4	Output Image 4	25
5.5	RESNET 50 Output	29
5.6	RESNET 50 Training progress	30
5.7	RESNET 50 Confusion Matrix	31
5.8	RESNET 101 Output	32
5.9	RESNET 101 Training Progress	32
5.10	RESNET 101 Confusion Matrix	33
5.11	AlexNet Training Progress	34
5.12	AlexNet Confusion Matrix	35
5.13	Accuracy percentage of RESNET and AlexNet	36

LIST OF TABLES

TABLE NO	NAME OF THE TABLE	PAGE NO
5.1	Datasets of Hookworm	23
5.2	Feature Extraction Parameters	26

CHAPTER 1

INTRODUCTION

In advanced clinical procedures, Wireless Capsule Endoscopy is being used. Even with the aid of visual aids, detecting the hookworm remains a difficult task. Many methodologists exist to overcome this, with CNN being the most advanced and latest. As a result of the research, an idea for detecting the hookworm utilizing a moderate amount of data has been proposed (Anuja Kharatmol & A.M. Bagader 2019). An internal sponger known as a roundworm causes hookworm infection. It's a major source of worry for both mom and baby. To characterize the hookworm images, an Adaboost classifier was used (Lakshminarayanan & N. Muthukumaran 2021). It has a tubular construction with a semi-transparent greyish white or pinkish body. WCE is a common diagnostic tool for inflammatory illnesses and disorders (Maheswaran & N.Indumathi 2021). Over 1.5 billion individuals are affected by soil transmitted helminths (STHs), which include the hookworms *Necator americanus* and *Ancylostoma SPP.*, *Ascaris lumbricoides*, and *Trichuris trichuria* (Malathi Manuel & Karthik Ramanujam 2021). The automated hookworm detection utilizing the WCE technique has been the subject of numerous investigations. Artificial neural networks underpin the vast majority of deep learning approaches. Deep learning is used to execute effective data analysis, and it has two properties: supervised and unsupervised feature presentation learning. Various interconnected computer units make up a neural network (Monisha, et al., 2020). Deep learning models for WCE photos improve detection accuracy, however model training necessitates a large amount of labelled data. It provides a patient-friendly, non-invasive, and painless gastrointestinal tract examination (Prabhananthakumar Muruganantham & Senthil Balakrishnan 2021). Intestinal inflammation, increasing iron or protein deficiency anemia, mucosa damage, and malnutrition are all major consequences of hookworm infection in humans.

By examining its distinct traits, a series of fresh strategies were presented to capture its characteristics (Priya Vadhana, et al., 2020). Because of the low nature of pictures, proximity of incidental issues, complex gastrointestinal structure, and variable appearances to the external shading and surface, developing customized and entirely robotized hookworm recognition and characterization models is a difficult work. The many improvements in hookworm location using neural networks, as well as their varied types, were also discussed (Rashmita Khilar & Muthu Subramanian 2020). Machine learning algorithms, a type of AI, are used to provide time-saving viewing modes and lesion detecting characteristics. CADs of hookworms with a promising 88.5 percent accuracy and detection of celiac disease are two specialized applications of deep learning that have been researched in WCE that do not fall into the previous categories. As a result of the introduction of deep learning, AI is becoming more dependable and will be relied on more (Roberto Trasolini & Michael Byrne 2021). The medical diagnostic process for a variety of disorders has been changed by artificial intelligence (AI). Because interpreting capsule endoscopy movies by hand is a time-consuming and error-prone operation, computerized techniques to automate the process have been developed. The advancement of CNN over the last decade has allowed AI to detect several lesions simultaneously with improving sensitivity and accuracy. Although AI technology can be employed as an auxiliary second observer in capsule endoscopy, it is envisaged that in the not-too-distant future, it will effectively reduce reading time and become a self-contained, integrated reading system (Sang Hoon Kim & Yun Jeong Lim 2021). An independent test set of 10,529 small bowel images, including 531 hookworm images, was used to compute the area under the receiver operating characteristic wave, as well as its sensitivity, specificity, and accuracy. At a probability score cutoff of 0.485, the accuracy was 92.2, 91.1, and 91.2 percent (Tao Gan & Shuaicheng Liu 2021). One of the most common disorders investigated by GI endoscopy is gastrointestinal disease (GI). In the field of GI endoscopy image processing, deep learning, particularly CNN, has recently made strides.

It covers the most important Deep Learning applications in GI image detection, classification, segmentation, recognition, and localization, among other things (Wenj Du, et al., 2019). Automatic detection of lesions in WCE images is done using convolutional neural networks. A method for recognising numerous lesions on capsule endoscopic images is suggested, in which common vascular and inflammatory lesions can be discovered automatically and fast. Efficient Net fine-tunes the extraction of the endoscopic image feature using weakly supervised learning. The model was compared to the ResNet 121 and Inception Net v4 models in terms of accuracy and speed. For vascular and inflammatory lesions, it has a sensitivity of 96.67 percent and 93.33 percent, respectively. 96.11 percent of the time was accurate (Xudong Guo, et al., 2021). The dog hookworm, *Ancylostoma caninum* (Nematoda, Ancylostomatidae), is an intestine parasitic nematode that feeds on blood and can cause ancylostomiasis in people. Through Illumina deep sequencing technology, the entire mitochondrial genome of this hookworm was sequenced. The entire genome was 13,721 base pairs long and encoded 36 genes, including 12 protein-coding genes, 22 transfer RNAs, and two ribosomal RNAs. Phylogenic investigations among Ancylostomatidae nematodes can benefit from mitochondrial DNA data (Yue Xie & Ziyi Xu 2019).

CHAPTER 2

LITERATURE SURVEY

Anuja Kharatmol & Bagader (2019), Hookworms are a plague to human health, and detecting them is always a difficult work for medical science. As a result, in order to defeat this wireless capsule, In sophisticated clinical procedures, endoscopy is used. Even yet, locating the hook remains a difficult task. Even the photographic sights gave me the creeps. So, in order to overcome the numerous obstacles, There are approaches that have emerged from the most advanced and recent research. One method is to use a Convolution neural network (CNN). The CNN's main flaw is that it usually requires a lot of data. Labelled data for parameter training and fine-tuning and the majority of most of the time, it is impossible to supply such a significant amount of data for the analysis the procedure for detection. As a result, the proposed methodology advances a concept. Using a moderate amount of data to detect the hookworm incorporates picture data weighted feature selection, Region selection, and Convolutional neural networks are of particular importance, as are fuzzy neural networks. Hookworms are easily found using this classification method.

Lakshminarayanan & Muthukumaran (2020), An internal sponger known as a roundworm causes hookworm infection. Hookworm infection is a major source of concern for both motherly and baby filthiness in underdeveloped countries, as a result of a lack of sanitation. The current hookworm detection system is made up of hybrid convolutional neural networks, including an explicit edge extraction framework as well as a hookworm classification framework. Pooling layers are proposed to combine the cylindrical zones derived from the edge extraction framework and the trait map derived from the hookworm scientific classification framework. The profiles, widths, and bend directions of the hookworms vary. Customized hookworm detection is challenging due to these challenges. With the development of the Hookworm detection in the proposed method, a contourlet change was applied. Standard procedures were used in this study. The highlights of each

form were separated in this study using standard deviation, skewness, entropy, mean, and liveliness. These projections proved to be correct. To characterize the hookworm images, an AdaBoost classifier was used. The precision and scope of the territory examined under bend in recognizing the hookworm are demonstrated in this research, demonstrating its scientific value.

Maheswaran & Indhumathi (2021), Hookworms are parasitic roundworms that feed on the blood in the intestine and cause helminthiasis, a type of infection. The body is greyish white or pinkish semi-transparent and has a tubular form. Blood loss, which causes anemia, and protein loss are the two most serious side effects of hookworm infection. WCE (Wireless Capsule Endoscopy) is a common diagnostic procedure for inflammatory illnesses and disorders. The existing technique employs two CNN networks to detect hookworms: edge extraction and hookworm categorization. To reduce noise from the dataset, the suggested system includes a Median filter. To detect the edges of hookworm, Canny Edge detection is employed. Compared to other edge detection approaches, this methodology has a poor SNR (Signal to Noise Ratio). To employ CNN as a classifier, the architecture of the CNN (Convolutional Neural Network) is changed. It divides the dataset into two categories: the hookworm and the standard Wireless Capsule Endoscopy (WCE).

Malathi Manuel & Karthik Ramanujam (2021), Over 1.5 billion people are affected by soil-transmitted helminthes (STH), which include the hookworms *Necator americanus* and *Ancylostoma* spp., *Ascaris lumbricoides*, and *Trichuris trichiura*, and are estimated to have caused 1.9 million disability-adjusted life years (DALYs). With the coordinated efforts over the years, there has been a concerted push to extend and improve targeted mass drug administration (MDA) programs. Infections in some endemic locations have tended to be of lower severity in the last decade, despite declining occurrence. Low level of intensity for the detection of STH, traditional microscopy-based approaches are advised. In low-intensity situations, parasitological surveys have been demonstrated to be less sensitive. As through MDA and improved sanitation, communities are making headway in eliminating STH. There is a pressing need for very sensitive approaches that can detect the genuine prevalence of STH in order to assess it.

Monisha, et al., (2020), Wireless capsules can be used to check inflammatory bowel illnesses and problems. Endoscopy is a procedure that involves the examination of the inside (WCE). Many attempts have been made to study the automated detection of hookworms utilizing the WCE approach. Hookworm is one of the most frequent parasites. It's a little tubular construction with a greyish white or pinkish semi-transparent surface.

Prabhananthakumar Muruganantham & Senthil Murugan Balakrishnan (2021), Due to the intrinsic difficulties in accessing a volute setting in the human body, abdominal bleeding, ulcers, tumours, Crohn's disease, Celiac disease, and other disorders of the gastrointestinal tract (GI) are difficult to detect. WCE (Wireless Capsule Endoscopy) is a painless, non-invasive, and patient-controlled GI tract study. While utilizing Deep Learning Models to detect abnormalities in WCE photos enhances detection accuracy, it requires a large amount of labelled data for model training. However, these deep models are difficult to explain and do not include expert knowledge into the decision-making process. This survey attempts to determine the advantages of employing semi-supervised deep learning models over supervised deep learning methods in the Wireless Capsule Endoscopy (WCE) anomaly by considering these factors.

Priya Vandhana, et al., (2020), Hookworm is a prominent cause of maternal and infant morbidity, as it is one of the most frequent human Helminths. Infection with hookworm poses a major hazard to human health, compromising children's physical and intellectual development. Hookworm has infected over 600 million people worldwide, according to reports. The use of wireless capsule endoscopy (WCE) to investigate inflammatory bowel illnesses and disorders has become commonplace. Due to low image quality, the presence of foreign objects, the complicated structure of the gastrointestinal tract, and the wide range of color and texture appearances, automatic hookworm identification is a difficult operation. Infection with hookworms during pregnancy can result in the fetus's growth being stunted, as well as premature birth and low birth weight. In youngsters, hookworm can cause cognitive, intellectual, and development issues. This is a unique opportunity. The identification of hookworm in humans is an example of this effort.

Rashmita Khilar & Muthu Subramaniyan (2020), WCE (Wireless Capsule Endoscopy) has been a widely employed demonstration approach for examining a wide range of flammable diseases and disarrays. Because of the low nature of pictures, proximity of incidental concerns, complex gastrointestinal system, and variable appearances to the extent shading and surface, developing customized and entirely robotized hookworm recognition and characterization models is a difficult work. A few efforts have been undertaken to thoroughly investigate the robotized hookworm discovery from WCE images. Pre and post preparing specialist application, a thorough examination is conducted to identify Hookworm in Endoscopy images and its partners. A comprehensive report on artificial intelligence (AI) systems and highlight extraction methods was studied. The many developments in Hookworm location using neural systems, as well as their varied types, were also discussed.

Roberto Trasoloni & Michael Byrne (2021), Due to its emphasis on pattern recognition in capsule endoscopy, it is well-suited to artificial intelligence-based interpretation. images that are still Viewing modalities that save time and lesion detection. Machine learning algorithms are used in the existing features. Artificial intelligence in the form of rithms. Currently available applications. Due of its low sensitivity, it demands close human monitoring in the opinion of an expert reader. However, with the introduction of deep learning, Artificial intelligence is becoming more dependable as it learns and will be relied upon more and more. We go over the important points. Artificial intelligence developments in capsule endoscopy, recent works, as well as a quick examination of artificial intelligence development to aid historical comprehension It's worth noting that recent Artificial intelligence improvements have not yet been made. It is immature to judge the effectiveness of something that has been implemented into practice.

Sang Hoon Kim & Yun Jeong Lim (2021), The medical diagnostic process for a variety of disorders has been transformed by artificial intelligence (AI). Because interpreting capsule endoscopy movies by hand is a time-consuming and error-prone operation, computerized techniques to automate the process have been developed. Convolutional neural networks

(CNNs) have improved in accuracy and sensitivity over the last decade, allowing AI to detect many lesions at the same time. Computer-aided reading systems in capsule endoscopy are currently in the preclinical stage due to the difficulty of evaluating CNN performance and the specific properties of capsule endoscopy images. Although AI technology can be employed as a second observer in capsule endoscopy, it is believed that in the near future, it will be able to effectively reduce reading time and eventually become an independent, integrated reading system.

Tao Gan & Shuaicheng Liu (2021), Capsule endoscopy (CE) is used to diagnose ancylostomiasis, a prevalent small intestinal parasite condition for which no computer-aided clinical detection approach exists. We wanted to build a convolutional neural network (CNN)-based artificial intelligence system that could detect hookworms in CE photos automatically. We used 11236 CE pictures of hookworms to train a deep CNN system based on a YOLO- V4 (You Only Look Once-Version4) detector. Using an independent test set of 10,529 small-bowel images, including 531 images of hookworms, we evaluated its performance by calculating the area under the receiver operating characteristic curve, as well as its sensitivity, specificity, and accuracy. After evaluating 10,529 test images, the trained CNN system took 403 seconds. The detection of hookworms had a large region under the curve. For detecting hookworms in CE pictures, we built and tested a CNN-based approach. We expect that by integrating this high-accuracy, fast, and oversight-proof approach with other CNN systems, it will become a valuable supplement for detecting intestinal anomalies in CE pictures. ChiCTR2000034546 (a clinical study of artificial intelligence-aided diagnosis for hookworms in the small intestine using capsule endoscopy pictures) is the number assigned to this study.

Wenju Du, et al., (2019), GI endoscopy is used to examine gastrointestinal (GI) disease, which is one of the most common diseases. Deep learning (DL), specifically convolutional neural networks (CNNs), has recently made strides in the field of GI endoscopy image processing. The use of DL approaches to the analysis of GI pictures is the subject of this review. We compiled and reviewed the most recent published research on prevalent

clinical gastrointestinal disorders, as well as the key applications of deep learning in GI image detection, classification, segmentation, recognition, localization, and other tasks. Finally, we talk about the challenges and future research objectives for GI image analysis using DL.

Xudong Guo, et al., (2021), The wireless capsule endoscopy (WCE) method generates tens of thousands of images of the digestive tract, making manual reading difficult. Automatic detection of lesions in WCE images is done using convolutional neural networks. However, there are few research on clinical multilesion identification, and balancing sensitivity to several lesions can be problematic. A method for recognising numerous lesions on capsule endoscopic images is suggested, in which common vascular and inflammatory lesions can be discovered automatically and fast. EfficientNet has been fine-tuned to extract endoscopic image characteristics based on poorly supervised learning. The suggested attention network is utilised as a classifier to generate three classes by combining spatial and channel characteristics. The model was compared to the ResNet121 and InceptionNetV4 models in terms of accuracy and speed. It was put to the test on 4143 participants from a public WCE picture dataset. The approach has a sensitivity of 96.67 percent for vascular lesions and 93.33 percent for inflammatory lesions, according to a database of computer-assisted diagnosis for capsule endoscopy. Precision was 92.80% for vascular lesions and 95.73 percent for inflammatory lesions. The accuracy was 96.11 percent, up 1.11 percent from the current InceptionNetV4 network. An picture prediction takes only 14 milliseconds, which is a much better balance of accuracy and speed. For the rapid reading of clinical capsule endoscopes, this procedure can be employed as a supplementary diagnostic method for professionals.

Yue Xie & Ziyi Xu (2019), *Ancylostoma caninum* (Nematoda, Ancylostomatidae), a blood-feeding intestinal parasitic nematode that can cause ancylostomiasis in humans, is a blood-feeding intestinal parasitic nematode that can cause ancylostomiasis. This study used Illumina deep sequencing technology to sequence the entire mitochondrial genome of this anthroponotic hookworm.

CHAPTER 3

AIM AND SCOPE

3.1 AIM

This survey aims to identify the opportunities for using semi supervised deep learning modules over supervised deep learning methods in Wireless Capsule Endoscopy anomaly detection of classification. In underdeveloped areas, hookworm infection is a frequent parasitic infection. In people who have been exposed to them, they primarily cause iron deficiency anemia. This activity examines the diagnosis and treatment of hookworm infections, emphasizing the need of collaboration among inter professional team members in providing well-coordinated care and improving patient outcomes.

3.2 SCOPE

We propose a series of creative ways to capture its qualities in this research by studying its distinctive properties, with the goal of reducing the amount of photographs a clinician must analyze. Experiments on many aspects show that the suggested method is a reliable hookworm detection classification tool with promising results. This work has made the following contributions: The image is enhanced with a guided filter, which is a non-iterative, quick, and precise edge-preserving filtering technique. The content of a guidance image, which might be the input image or another image, is used to calculate the filtering output of the guided filter. Because color guidance images can better preserves, guided filters employ color images for implementation. The segment is subjected to morphological operations. The CNN (Convolutional Neural Network) is presented to classify the hookworm images, whether hookworm is present or not in WCE photos, using features extraction and classification of the dataset.

CHAPTER 4

MATERIALS AND METHODS

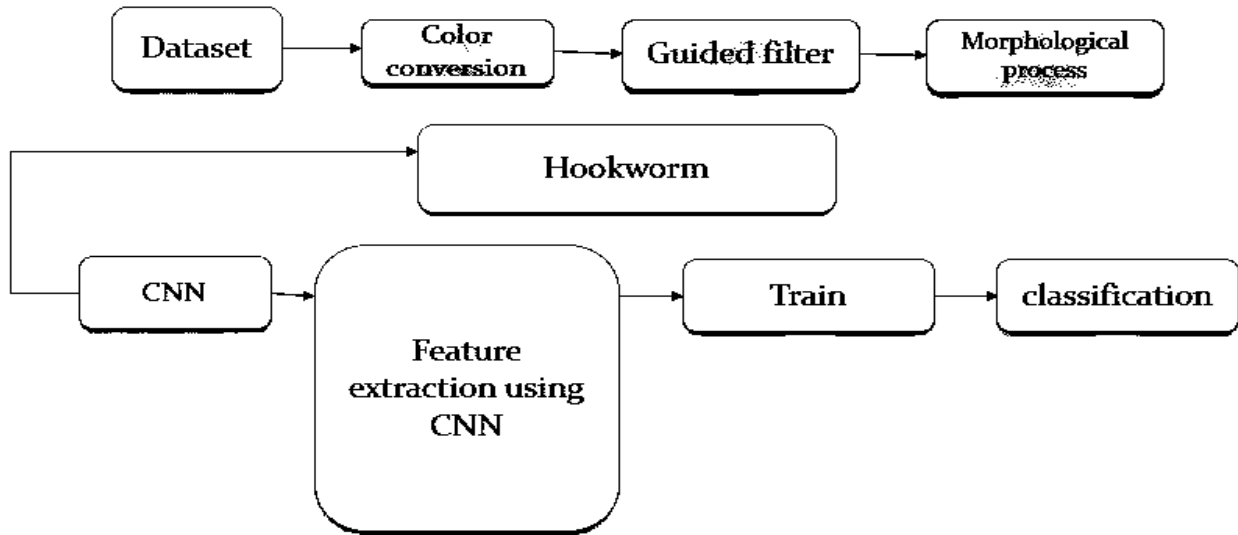


Fig: 4.1: Block Diagram of Hookworm Detection

4.1 IMAGE ACQUISITION

The image capture stage is the first step in every vision system's development. Following the acquisition of the image, several processing methods can be applied to it in order to execute the numerous vision tasks that are required today. However, even with the aid of some sort of picture augmentation, if the image has not been taken adequately, the planned tasks may not be possible. The development of a digitally encoded representation of an object's visual qualities, such as a physical scene or an object's inner structure, is known as digital imaging or digital image acquisition. Processing, compression, storage, printing, and display of such images are frequently thought to be included in the term. One of the most significant advantages of a digital image over a traditional photograph is that it can be scaled up to any size.

The type of electromagnetic radiation or other waves that communicate the information that makes up the image through changing attenuation as they pass through or reflect off objects can be used to classify digital images. Image sensors transform information into digital signals, which are then processed by a computer and output as a visible-light image in all types of digital imaging. The medium of visible light, for example, enables digital photography (including digital filmmaking) using a variety of digital cameras (including digital video cameras). Digital X-ray imaging (digital radiography, fluoroscopy, and CT) is possible with X-rays, and digital gamma ray imaging is possible with gamma rays (digital scintigraphy, SPECT, and PET). Ultrasonography (such as medical ultrasonography) and sonar are made possible by sound, while radar is made possible by radio waves. The advantages of digital imaging are numerous.

4.1.1 2D Image Input

A monochrome (grayscale) image that has been digitized is the fundamental two-dimensional image. Describe image as a two-dimensional light intensity function $f(x,y)$, where x and y are spatial coordinates and the value of f at every position (x, y) is proportional to the image's brightness or grey value. The spatial and greyscale values of a digitized image have been made distinct. Intensities sampled to 8 bits and measured across a regular grid in the x and y dimensions (256 values).

4.2 IMAGE PRE-PROCESSING

The actions taken to format images before they are used in model training and inference are referred to as image preprocessing. Resizing, orienting, and color adjustments are all examples of this.

4.2.1 Gray Image

A grayscale or greyscale image is one in which each pixel's value is a single sample indicating only an amount of light, carrying only intensity information in digital photography, computer-generated imaging, and colorimetry. Grayscale images are

a kind of black-and-white or gray monochrome, are composed exclusively shades of gray. The contrast ranges from black at weakest intensity to white at the strongest.

Grayscale images differ from one-bit bi-tonal black-and-white images, which are images with only two colors: black and white in the context of computer imaging (also called bi-level or binary images). Many hues of grey are seen in grayscale photographs.

When only a single frequency (in practice, a restricted spectrum of frequencies) is collected, grayscale images are created by measuring the intensity of light at each pixel according to a certain weighted combination of frequencies (or wavelengths). In theory, the frequencies might come from any part of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.).

A colorimetric (or, more precisely, photometric) grayscale image is one with a defined grayscale color space that maps stored numeric sample values to the achromatic channel of a standard color space, which is based on measured human visual qualities. If the original color image has no defined color space, or if the grayscale image is not intended to have the same human-perceived achromatic intensity as the color image, then there is no unique mapping from such a color image to a grayscale image.

4.2.2 Grayscale as Single Channels of Multichannel Color Images

Color images are frequently composed of multiple stacked color channels, each reflecting the channel's value levels. RGB photos, for example, include three distinct channels for the primary color components of red, green, and blue; CMYK images, on the other hand, have four channels for cyan, magenta, yellow, and black ink plates, among other things.

A whole RGB color image is separated into its color channels in this example. The isolated color channels are displayed in natural hues on the left, while their grayscale equivalents are displayed on the right:

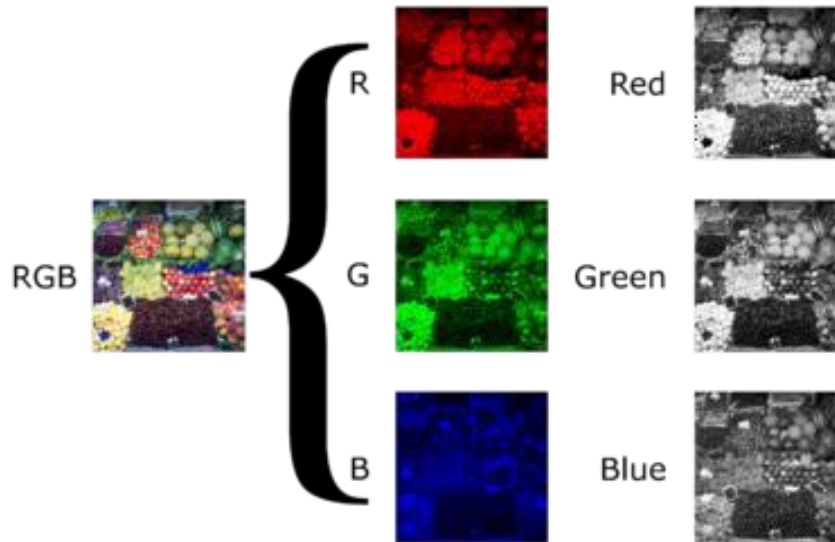


Fig: 4.2: Conversion of RGB to Gray

It's also feasible to combine their grayscale channels to create a full color image. Artist effects can be achieved instead of faithfully recreating the original image by manipulating channels, employing offsets, rotating, and other manipulations.

4.3 IMAGE ENHANCEMENT

In Matlab, the effect of image enhancement, the practice of modifying digital photographs such that the results are more suited for display or additional image analysis is known as image enhancement. For example, eliminate noise, sharpen, or brighten an image to make it simpler to spot important details.

4.3.1 GUIDED FILTER

We present the guided filter as a new explicit picture filter in this study. The guided filter, which is derived from a local linear model, calculates the filtering output by taking into account the content of a guidance image, which can be the input image or another image. The guided filter, like the popular bilateral filter, can be employed as an edge-preserving smoothing operator, although its behavior near edges is better. Beyond smoothing, the guided filter can also transfer the structures of the guidance image to the filtering output, allowing for novel filtering applications such as dehazing and guided feathering.

Furthermore, regardless of the kernel size or the intensity range, the guided filter has a natural fast and non-approximate linear time algorithm. Edge-aware smoothing, detail improvement, HDR compression, image matting, feathering, dehazing, joint upsampling, and other computer vision and computer graphics applications all benefit from the use of a guided filter.

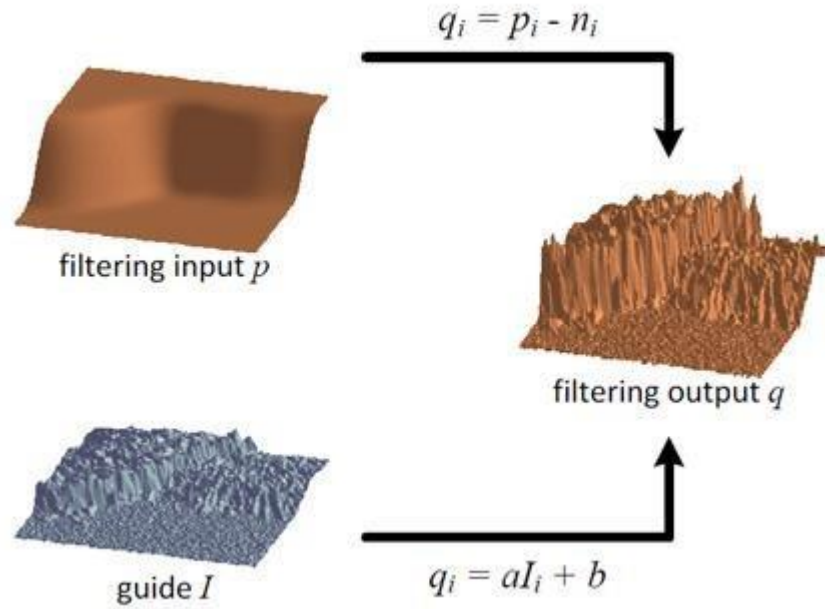


Fig: 4.3: Guided Filter

4.3.2 WIENER FILTER

The Wiener filter is a signal processing filter that uses linear time-invariant (LTI) filtering of an observed noisy process to obtain an estimate of a desired or goal random process, with known stationary signal and noise spectra and additive noise. Between the estimated random process and the intended process, the Wiener filter reduces the mean square error. The Wiener filter's purpose is to compute a statistical estimate of an unknown signal by taking a similar signal as an input and filtering it to create the estimate as an output. The known signal, for example, could be made up of an unknown signal of interest that has been tainted by additive noise.

The Wiener filter can be used to remove noise from a corrupted signal and estimate the underlying signal. The Wiener filter is based on a statistical approach, and a more statistical account of the theory is given in the minimum mean square error (MMSE) estimator article.

Typical deterministic filters are built with a specific frequency response in mind. The Wiener filter, on the other hand, is designed in a unique way. The spectral parameters of the original signal and the noise are assumed to be known, and the linear time-invariant filter whose output comes as close to the original signal as possible is sought. The following are the characteristics of Wiener filters:

- **Assumption:** Signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation
- **Requirement:** The filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution)
- **Performance criterion:** Minimum Mean-Square Error (MMSE)

This filter is frequently used in the process of deconvolution for this application.

4.3.3 HISTOGRAM EQUALIZATION:

This method is commonly used to improve the global contrast of a large number of photos, especially when the image's useable data is represented by close contrast values. The intensities can be more evenly spread on the histogram after this change. This permits low-contrast areas to obtain more contrast. By efficiently spreading out the most frequent intensity values, histogram equalization achieves this.

4.3.4 ADAPTIVE HISTOGRAM EQUALIZATION:

A computer image processing technique called Adaptive Histogram Equalization (AHE) is used to improve image contrast. The adaptive approach differs from traditional histogram equalization in that it computes numerous histograms, each corresponding to a different portion of image, then uses them to disperse the image's brightness values.

As a result, it's a good choice for boosting local contrast and sharpening edge definition in each image region. However, in relatively homogeneous portions of an image, AHE has a propensity to over amplify noise. By restricting the amplification, contrast limited adaptive histogram equalization (CLAHE), a type of adaptive histogram equalization, prevents this.

4.4 IMAGE SEGMENTATION

The division of a picture into sections or regions is known as image segmentation. The features of the pixels in a picture are commonly used to divide the image into portions. Looking for abrupt discontinuities in pixel values, which usually imply edges, is one technique to detect regions in an image. The image is segmented into numerous matrices in the segmentation process, which is utilized to analyze it. The segmentation block receives the edge detected image from the edge extraction network, which is defined by the Structured Random Forest approach. This makes it easier to distinguish hookworm tubular patterns from undesirable distortions in the backdrop.

Clustering based segmentation is a pixel-wise segmentation method for performing Image Segmentation. We aim to cluster the pixels that are adjacent in this type of segmentation. The image is divided into clusters (disjoint groups) of pixels with comparable properties by a clustering technique. It would divide the data items into clusters, with the components in one cluster being more similar to the elements in other clusters. The k-means clustering algorithm is commonly used because it is simple and effective.

4.4.1 K-means Clustering

K-means is a machine learning technique that is simple and unsupervised. It uses a set of clusters to categorize an image. It begins by splitting the image space into k pixels, each of which represents one of the k group centroids. Then, based on the distance between each object and the centroid, they assign each object to the group. The centroids can be moved and reassigned once the algorithm has assigned all pixels to all clusters.

4.5 HOOKWORM CLASSIFICATION NETWORK

4.5.1 CONVOLUTION NEURAL NETWORK ARCHITECTURE

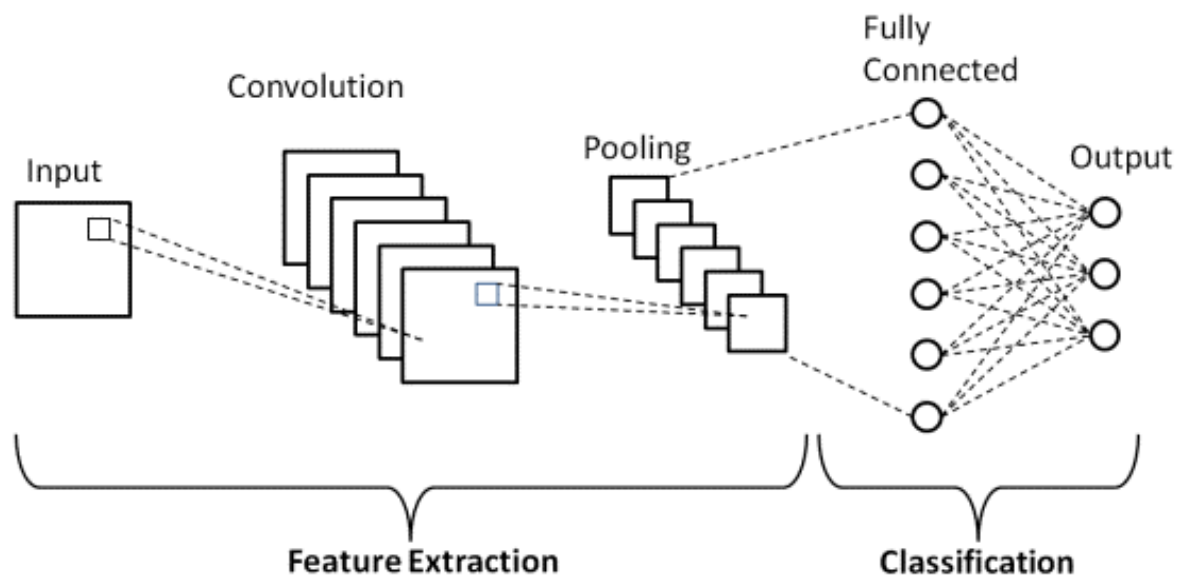


Fig: 4.4: CNN Diagram

- A CNN model is a form of neural network that allows us to extract higher representations for picture content. Unlike traditional image recognition, which requires the user to define the image features, CNN takes the image's raw pixel data, trains the model, and then extracts the features for improved categorization.
- Convolutional neural networks are one of the most important aspects of neural networks (CNN). They're made up of neurons with weights and biases that can be learned. Each neuron receives a large number of inputs and then computes a weighted total, which it then runs through an activation function before responding with an output.
- We utilize a specific sort of Artificial Neural Network called a Convolutional Neural Network to train an algorithm how to recognize things in photos (CNN). Their name comes from one of the network's most significant operations: convolution. The brain is the source of inspiration for Convolutional Neural Networks.

- A 4D array is likewise produced by the CNN. Where the batch size is the same as the input batch size, but the images other three dimensions may vary based on the filter, kernel size, and padding values we apply. The convolutional layer, the pooling layer, and the fully connected layer are the three layers that make up a CNN.

4.5.2 ALEX NET

The convolutional neural network (CNN) architecture AlexNet is named after. Alex Krizhevsky collaborated with Ilya Sutskever and Geoffrey Hinton, who served as Krizhevsky's Ph. D. advisor, on the design. On September 30, 2012, AlexNet took part in the ImageNet Large Scale Visual Recognition Challenge.

AlexNet had eight layers: the first five were convolutional layers, followed by max-pooling layers in some cases, and the final three were fully linked layers. It used the non-saturating ReLU activation function, which outperformed tan h and sigmoid in terms of training performance. Convolutional Neural Networks (CNNs) have long been the model of choice for object recognition because they are powerful, easy to control, and even easier to train.

When employed on millions of photos, they do not exhibit any dangerous levels of overfitting. Their performance is nearly equivalent to that of similar-sized conventional feedforward neural networks. The only issue is that high-resolution photographs are difficult to apply them to. At the ImageNet scale, a GPU-optimized innovation that reduced training durations while enhancing performance was required. There are eight layers in the AlexNet, each with its own set of parameters that can be learned. The model has five layers, each of which uses Relu activation and comprises of a combination of max pooling and three fully linked layers.

- ReLU Nonlinearity is a term used to describe the nonlinearity of the ReLU Instead of the tanh function, which was common at the time, AlexNet employs Rectified Linear Units (ReLU).

- Several graphics processing units GPUs had 3 GB of RAM back then (nowadays those kinds of memory would be rookie numbers). The training set comprised 1.2 million photos, so this was exceptionally terrible. AlexNet supports multi-GPU training by placing half of the model's neurons on one GPU and the other half on a different GPU. This not only allows for the training of a larger model, but it also reduces the amount of time required
- Overlapping Pooling is a term used to describe a situation where two or more pools overlap. The outputs of adjoining groups of neurons are traditionally "pooled" in CNNs, with no overlap. The authors saw a 0.5 percent drop in error when they added overlap, and they discovered that models with overlapping pooling are more difficult to overfit.

Overfitting is a problem that occurs when a person's clothing is too tight. AlexNet has 60 million parameters, which presented a significant overfitting problem. Overfitting was reduced using two techniques:

- Data Augmentation is a term that refers to the addition of information to an existing dataset to add more variety to their data, the author utilized label-preserving modification. They created picture translations in particular, as well as horizontal reflections, resulting in a 2048-fold increase in the training set. They also used Principle Component Analysis (PCA) to modify the intensities of RGB channels, lowering the top-1 mistake rate by over 1%.
- Dropout. This method entails randomly "turning off" neurons (e.g. 50 percent). This means that each iteration uses a different sample of the model's parameters, forcing each neuron to have more resilient characteristics that can be employed with other random variables.

A pooling operation that determines the maximum value for patches of a feature map and uses it to produce a downsampled (pooled) feature map is known as max pooling. After a convolutional layer, it is generally used.

4.5.3 RESNET50

ResNet-50 is a 50-layer deep convolutional neural network. The ImageNet database [1] contains a pre-trained version of the network that has been trained on over a million photos. The network can identify photos into 1000 different object categories, including keyboard, mouse, pencil, and a variety of animals.

- Model ResNet-50 each level of the ResNet-50 model has a convolution and identity block. There are three convolution layers in each convolution block, and there are three convolution layers in each identity block. Over 23 million parameters can be trained with the ResNet-50.
- ResNet50 is a RESNET version of 48 convolutional layers, one MaxPool layer, and one Average Pool layer. There are 3.8×10^9 floating point operations on it. It's a well-known expression.
- The network can handle images with heights and widths that are multiples of 32, as well as a channel width of three. We'll assume the input size is $224 \times 224 \times 3$ for the sake of simplicity. Initial convolution and max-pooling are performed with 77% and 33% kernel sizes, respectively, in every ResNet architecture.
- After that, the network's Stage 1 begins, which consists of three Residual blocks, each with three layers. The kernels used to perform the convolution process in each of the three layers of stage 1's block are 64, 64, and 128 bits in size.

- The identity relationship is indicated by the curved arrows. The dashed connecting arrow indicates that the convolution operation in the Residual Block is conducted with stride 2, reducing the size of the input by half in height and width while doubling the channel width.
- As we advance through the stages, the channel width doubles and the input size is cut in half. Bottleneck design is important for deeper networks like ResNet50 and ResNet152.
- The convolutions in the first, third, and eleventh levels are 1, 3, and eleven. The 11 convolution layers are in charge of shrinking and restoring the dimensions. With lower input/output dimensions, the 33rd layer is left as a bottleneck.
- Finally, the network has a fully linked layer with 1000 neurons, followed by an Average Pooling layer (ImageNet class output).

4.5.4 RESNET101

- ResNet-101 is a 101-layer convolutional neural network. You can load a pre-trained version of the network from the ImageNet database which has been trained on over a million photos. The network can identify photos into 1000 object categories, including keyboards, mice, pencils, and a variety of animals.
- To tackle the vanishing gradient problem, the ResNet101 architecture uses shortcut connections. ResNet's basic building block is a Residual block, which is used repeatedly throughout the network.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 RESEARCH DATABASE

Hookworm infection is caused by a parasite called *Ancylostoma duodenale*. It's an intestine infection that can result in an itchy rash, gastrointestinal issues and finally iron deficiency anemia owing to blood loss. The Wireless Capsule Endoscopy Image depicts the interior of a human's small intestine. Table 5.1 shows the datasets of Hookworm. This data set is used as the input image, and it goes through image preprocessing, which includes RGB to Gray conversion. The enhanced and segmented image is then used to detect the presence of hookworm.

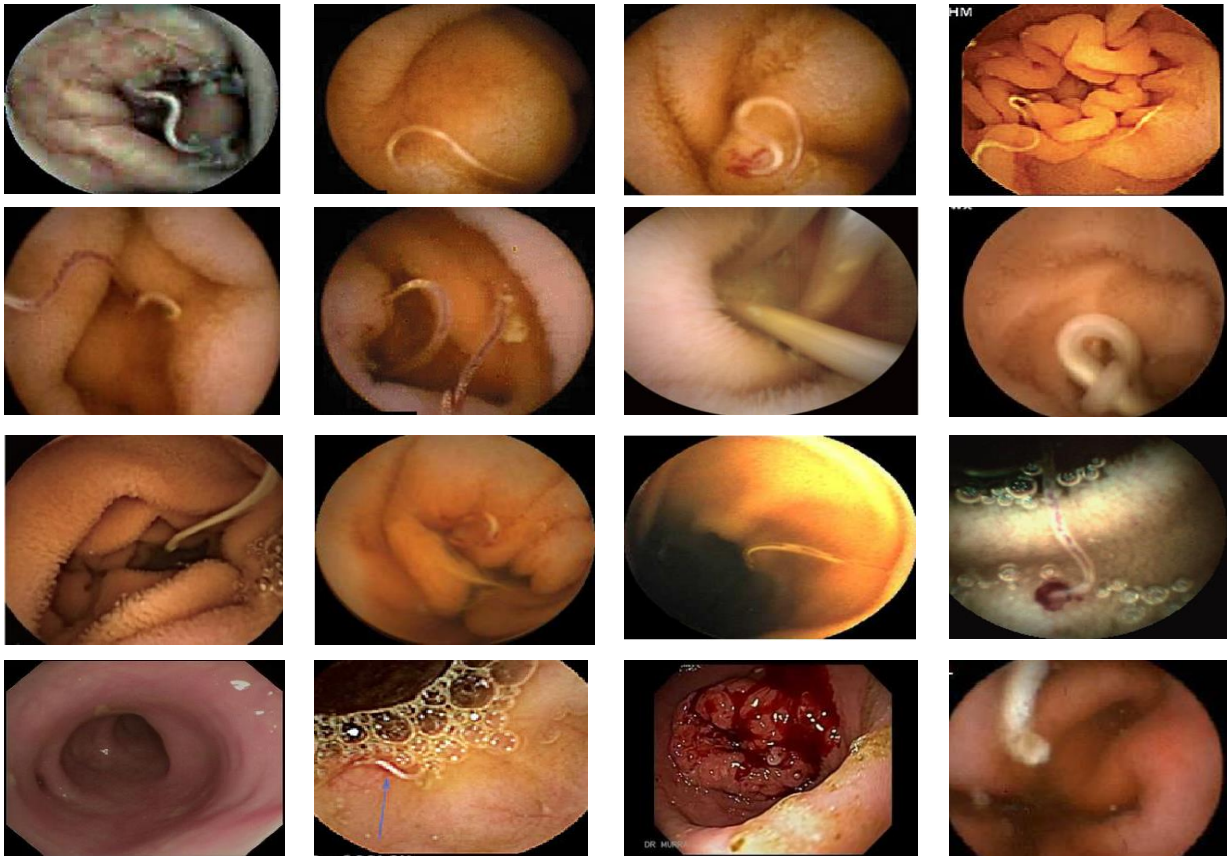


Table 5.1: Datasets of Hookworm

5.2 RESULTS

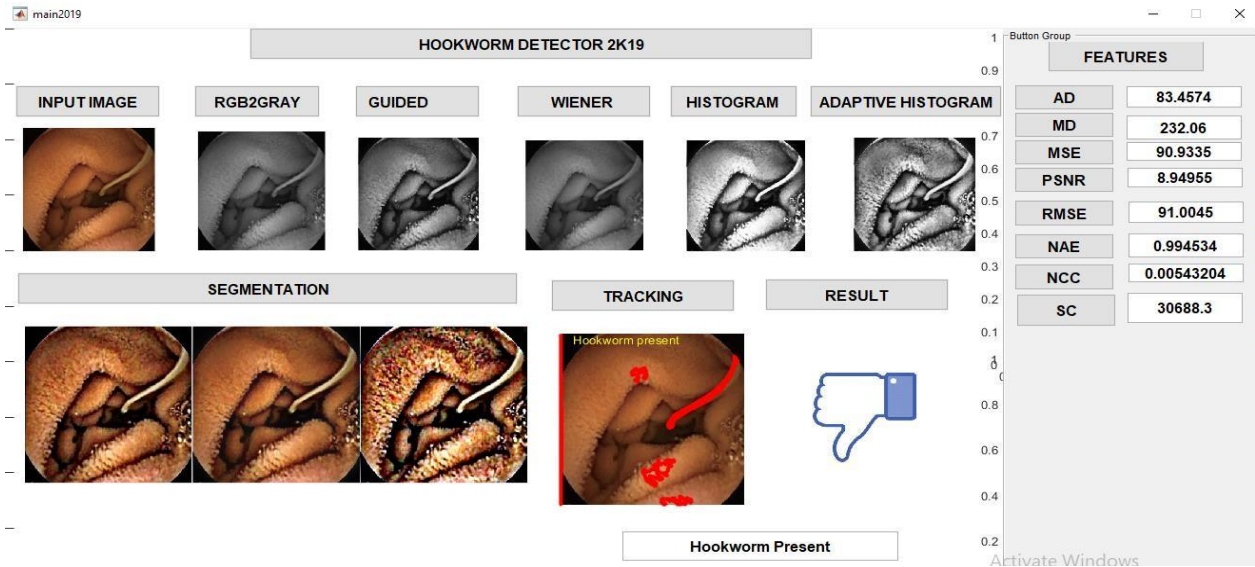


Fig: 5.1: Output Image 1

Presence of Hookworm is shown in Fig: 5.1, 5.2, 5.3 and 5.4. The usage of Matlab software and the CNN algorithm can do this. AlexNet is a CNN algorithm that is highly specialized. This network accepts an image as input and returns a label for each object in the image. The input image is first taken and then Pre-processed. The RGB to Gray color conversion is used to transform a color image into a Gray image. The image enhancement task can now be carried out on the preprocessed image.

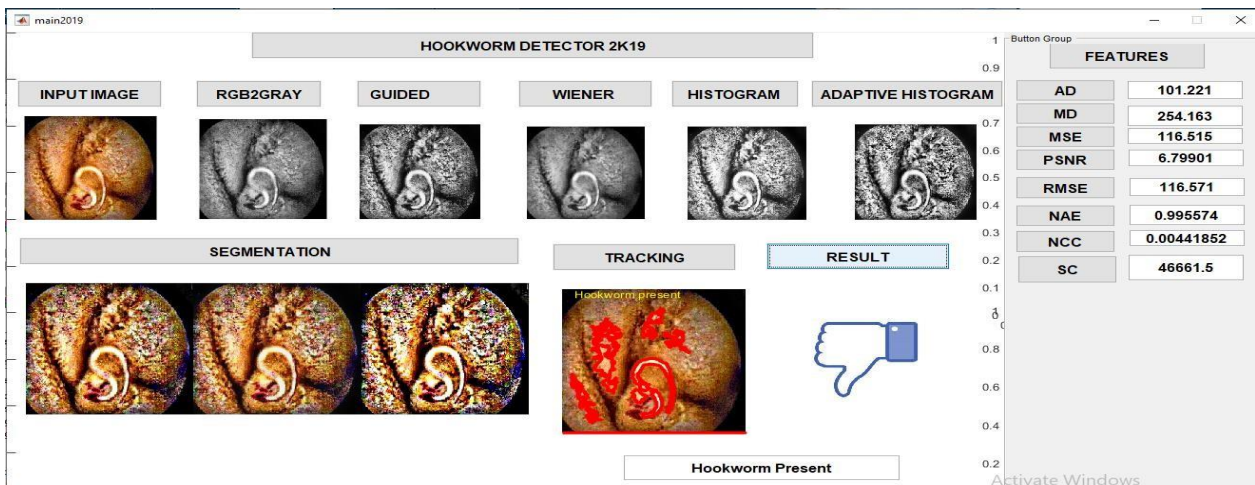


Fig: 5.2: Output Image 2

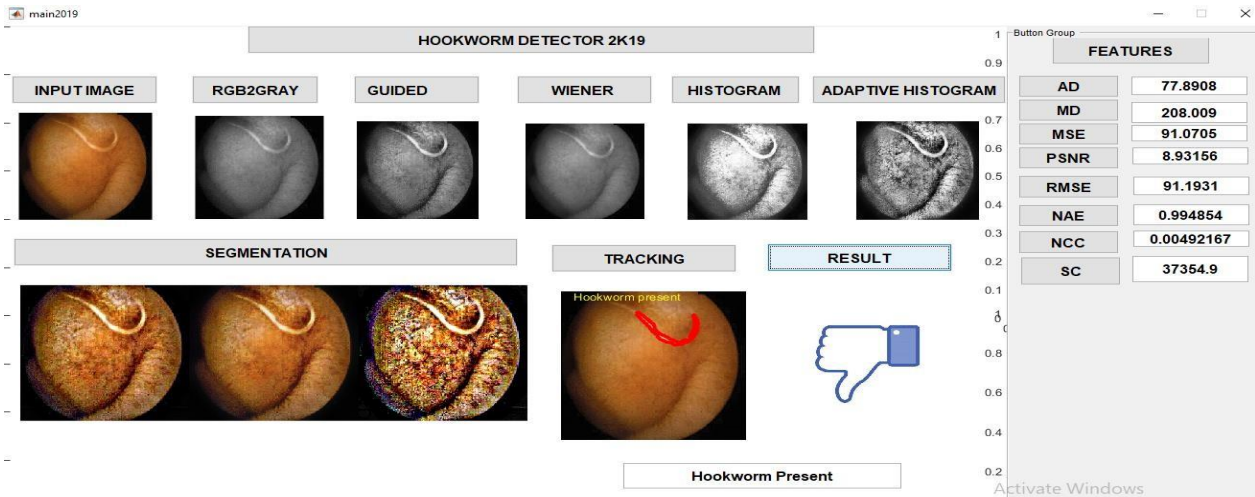


Fig: 5.3: Output Image 3

The preprocessed image is now ready for improvement. The undesired noise is reduced with the help of a Guided filter. It can also be used as a smoothing operator that preserves the edges. The histogram equalization approach, as well as adaptive histogram equalization, is an image processing technique that uses the histogram to alter the contrast of a picture. It spreads out the most common pixel intensity values or stretches out the image's intensity range to improve the image's contrast.

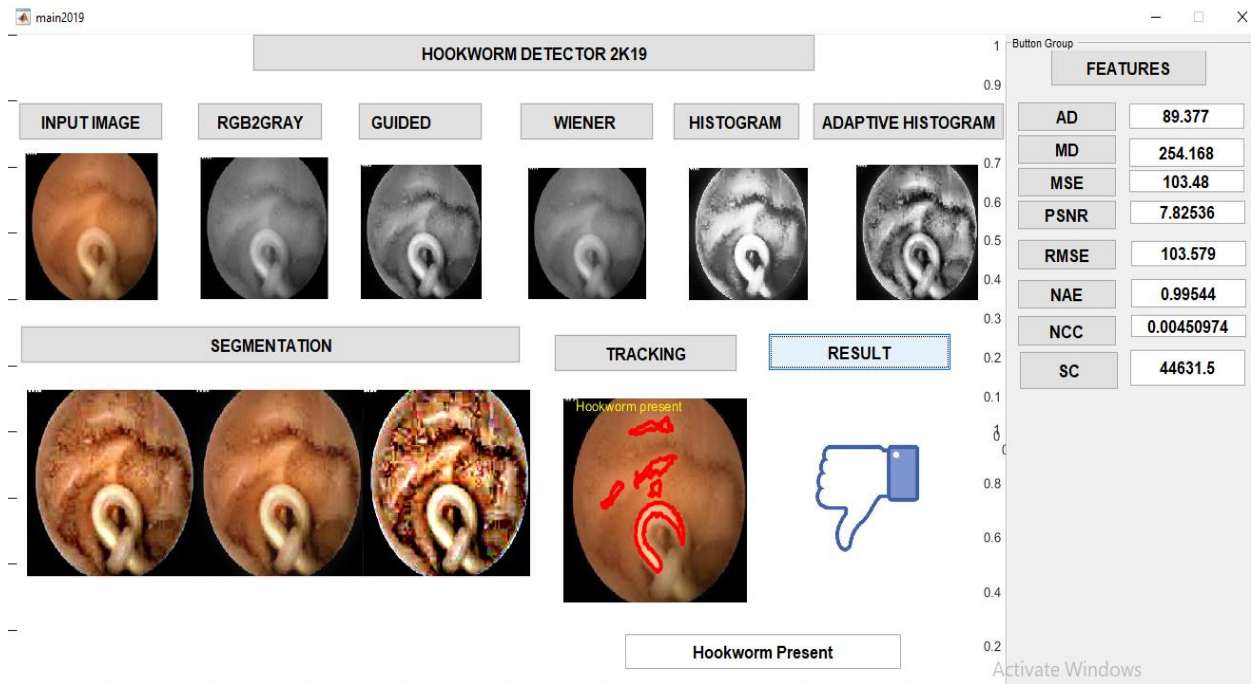


Fig: 5.4: Output Image 4

The resulting image is then relocated in order to be segmented. The purpose of segmentation is to make an image's representation more meaningful and easier to examine by simplifying and/or changing it. By labelling connecting components, we can trace the hookworm. As a result, the presence of hookworm is successfully detected.

5.3 FEATURE EXTRACTION PARAMETERS

Output Image Number	AD	MD	MSE	PSNR	RMSE	NAE	NCC	SC
1	83.457	232.06	90.933	8.949	91.004	0.994	0.005	30688.3
2	101.221	254.163	116.515	6.799	116.571	0.995	0.004	46661.5
3	77.8908	208.009	91.071	8.931	91.193	0.994	0.004	37354.9
4	89.377	254.168	103.48	7.852	103.579	0.995	0.004	44631.5

Table 5.2: Feature extraction Parameters

Where,

- AD - Average Difference
- MD - Maximum Difference
- MSE - Mean Squared Error
- PSNR - Peak Signal to Noise Ratio
- RMSE - Root Mean Squared Error
- NCC - Normalized Cross-Correlation
- SC - Structural Content

5.4 DISCUSSION

Many image processing applications require the measurement of image quality. Image quality evaluation is closely related to image similarity evaluation, in which the difference (or similarity) between a degraded image and the original, unaltered image is used to determine quality. Image quality can be assessed in two ways: subjectively and objectively. Subjective assessments are costly and time-consuming to do. Automated, mathematically specified algorithms perform objective evaluations. Subjective measures can be used to confirm if objective measurements are accurate.

As a result, in recent years, objective approaches have gotten a lot of attention. The mean squared error (MSE) and peak signal-to-noise ratio (PSNR) are two well-known objective picture quality evaluation methodologies (PSNR).

MSE and PSNR are basic and straightforward to use. Many image processing methods rely on picture quality measurement. The quality of photos and videos may decline visibly from the time they are collected until they are viewed by a human observer due to intrinsic physical limits and economic considerations. Identifying the picture quality measurements that are most sensitive to these distortions would aid in the methodical design of coding, communication, and imaging systems, as well as the improvement or optimization of image quality for a desired level of service at a low cost. These measurements come in a wide range of types. The following are some of the available image quality measurements.

I. Mean Squared Error (MSE)

Calculating an error signal by subtracting the test signal from the reference and then determining the average energy of the error signal is an apparent technique to measure this similarity. The mean-squared error (MSE) is the most straightforward and extensively used full-reference image quality metric. This measure is commonly used in signal processing and has the following definition:

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (x(i, j) - y(i, j))^2$$

Where $x(i, j)$ denotes the original (reference) image, $y(i, j)$ is the distorted (modified) image, and i and j denote the MN image's pixel positions. If $x(i, j) = y(i, j)$, MSE is zero.

II. Peak signal to Noise Ratio (PSNR)

The PSNR is measured in decibels and is proportional to the Mean Squared Error in the inverse direction. The equation specifies it.

$$PSNR = 10 \log_{10} \frac{(2^n - 1)^2}{MSE}$$

III. Average Difference (AD)

The difference between the reference signal and the test image is simply averaged. The equation specifies it. The following is the definition of this measure, which is often used in signal processing.

$$AD = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (x(i, j) - y(i, j))$$

IV. Maximum Difference (MD)

The error signal's maximum value is MD the difference between the reference signal and test image.

$$MD = MAX |x(i, j) - y(i, j)|$$

V. Mean Absolute Error (MAE)

The average of the absolute difference between the reference signal and the test image is referred to as the MAE. The equation specifies it.

$$MAE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N |x(i, j) - y(i, j)|$$

VI. Normalized Cross-Correlation (NK)

The correlation function can be used to calculate the distance between two digital images. The equation for normalized cross-correlation (NK) quantifies the similarity between two pictures.

$$NK = \frac{\sum_{i=1}^M \sum_{j=1}^N (x(i, j) \times y(i, j))}{\sum_{i=1}^M \sum_{j=1}^N (x(i, j))^2}$$

VII. Structural Content (SC)

SC is another correlation-based measure that compares two pictures. The original (reference) image is represented by $x(i, j)$, and the distorted (modified) image is represented by $y(i, j)$. The MSE and PSNR are the most straightforward and extensively used full-reference image quality indicators.

$$SC = \frac{\sum_{i=1}^M \sum_{j=1}^N (y(i, j))^2}{\sum_{i=1}^M \sum_{j=1}^N (x(i, j))^2}$$

5.5 PERFORMANCE ANALYSIS

5.5.1 RETNET 50

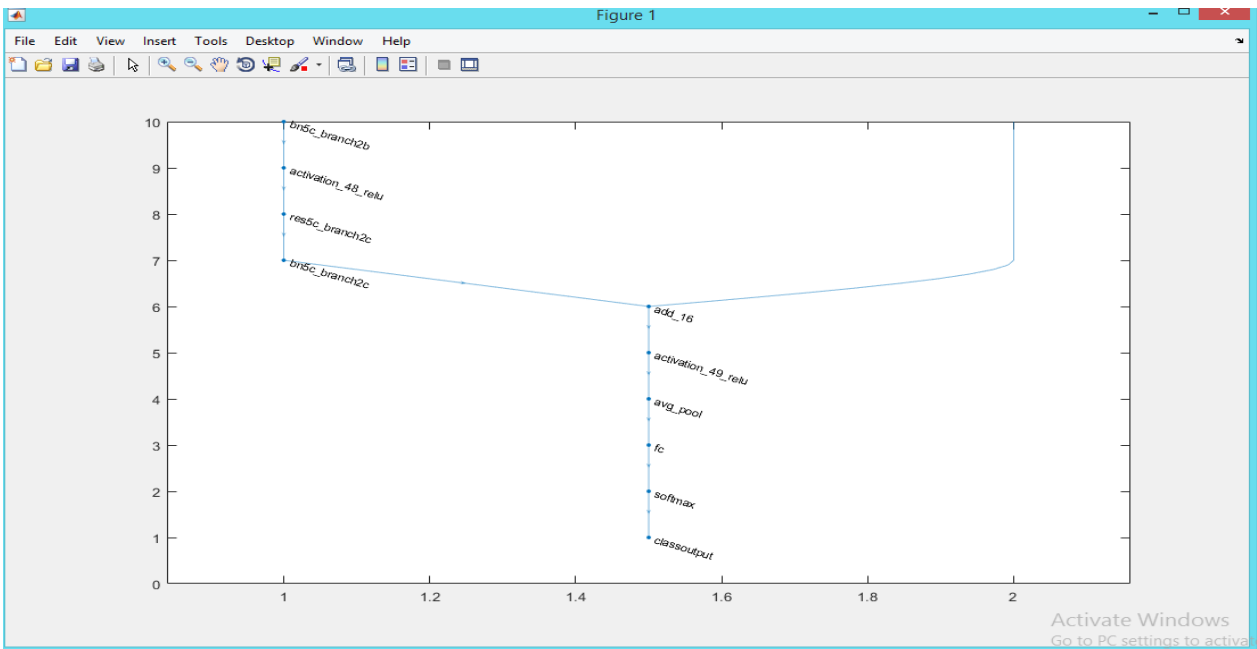


Fig: 5.5: RESNET 50 Output

Fig: 5.5 shows the RESNET 50 output. This image has 50 layers, one Max pool layer, and one Average pool layer in a convolutional layer version. It took care of the image's height and width. It is well-known for its 3.8×10^9 floating point operations formulation.



Fig: 5.6: RESNET 50 Training Progress

RESNET 50 Training Progress is depicted in Fig: 5.6. It displays the proportion of accuracy and loss, and it is accomplished through the training (smoothed), training, and validation processes. The outcome, training time (start time, elapsed time), training cycle (Epoch, Iteration, Iteration per epoch, and Maximum iterations), and Validation are all shown in these phases (Frequency). At Epoch 6, the RESNET 50 Training progress has a validation accuracy of 66.67 percent.

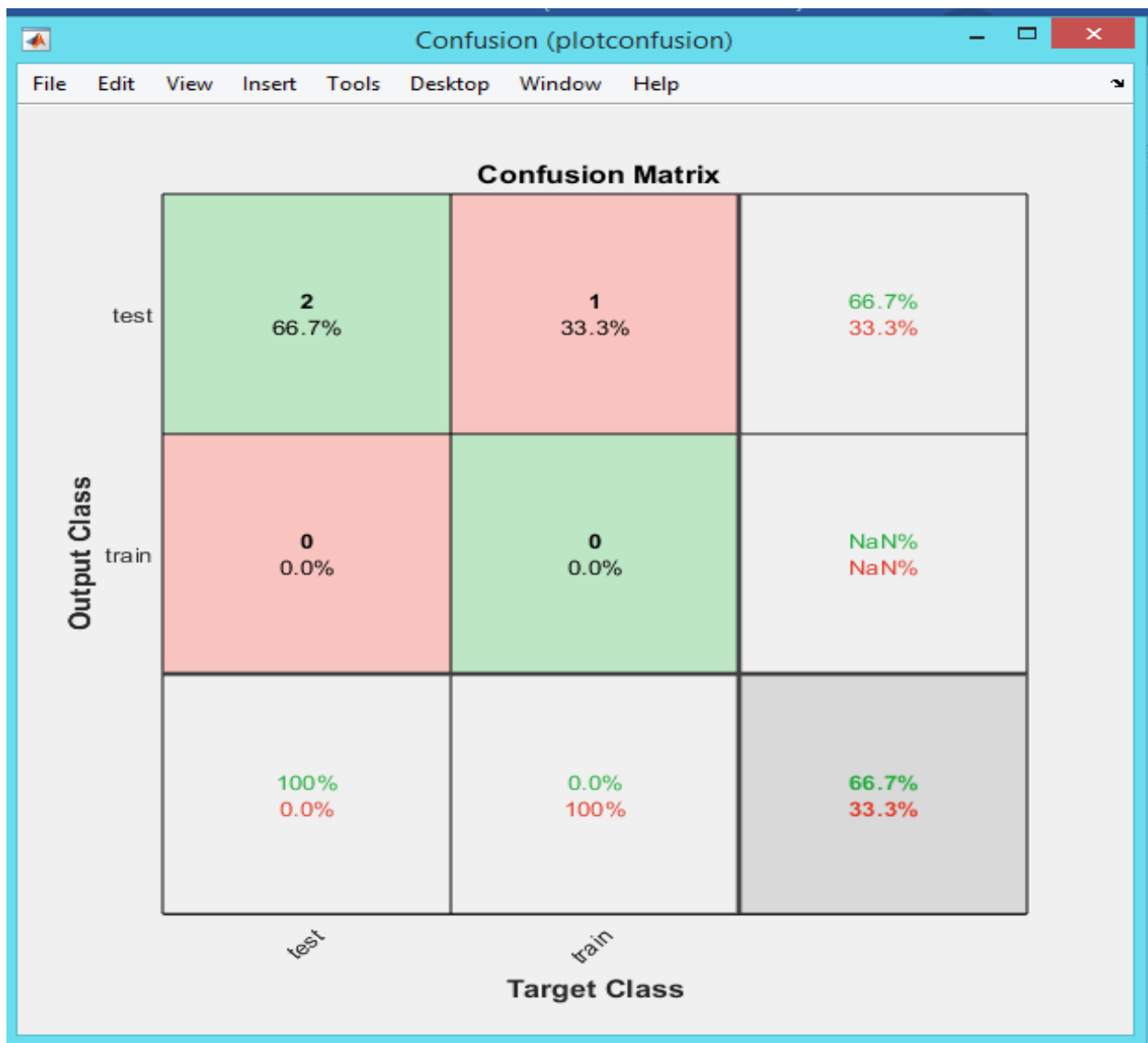


Fig: 5.7: RESNET 50 Confusion Matrix

The RESNET 50 Confusion Matrix is depicted in Fig: 5.7. It displays the output class and target class, which are test and train, respectively. It displays a 66.7 percent accuracy rate, which is made up of three residual blocks. The loss rate is approximately 33.3 percent.

5.5.2 ResNet 101

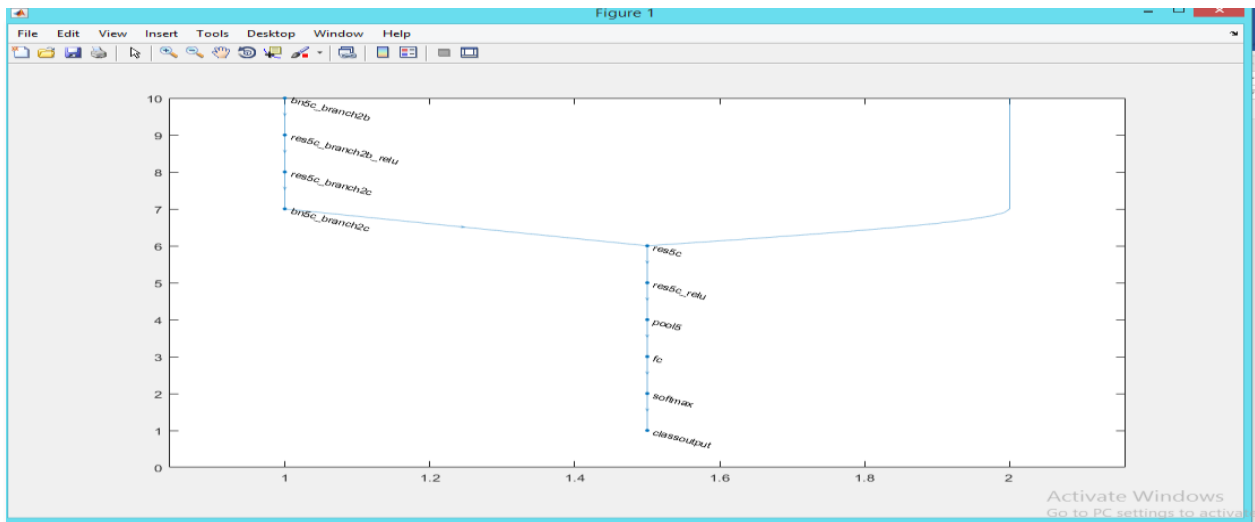


Fig: 5.8: RESNET 101 Output

RESNET 101 Output is depicted in Fig: 5.8. One pool is a 5 and the other is a soft max. This also dealt with images with heights and widths that required 3.8×10^9 floating point calculations. The soft max and pool 5 are aimed at points 2 and 4.

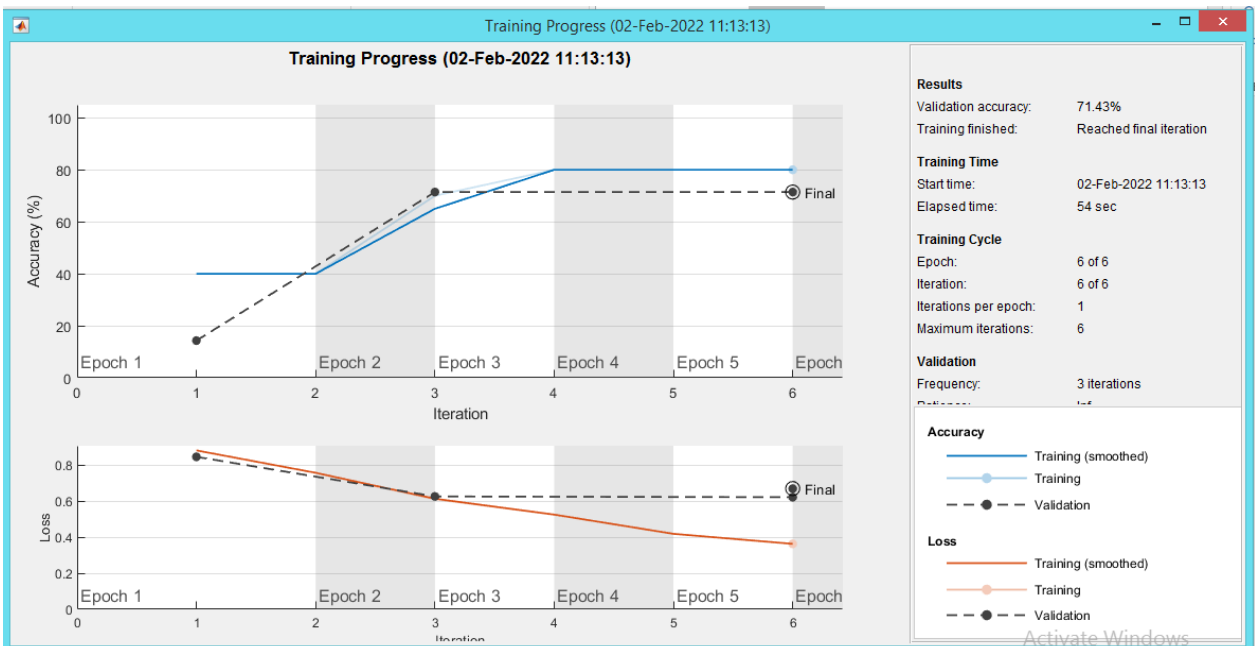


Fig: 5.9: RESNET 101 Training Progress

The progress of RESNET 101 Training progress is depicted in Fig: 5.9. Training time (start time and elapsed time), Training cycle (Epoch, iteration, iteration per epoch, maximum iterations), and validation are all included (Frequency). At Epoch 6, the RESNET 101 Training progress has a validation accuracy of 71.43 percent.

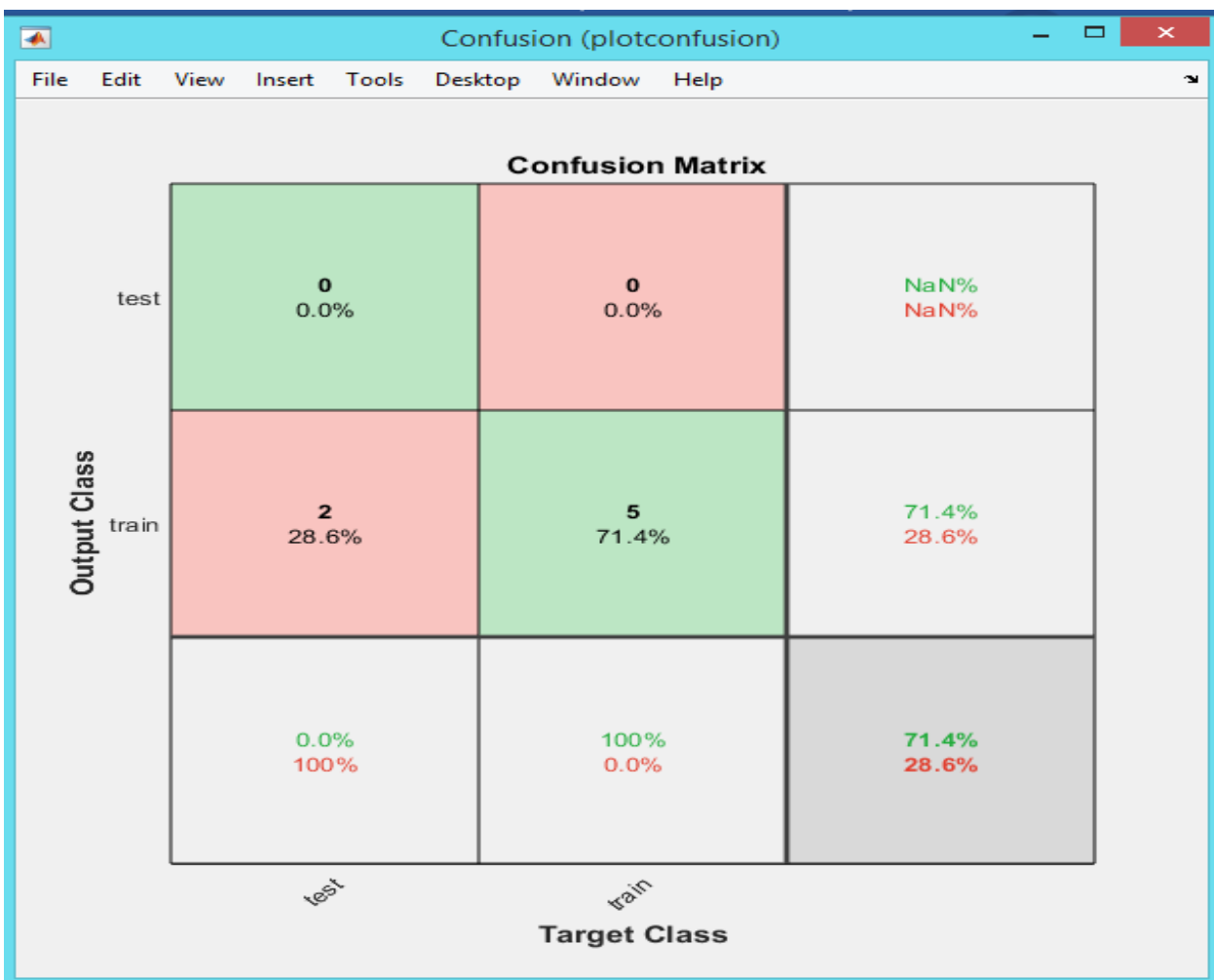


Fig: 5.10: RESNET 101 Confusion Matrix

RESNET 101 Confusion Matrix is depicted in Fig: 5.10. It also has an output class, as well as a target class, which includes test and train. It displays a 71.4 percent accuracy rate with three residual blocks. The loss rate is approximately 28.6 percent.

5.5.3 ALEXNET

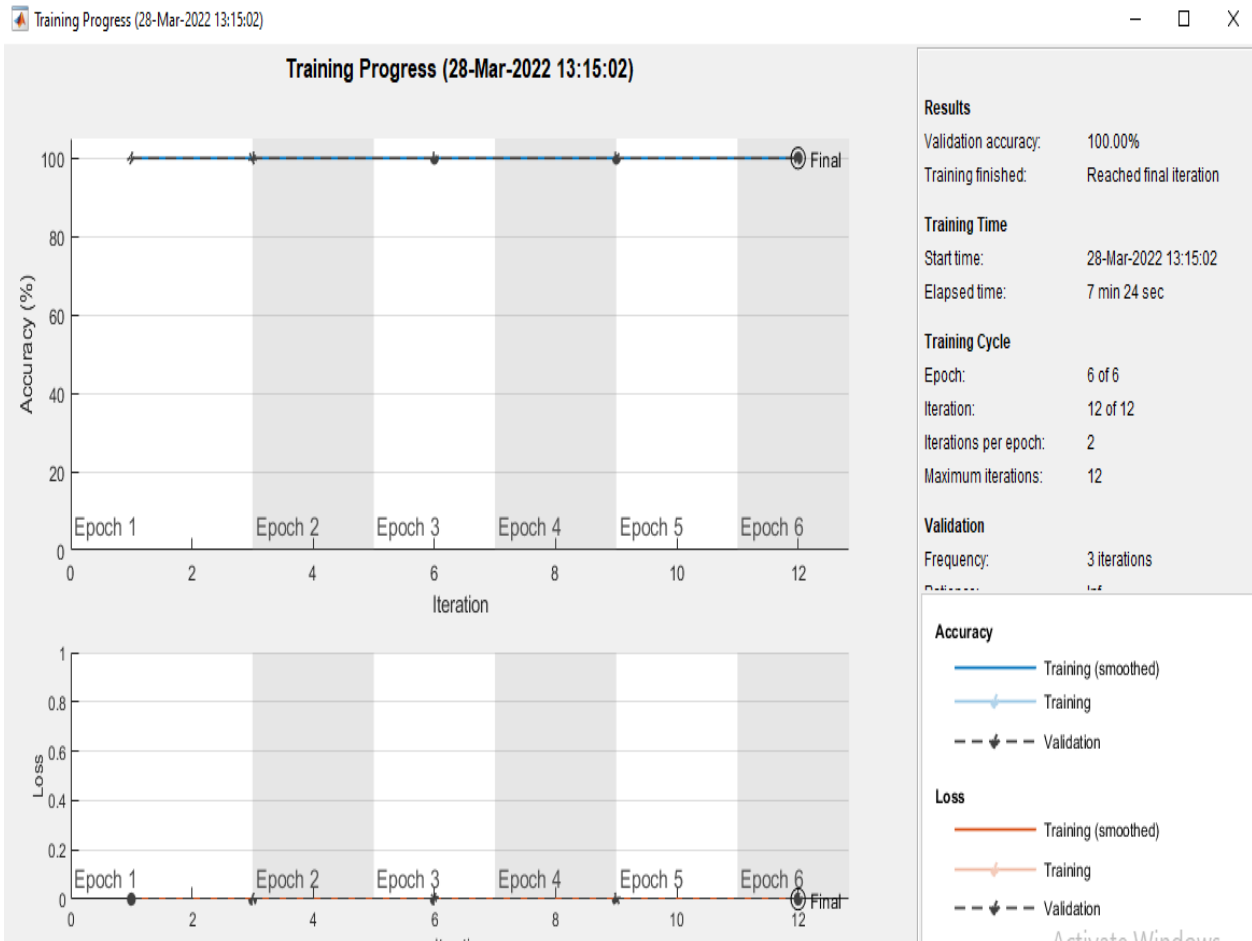


Fig: 5.11: AlexNet Training progress

AlexNet Training Progress is depicted in Fig: 5.11. Training time, Training cycle, and validation are all followed in the same way. The epoch is 6 of 6, the iteration is 12 of 12, the number of iterations per epoch is 2, the maximum iteration is 12, and the frequency is 3 iterations. The validation accuracy is 100.00 percent in this case.

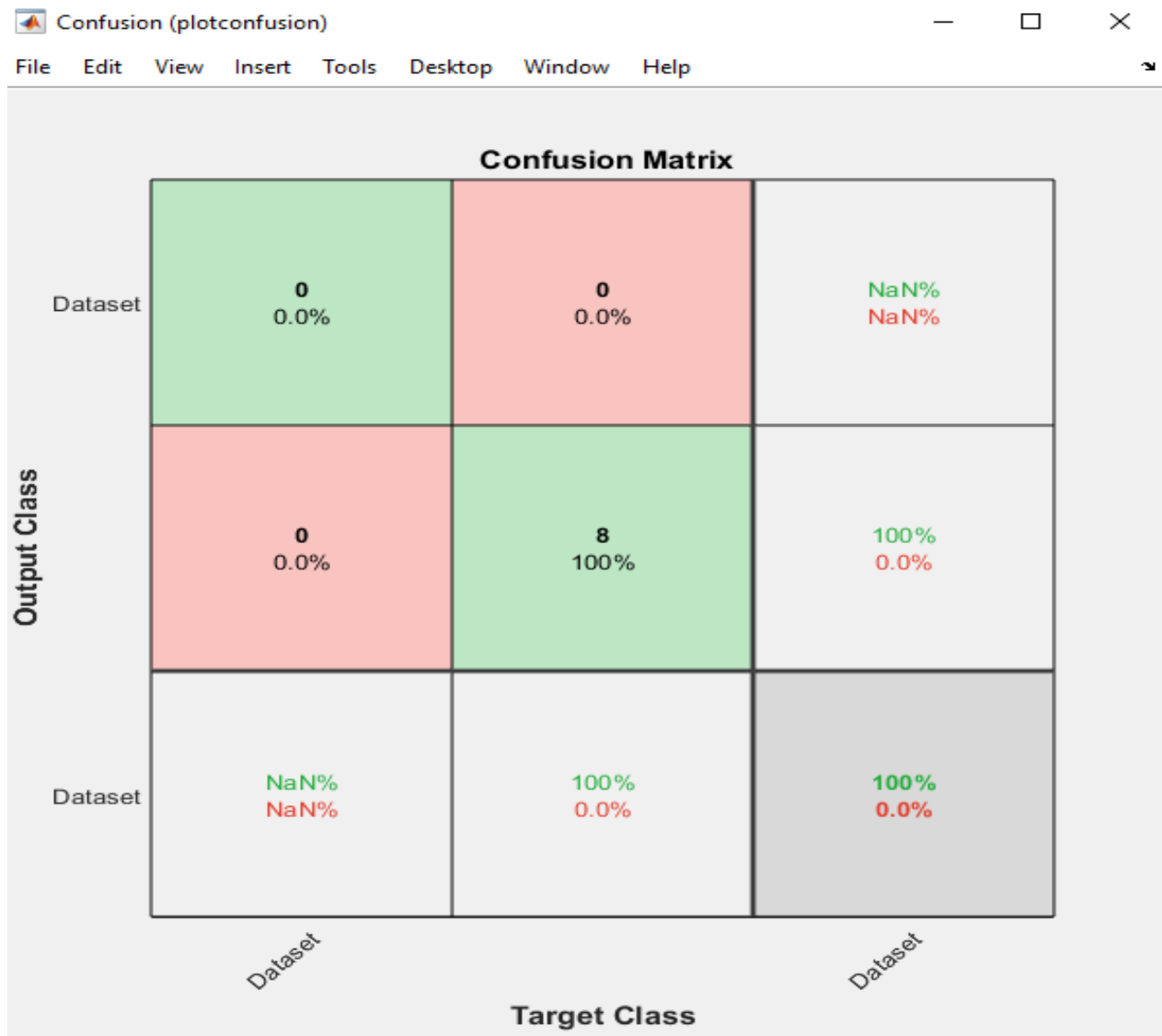


Fig: 5.12: AlexNet Confusion Matrix

AlexNet Confusion Matrix is shown in Figure 5.12. It has a dataset output and target class with a 100 percent accuracy with 0 percent loss.

5.6 COMPARISON OF RESNET AND ALEXNET

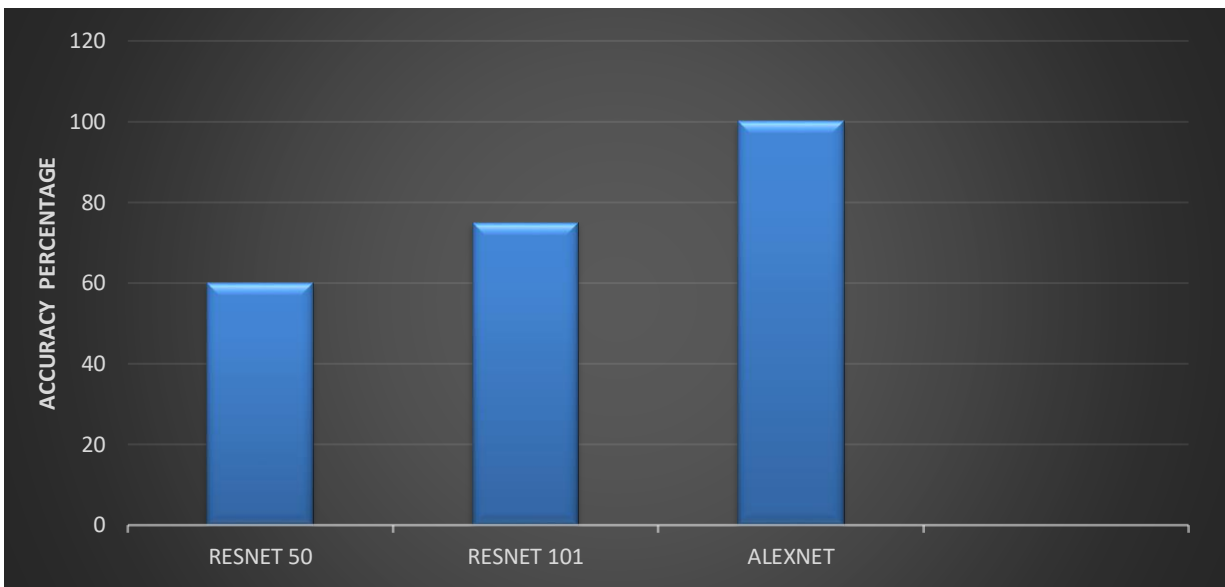


Fig: 5.13: Accuracy Percentage of RESNET and AlexNet

The comparison of RESNET 50, RESNET 101, and AlexNet is shown in Fig: 5.13. RESNET 50 has a 60 percent accuracy rate, whereas RESNET 101 has a 75 percent accuracy rate. When compared to RESNET 50 and RESNET 101, AlexNet is more accurate. AlexNet provides 100 percent accuracy in Hookworm detection, it was reported. It is the successful architecture of the ImageNet challenge. At the first layer, it employs a big filter and stride size. It employs an 8-layer network with a 48-by-48-pixel image input. AlexNet is a sophisticated model that can obtain maximum accuracies on even the most complex datasets.

CHAPTER 6

SUMMARY AND CONCLUSION

6.1 SUMMARY

The Intestinal Nematode/Intestinal Parasite *ANCYLOSTOMA DUODENALE* is found in the human intestines. Because of poor sanitation and hygiene, it primarily affects people. *ANCYLOSTOMA DUODENALE*, often known as hookworm, is a short tubular structure with a semi-transparent or pinkish body that is one of the most commonly seen human Helminths. Losing iron and protein can cause delayed growth and mental development in children who are frequently infected with hookworms. When a person comes into contact with polluted soil that contains the larva of hookworms, they become infected. Abdominal pain, nausea, fever, weight loss, and other symptoms of this infection can occur. Curve profiles, widths, and orientations vary among hookworms. For the programmed recognition of hookworm, these issues pose a huge challenge. The presence of a foreign substance, as well as the intricate structure of the gastrointestinal tract, make automatic identification of hookworm problematic. Wireless Capsule Endoscopy (WCE) has been applied to automatic hookworm detection. The Convolutional Neural Network method has demonstrated the impressive performance in various image and video analysis tasks. The identification of hookworm in humans, as well as its cure and removal from the human body, is demonstrated in this experiment. Experiments have been conducted on WCE datasets which demonstrate the effectiveness of the proposed Hookworm detection framework. The high sensitivity and accuracy of proposed method in detecting hookworm shows the potential for clinical application.

6.2 CONCLUSION

In this project, a novel deep hookworm detection framework is proposed for WCE images to model the visual appearance and tubular regions of hookworms, which contains an edge extraction network and a hookworm classification network. To integrate the two networks, two-level edge pooling is embedded into the shallow and deep parts of hookworm classification network, respectively. Experiments on a large dataset demonstrate that the proposed framework outperforms state-of-the-art methods with hand-drafted features as well as the off-the-shelf deep learning approaches. Since the proposed method detects the hookworms based on the whole images in this work, the influence of background cannot be completely avoided, even though the noisy edge maps have been filtered by MDMF and regularized edge pooling. To further improve the robustness and effectiveness of the method, we will explore the region based detection framework in our future work, which integrates the target location and pixel-level region as the supervised information to construct an end-to-end model. In addition, we plan to integrate temporal and spatial relationship between consecutive images to further boost the performance, and exploit advanced deep learning methods to detect other lesions for WCE images. As a result, image processing techniques are used to detect irregularities automatically. Because of its specific effortlessness and little effort, this strategy has an advantage. The end outcome will be precise and accurate.

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