DETECTING OF LUNG CANCER BY USING SEGMENTATION THROUGH PYTHON USING MACHINE LEARNING ALGORITHMS

A Project report submitted in partial fulfilment of the requirements for the award of the Degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES
(UGC AUTONOMOUS)

(Permanently Affiliated to AU, Approved by AICTE and Accredited by NBA & NAAC with 'A' Grade)
Sangivalasa, Bheemili mandal, Visakhapatnam dist. (A.P) 2021-2022

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CERTIFICATE

This is to certify that the project report entitled **"DETECTING OF LUNG CANCER BY USING SEGMENTATION THROUGH PYTHON USING MACHINE LEARNING ALGORITHMS"** submitted by ***S. Ravi Kumar (318126512046), S. Samuel David(31812612051), B. Sai Santosh (318126512005) and B. Hephzibah (318126512013)*** in partial fulfilment of the requirements for the award of the degree of ***Bachelor of Engineering in Electronics & Communication Engineering*** of Andhra University, Visakhapatnam is a record of Bonafide work carried out under my guidance and supervision.

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ACKNOWLEDGEMENT

We would like to express our deep gratitude to our project guide **Mrs. P. S. Mayura Veena,** Assistant Professor, M.Tech,(Ph.D.) Department of Electronics and Communication Engineering, ANITS, for his/her guidance with unsurpassed knowledge and immense encouragement. We are grateful to **Dr. V. Rajyalakshmi**, Head of the Department, Electronics and Communication Engineering, for providing us with the required facilities for the completion of the project work.

We are very much thankful to the **Principal and Management, ANITS, Sangivalasa,** for their encouragement and cooperation to carry out this work.

We express our thanks to all **teaching faculty** of Department of ECE, whose suggestions during reviews helped us in accomplishment of our project. We would like to thank all **non-teaching staff** of the Department of ECE, ANITS for providing great assistance in accomplishment of our project.

We would like to thank our parents, friends, and classmates for their encouragement throughout our project period. At last, but not the least, we thank everyone for supporting us directly or indirectly in completing this project successfully.

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ABBREVIATIONS

CT	:	Computer Tomography
MRI	:	Magnetic Resonance Imagining
NSCLC	:	Non-Small Cell Lung Cancer
SCLC	:	Small Cell Lung Cancer
DNA	:	Deoxyribonucleic Acid
DEXA	:	Dual-Energy X-Ray
PET	:	Positron Emission Tomography
SIFT	:	Scale Invariant Feature Transform
RGB	:	Red Green Blue
PDF	:	Probability Density Function
SAR	:	Synthetic Aperture Radar

ABSTRACT

Cancer refers to any one of a large number of diseases characterized by the development of abnormal cells that divide uncontrollably and have the ability to infiltrate and destroy normal body tissue. Cancer often has the ability to spread throughout your body. Among all the cancers lung cancer was the most common and fearful one. Most of the lung cancers are detected at the later stage this is causing increase in death rate. Cancer is detected using CT scan in most of the cases.

This project is based on detection of lung cancer cells by using machine learning algorithms. For this process a medical image will be considered, and then the image will be pre-processed for noise removal. Further segmentation is done to identify and separate desired tumour nodule and machine learning algorithm is used to detect the tumour cell.

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CHAPTER 1

INTRODUCTION

1.1 PROJECT OBJECTIVE:

The primary objective in this project is to identify the stage of cancer based on the size of tumour. Lung cancer is leading disease in present days. The identification of lung cancer at initial stages is of extreme importance because earlier detection is the only method to improve the survival rate. The presence of lung cancer can be diagnosed with the help of a CT image of the lungs. The manual detection by doctor may result in false reports. So, the objective in this project is need of computerized method for cancer detection. This project analyzes CT images using different image processing operations on them to get accurate detections. Here a CT image will be considered, and then the image will be pre-processed for noise removal and image enhancement. Further extraction of morphological features is carried out from the preprocessed image and determination of lung cancer takes place.

1.2 MOTIVATION:

With today's technology, doctors can replace every part of the human body, from bones to organs, hands and face except brain and lungs. Hence early detection of damage in the lungs or brain should be recognized to improve the survival rate of human beings. This is the main motivation of this project. There are many techniques to diagnose lung cancer such as Chest Radiograph (X-Ray), Computed Tomography (CT), Magnetic Resonance Imaging (MRI) etc. But even after analyzing these reports, doctors may not accurately predict the stage of cancer or size of tumour. Therefore, there is a great need for a new technology i.e., Image Processing Techniques which is a good tool to improve manual analysis and to predict more accurately the size of tumour cells.

1.3 LUNG CANCER DESCRIPTION

Lung cancer is cancer that starts in the lungs. The lungs are located in the chest. When you breathe, air goes through your nose, down your windpipe (trachea), and into the lungs, where it flows through tubes called bronchi. Most lung cancer begins in the cells that line these tubes.

1.3.1 There are two main types of lung cancer:

- Non-small cell lung cancer (NSCLC) is the most common type of lung cancer.
- Small cell lung cancer (SCLC) makes up about 20% of all lung cancer cases.

If the lung cancer is made up of both types, it is called mixed small cell/large cell cancer. If the cancer started somewhere else in the body and spreads to the lungs, it is called metastatic cancer to the lung.

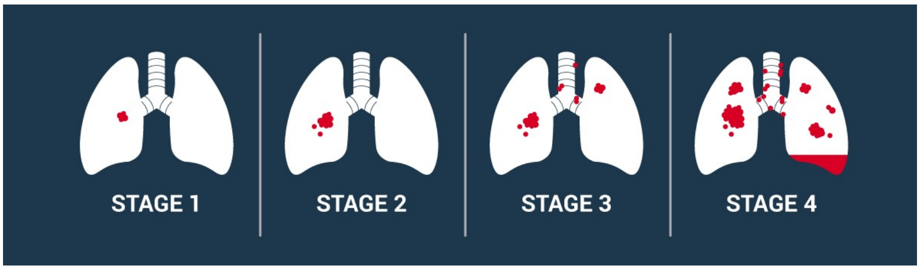


Fig.1.1)Lung cancer stages

Cancer can affect just about any part of the body, from the colon to the pancreas. Some cancers grow quickly, while others grow more slowly and are easier to treat. But of all the different cancers out there, one of the deadliest is lung cancer. Let's talk today about lung cancer. Cancer starts when cells begin to grow uncontrollably and form tumours. In the case of lung cancer, the tumours start in the lungs. Sometimes cancer starts somewhere else in the body and then spreads to the lungs. In that case, it's called metastatic cancer to the lung. Metastatic means disease that has spread. There are two types of lung cancer. The most common, and slower-growing form is non-small cell lung cancer. The other, faster-growing form is called small cell lung cancer. The most common way to get lung cancer is to smoke cigarettes. The more cigarettes you smoke and the earlier you start smoking, the greater your risk is. Even being around someone who smokes and breathing in the second-hand smoke from their cigarettes increases your risk of getting lung cancer. Even though smoking makes you much more likely to get lung cancer, you don't have to smoke or be exposed to smoke to get the disease. Some people who have lung cancer never lit up a cigarette in their life. They have been exposed to cancer-causing substances like asbestos, diesel fumes, arsenic, radiation, or radon gas. Or, they may not have had any known lung cancer risks. The most common signs of lung cancer are a cough that won't go away, chest pain, shortness of breath, weight loss, and fatigue. But just because you have these symptoms it doesn't mean that you have don't have lung cancer. These can also be signs of other conditions, like asthma or a respiratory infection. If you do have these symptoms, see your doctor. A chest x-ray, MRI, or CT scan can view the inside of your lungs to look for signs of cancer or other diseases. What happens if you do have lung cancer? Doctors divide lung cancer into stages. The higher the stage, the more the cancer has spread. For example, a stage 1 cancer is small and hasn't spread outside of the lungs. A stage 4 cancer has spread to the other organs, such as the kidneys or brain. Depending upon the type and stage of your lung cancer, you may need surgery to remove part or your entire lung. Or, your doctor may recommend radiation or chemotherapy to kill cancer cells. If you have lung cancer, how well you do depends upon the stage of your disease and the type of lung cancer that you have. Early-stage cancers have the highest survival and cure rates. Late-stage cancers are harder to treat. Because lung cancer can be so deadly, prevention is key. The most important that thing you can do is to stop smoking, and avoid being around anyone who does smoke.

1.4 WHAT CAUSES LUNG CANCER

Anyone can get lung cancer. Lung cancer happens when cells in the lung mutate or change. Various factors can cause this mutation (a permanent change in the DNA sequence of a gene) to happen. Most often, this change in lung cells happens when people breathe in dangerous, toxic substances. Even if you were exposed to these substances many years ago, you are still at risk for lung cancer. Talk to your doctor if you have been exposed to any of the substances listed below and take steps to reduce your risk and protect your lungs.

Fig. 1.2 Lung cancer causes

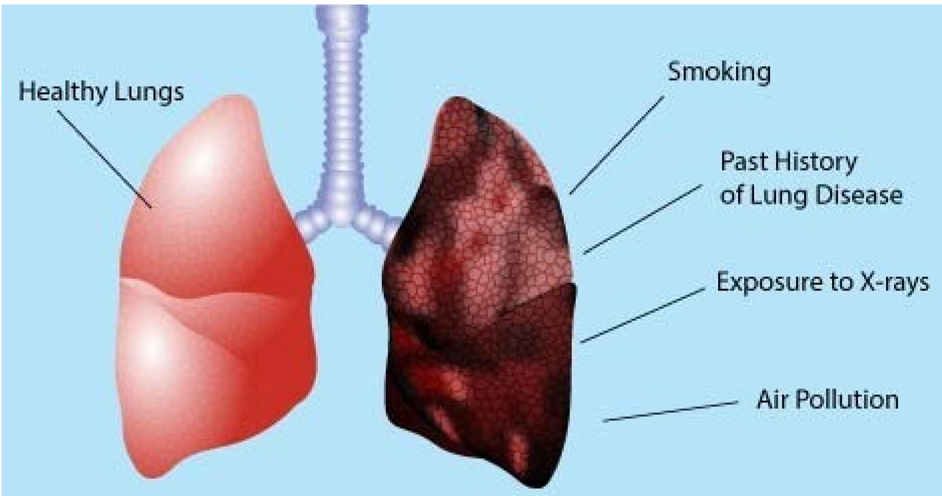


Fig.1.3 Difference of normal lung and affected lung.

Above figures denotes that the main factors which are causing lung cancer mostly.

1.4.1 Smoking

Smoking is the number one cause of lung cancer. It causes about 90 percent of lung cancer cases. Tobacco smoke contains many chemicals that are known to cause lung cancer. If you still smoke, quitting smoking is the single best thing you can do for your lung health.

Smokers are not the only ones affected by cigarette smoke. If you are a former smoker, your risk is decreased, but has not gone away completely—you can still get lung cancer. Non-smokers also can be affected by smoking. Breathing in second-hand smoke puts you at risk for lung cancer or other illnesses.

1.4.2 Causes in non-smokers:

Not all people who get lung cancer are smokers. Many people with lung cancer are former smokers, but many others never smoked at all. And it is rare for someone who has never smoked to be diagnosed with small cell lung cancer (SCLC), but it can happen.

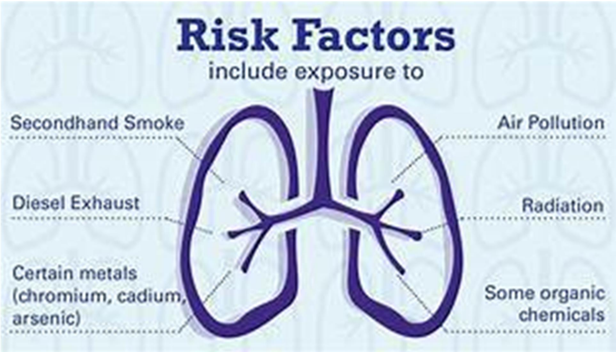


Fig 1.4 Risk factors for cause of lung cancer

Lung cancer in non-smokers can be caused by exposure to radon, second-hand smoke, air pollution, or other factors. Workplace exposures to asbestos, diesel exhaust or certain other chemicals can also cause lung cancers in some people who don’t smoke.

A small portion of lung cancers occur in people with no known risk factors for the disease. Some of these might just be random events that don’t have an outside cause, but others might be due to factors that we don’t yet know about.

Lung cancers in non-smokers are often different from those that occur in smokers. They tend to occur in younger people and often have certain gene changes that are different from those in tumours found in smokers. In some cases, these gene changes can be used to guide treatment.

1.4.3 Radon

Radon exposure is the second-leading cause of lung cancer. Radon is a colourless, odourless radioactive gas that exists naturally in soil. It comes up through the soil and enters buildings through small gaps and cracks. One out of every 15 homes in the U.S. is subject to radon exposure. Exposure to radon combined with cigarette smoking seriously increases your lung cancer risk.

1.4.4 Hazardous Chemicals

Exposure to certain hazardous chemicals poses a lung cancer risk. Working with materials such as asbestos, uranium, arsenic, cadmium, chromium, nickel and some petroleum products is especially dangerous. If you think you may be breathing in hazardous chemicals at your job, talk to your employer and your doctor to find out to protect yourself.

1.4.5 Particle Pollution

Particle pollution refers to a mix of very tiny solid and liquid particles that are in the air we breathe. Evidence shows that particle pollution—like that coming from that exhaust smoke—increases the risk of lung cancer.

1.4.6 Genes

Genetic factors also may play a role in one's chances of developing lung cancer. A family history of lung cancer may mean you are at a higher risk of getting the disease. If others in your family have or ever had lung cancer, it's important to mention this to your doctor.

1.5 Brief idea of project:

Cancer is a disease in which some of the body's cells grow uncontrollably and spread to other parts of the body. Cancer can start almost anywhere in the human body, which is made up of trillions of cells. Actually there are many types of cancers which are causing deaths every year out of all those lung cancer is the most affected one. Lung cancer is most dangerous and serious cancer. Early stage detection and diagnosis is the only way to recover from lung cancer. usage of more plastic, air pollution, harmful carcinogenic released gases from industries, harmful gases from volcano eruption and air jets all these human actions leads to lung cancer.

Lung cancer varies differently from person to person, depending on the size of the tumour and the stage it is in. Stage I is considered as when the cancer is restricted to the lung. Stage II is when the cancer is limited to the chest. Stage III is when the tumour grows larger and appears in the CT scan. Stage IV is confined to spreading cancer cells to other parts of the body and growth of tumours in other parts as well. Analysing CT scan image of lungs and predicting stage of cancer based on tumour requires a high level of skill and concentration, and is possible only by the expert doctors or radiologists. CT stands for computerized tomography where passing of X-rays inside the human body takes place. There are many other image processing methods and techniques such as MRI, Ultrasound, DEXA, X-ray and PET, but CT scan is best recommended because CT scan is best accurate and noise is very less as compared to others.

As medical images may have noise, the CT image is passed to the second step, i.e., pre-processing where median filter is used in this paper for elimination of noise. Then conversion of image into binary followed by segmentation is done where CT image is partitioned into some sets of pixels and obtaining of tumour (white) region pixels i.e., extraction of required and interested region (which are the white regional pixels in different places present in the lungs, eliminating the other part of the lung which is not affected takes place).

Various simple segmentation techniques such as watershed algorithm and different morphological operations like dilation, erosion, opening to apply big mask were used in this paper. Last step is feature extraction to decide whether those white regional pixels were still initial cancer cells or tumour is decided here and area and diameter of those white regional pixels are extracted and based on the size value of the white grouped pixels, exact tumours are separated out and based on radius value of tumour, classification of lung cancer into various stages is decided in this project. In feature extraction fore ground -background and

SIFT (scale-invariant feature detection) techniques are used to extract required features of tumour module. Based on size of tumour module stage of cancer is detected. By knowing size of tumour nodule it becomes easier for the radiologists/doctors to easily find the stage of cancer instantly. Proper medication like radiotherapy or surgery can be done if the tumour's size is large. Early detection of stage and diagnosis are the only prevention steps of lung cancer.

CHAPTER 2

PRE-PROCESSING

2.1 INTRODUCTION TO IMAGE PREPROCESSING

Preprocessing is a typical name for procedures applied to both input and output intensity images. These images are indistinguishable from the original data taken by the sensors. Basically, image pre processing is a method to transform raw image data into a clean image data, as most of the raw image data contain noise and contain some missing values or incomplete values, inconsistent values, and false values. Missing information means lacking of certain attributes of interest or lacking of attribute values. Inconsistent information means there are some discrepancies in the image. False value means error in the image value. The purpose of pre-processing is an enhancement of the image data to reduce reluctant falsifications or to improve some image features vital for additional processing. Some will contend that image pre-processing is not a smart idea, as it alters or modifies the true nature of the raw data. Nevertheless, smart application of image pre-processing can offer benefits and take care of issues that finally produce improved global and local feature detection.

Image pre-processing may have beneficial effects on the excellence of feature extraction and the outcomes of image analysis. Image pre-processing is similar to the scientific standardization of a data set, which is a general step in many feature descriptor techniques. Image pre-processing is used to correct the degradation of an image. In that case, some prior data or information is important such as information about the nature of the degradation, information about the features of the image

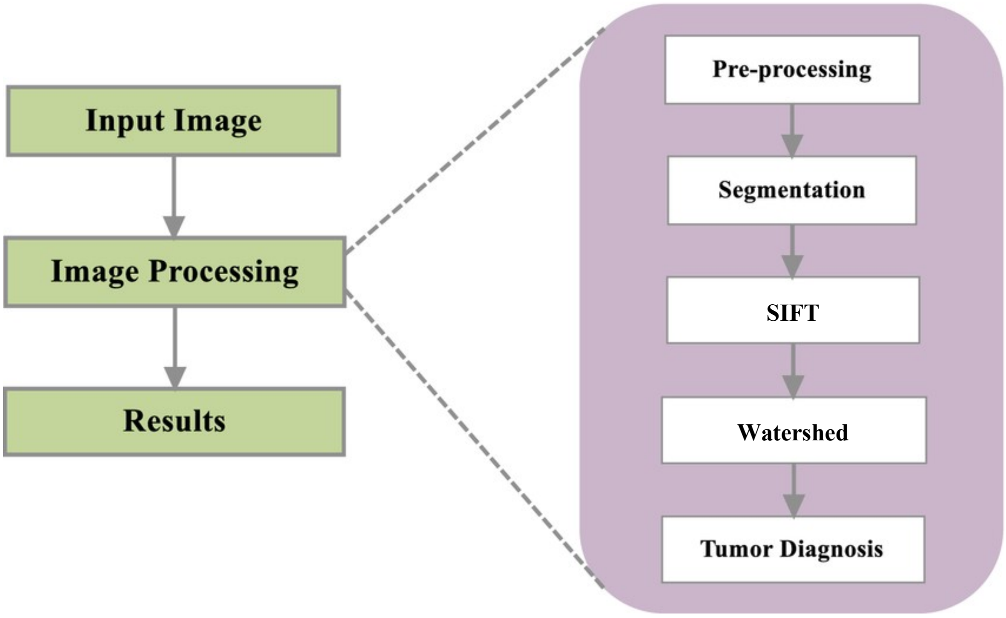


Fig.2.1 Steps involved in Image Processing

capturing device, and the conditions under which the image was obtained.

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too. Image processing basically includes the following three steps: Importing the image via image acquisition tools; Analysing and manipulating the image; Output in which result can be altered image or report that is based on image analysis. There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques.

Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too. Image processing basically includes the following three steps. · Importing the image with optical scanner or by digital photography. · Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs. · Output is the last stage in which result can be altered image or report that is based on image analysis.

Purpose of Image processing The purpose of image processing is divided into 5 groups. They are:

1. Visualization – Observe the objects that are not visible.
2. Image sharpening and restoration – To create a better image.
3. Image retrieval – Seek for the image of interest.
4. Measurement of pattern – Measures various objects in an image.
5. Image Recognition – Distinguish the objects in an image.

Types The two types of methods used for Image Processing are Analog and Digital Image Processing. Analog or visual techniques of image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. The image processing is not just confined to area that has to be studied but on knowledge of analyst. Association is another important tool in image processing through13 visual techniques.

Digital Processing techniques help in manipulation of the digital images by using computers. As raw data from imaging sensors from satellite platform contains deficiencies. To get over such flaws and to get originality of information, it has to undergo various phases of processing. The three general phases that all types of data have to undergo while using digital technique are Pre- processing, enhancement and display, information extraction.

2.1.1 Applications:

1. Intelligent Transportation Systems – This technique can be used in Automatic number plate recognition and Traffic sign recognition.

2. Remote Sensing – For this application, sensors capture the pictures of the earth's surface in remote sensing satellites or multi – spectral scanner which is mounted on an aircraft. These pictures are processed by transmitting it to the Earth station. Techniques used to interpret the objects and regions are used in flood control, city planning, resource mobilization, agricultural production monitoring, etc.

3. Moving object tracking – This application enables to measure motion parameters and acquire visual record of the moving object. The different types of approach to track an object are: · Motion based tracking · Recognition based tracking

4. Defence surveillance – Aerial surveillance methods are used to continuously keep an eye on the land and oceans. This application is also used to locate the types and formation of naval vessels of the ocean surface. The important duty is to divide the various objects present in the water body part of the image. The different parameters such as length, breadth, area, perimeter, compactness are set up to classify each of divided objects. It is important to recognize the distribution of these objects in different directions that are east, west, north, south, northeast, northwest, southeast and south west to explain all possible formations of the vessels. We can interpret the entire oceanic scenario from the spatial distribution of these objects.

5. Biomedical Imaging techniques – For medical diagnosis, different types of imaging tools such as X- ray, Ultrasound, computer aided tomography (CT) etc are used. Some of the applications of Biomedical imaging applications are as follows: · Heart disease identification– The important diagnostic features such as size of the heart and its shape are required to know in order to classify the heart diseases.

To improve the diagnosis of heart diseases, image analysis techniques are employed to radiographic images. · Lung disease identification – In X- rays, the regions that appear dark contain air while region that appears lighter are solid tissues. Bones are more radio opaque than tissues. The ribs, the heart, thoracic spine, and the diaphragm that separates the chest cavity from the abdominal cavity are clearly seen on the X-ray film. · Digital mammograms – This is used to detect the breast tumour. Mammograms can be analysed using Image processing techniques such as segmentation, shape analysis, contrast enhancement, feature extraction, etc.

6. Automatic Visual Inspection System – This application improves the quality and productivity of the product in the industries. · Automatic inspection of incandescent lamp filaments – This involves examination of the bulb manufacturing process. Due to no uniformity in the pitch of the wiring in the lamp, the filament of the bulb gets fused within a short duration. In this application, a binary image slice of the filament is created from which the silhouette of the filament is fabricated. Silhouettes are analyzed to recognize the non uniformity in the pitch of the wiring in the lamp. This

system is being used by the General Electric Corporation. · Automatic surface inspection systems – In metal industries it is essential to detect the flaws on the surfaces. For instance, it is essential to detect any kind of aberration on the rolled metal surface in the hot or cold rolling mills in a steel plant. Image processing techniques such as texture identification, edge detection, fractal analysis etc are used for the detection. · Faulty component identification – This application identifies the faulty components in electronic or electromechanical systems. Higher amount of thermal energy is generated by these faulty components. The Infra-red images are produced from the distribution of thermal energies in the assembly. The faulty components can be identified by analyzing the Infra-red images.

2.2 GRAY SCALE IMAGE:

In the digitized world a gray scale image is a computerized/digital image in which the estimation of every pixel is an individual example, i.e., it conveys just power or intensity i.e. white or black in terms of display Pictures of this kind, otherwise called white (maximum amplitude) and dark (minimum amplitude) pictures, comprise selective shades of dim. Gray scale pictures are the after effect of measuring the amplitude of light at every pixel in a single band of the light spectrum. They can likewise be obtained from a full coloured picture. The explanation for picking gray scale picture is even least pixel power is additionally useful in recognizing changes in the cells. In fact, a dim shading is one in which the R, G, B planes have equal intensity, the intensity level represented as a number from decimal 0 to 255. For each pixel in a RGB gray scale picture, G = B = R. The amplitude differs in extent with the number speaking to the brightness levels of the RGB hues. Dark is spoken to by R=G=B=0 and white is spoken to by R=G=B=255.

Fig.2.2.1 Normal digital image

Fig.2.2.2 Grey Scale image

2.3 HISTOGRAM EQUALIZATION:

A histogram of an image is the graphical interpretation of the image's pixel intensity values. It can be interpreted as the data structure that stores the frequencies of all the pixel intensity levels in the image. Histogram Equalization is a computer image processing technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image.

Histogram equalization is used to enhance contrast. It is not necessary that contrast will always be increase in this. There may be some cases were histogram equalization can be worse. In those cases the contrast is decreased.

This method usually increases the global contrast of many images, especially when the image is represented by a narrow range of intensity values. Through this adjustment, the intensities can be better distributed on the histogram utilizing the full range of intensities evenly. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the highly populated intensity values which are used to degrade image contrast.

The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are either over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique adaptive to the input image and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered.

The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal. In scientific imaging where spatial correlation is more important than intensity of signal (such as separating DNA fragments of quantized length), the

small signal to noise ratio usually hampers visual detections. Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images to which one would apply a false-colour. Also histogram equalization can produce undesirable effects (like visible image gradient when applied to images with low colour depth. For example, if applied to 8-bit image displayed with 8-bit grey scale palette it will further reduce colour depth (number of unique shades of gray) of the image. Histogram equalization will work the best when applied to images with much higher colour depth than palette size, like continuous data or 16-bit gray-scale images.

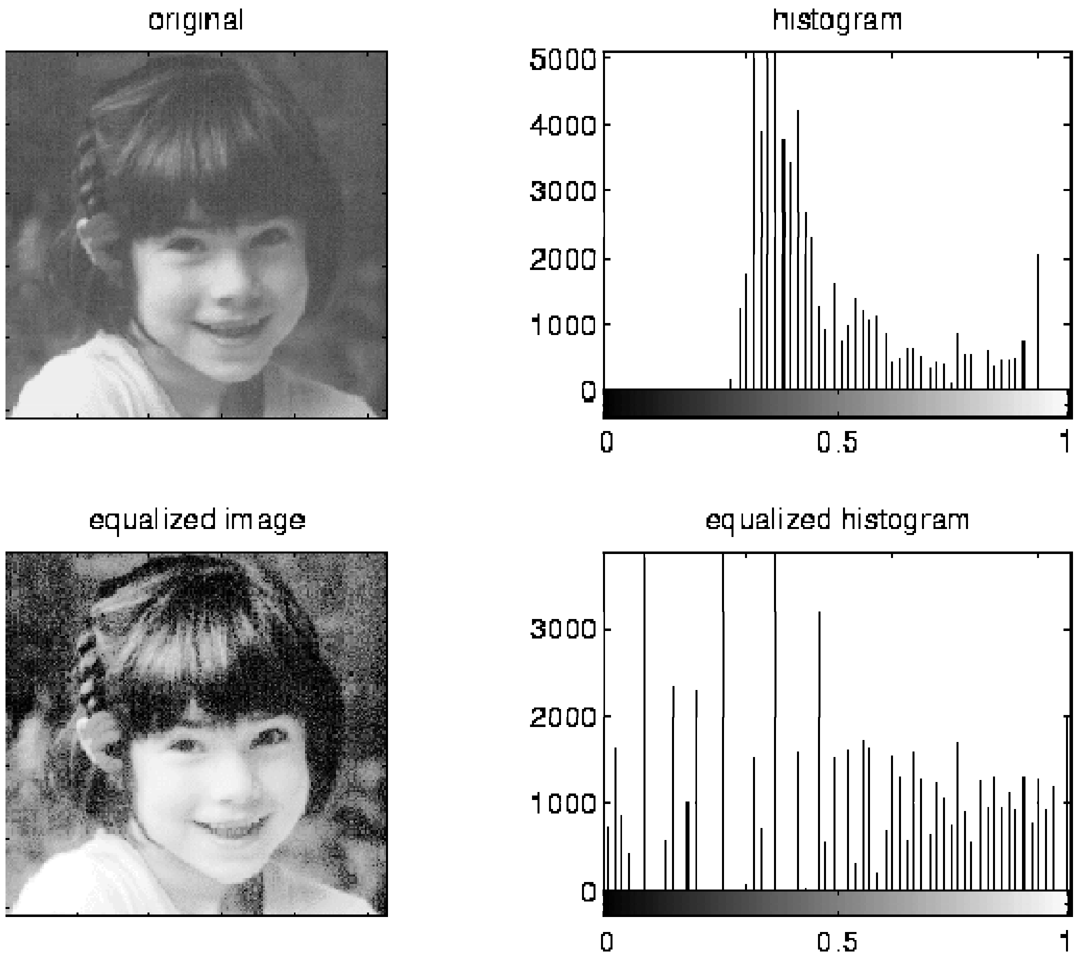


Fig.2.3 Histogram Equalization

There are two ways to think about and implement histogram equalization, either as image change or as palette change. The operation can be expressed as P(M(I)) where I is the original image, M is histogram equalization mapping operation and P is a palette. If we define a new palette as P'=P(M) and leave image I unchanged then histogram equalization is implemented as palette change or mapping change. On the other hand, if palette P remains unchanged and image is modified to I'=M(I) then the implementation is accomplished by image change. In most cases palette change is better as it preserves the original data.

2.4 WHAT IS NOISE?

Noise is typically defined as a random variation in brightness or colour information and it is frequently produced by technical limits of the image collection sensor or by improper environmental circumstances. These difficulties are frequently inevitable in real scenarios, making image noise a common issue that must be addressed with appropriate denoising approaches.

Image noise is random variation of brightness or colour information in images, and is usually an aspect of electronic noise. It can be produced by the image sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that obscures the desired information. The original meaning of "noise" was "unwanted signal"; unwanted electrical fluctuations in signals received by AM radios caused audible acoustic noise ("static"). By analogy,

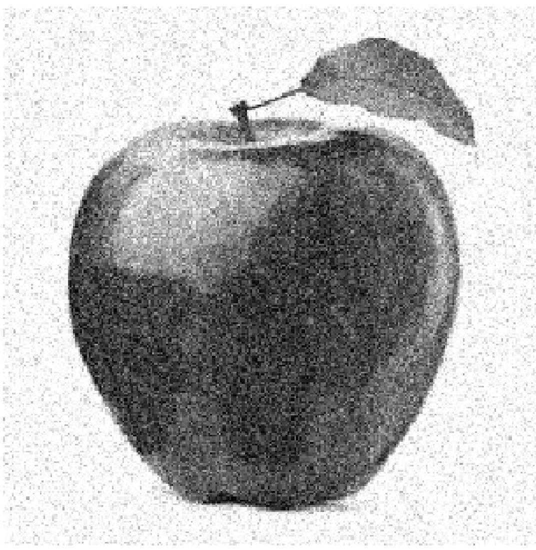


Fig.2.4 Noise image

unwanted electrical fluctuations are also called "noise".

Denoising an image is a difficult task since the noise is tied to the image's high-frequency content, i.e. the details. As a result, the goal is to strike a balance between suppressing noise as much as possible while not losing too much information. Filter-based approaches for picture denoising, such as the Inverse, Median, and Wiener Filters, are the most often utilized.

The presence of noise in an image might be additive or multiplicative. In the Additive Noise Model, an additive noise signal is added to the original signal to produce a corrupted noisy signal that follows the following rule:

$w(x, y) = s(x,y) + n(x,y)$

Here, $s(x, y)$ represents the original image intensity and $n(x,y)$ represents the noise supplied to produce the corrupted signal $w(x,y)$ at (x,y) pixel position. Similarly, the Multiplicative Noise Model multiplies the original signal by the noise signal.

2.4.1 Sources of Noise

During picture acquisition and transmission, noise may be introduced into the image. The introduction of noise into the image could be caused by several factors. The quantification of noise is determined by the number of corrupted pixels in the image.

Image noise can range from nearly invisible specks on a digital snapshot taken in good lighting to optical and radio astronomical images that are almost totally noise, from which a small amount of information can be extracted by complex processing. Such a level of noise would be inappropriate in a photograph since it would be impossible to identify the subject.

The following are the primary sources of noise in digital images:

- Environmental factors may have an impact on the imaging sensor.
- Low light and sensor temperature may cause image noise.
- Dust particles in the scanner can cause noise in the digital image.
- Transmission channel interference.

2.5 Different Types of Noise

The pattern of the noise, as well as its probabilistic properties, distinguishes it. There is a wide range of noise types. While we focus primarily on the most important forms, these are Gaussian noise, salt and pepper noise, poison noise, impulse noise, and speckle noise.

2.5.1 Gaussian Noise

It is commonly known that Gaussian noise is statistical noise with a probability density function (PDF) equal to the normal distribution. Gaussian noise has a uniform distribution throughout the signal.

A noisy image has pixels that are made up of the sum of their original pixel values plus a random Gaussian noise value. The probability distribution function for a Gaussian distribution has a bell shape. Additive white Gaussian noise is the most common application for Gaussian noise in applications.

The below figure shows the Gaussian distribution function (probability distribution function) of Gaussian noise and pixel representation of Gaussian noise.

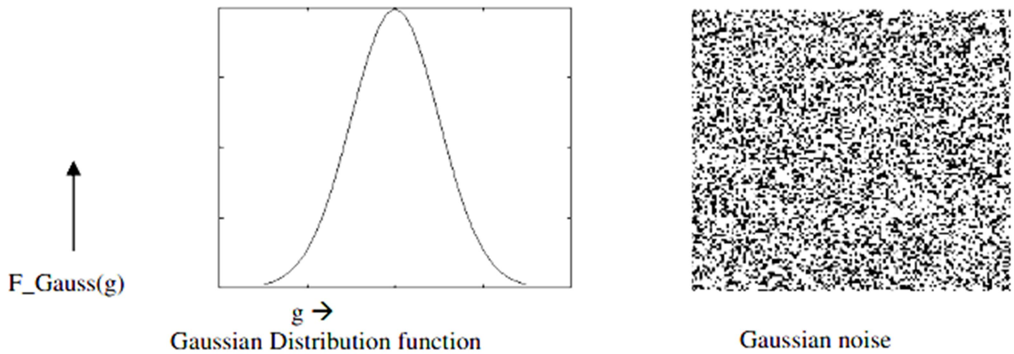


Fig.2.5.1 Gaussian Noise

2.5.2 Salt and Pepper Noise

A type of noise commonly seen in photographs is salt and pepper noise. It manifests as white and black pixels that appear at random intervals. Errors in data transfer cause this form of noise to appear. The values a and b in salt pepper noise are different. Each has a probability of less than 0.1 on average. The corrupted pixels are alternately set to the minimum and highest value, giving the image a "salt and pepper" appearance. The distribution and pixel representation of this noise is shown below. The use of a median filter, morphological filter, or contra harmonic mean filter is an effective noise eradication strategy for this type of noise. In situations when quick transients, such as improper switching, occur, salt and pepper noise creeps into images.

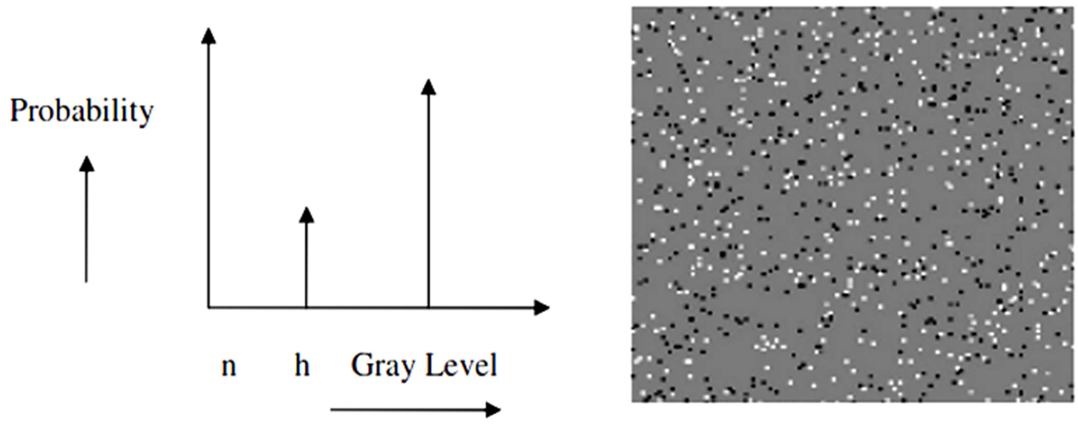


Fig.2.5.2 salt and pepper noise

2.5.3 Speckle Noise

Unlike Gaussian or Salt and Pepper noise, speckle noise is multiplicative noise. In diagnostic examinations, this reduces image quality by giving images a backscattered wave appearance caused by many microscopic dispersed reflections flowing through internal organs. This makes it more difficult for the observer to distinguish fine details in the images. The distribution and pixel representation of this noise is shown below. This type of noise can be found in a wide range of systems, including synthetic aperture radar (SAR) images, ultrasound imaging, and many more.

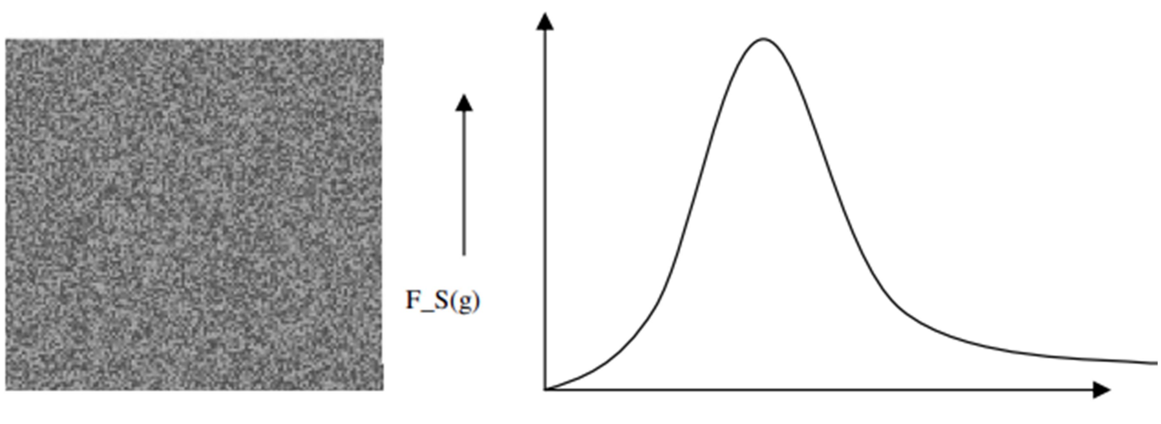


Fig.2.5.3 Speckle noise image.

2.5.4 Poison Noise

Poisson noise is produced by the image detectors’ and recorders’ nonlinear responses. This type of noise is determined by the image data. Because detecting and recording procedures incorporate arbitrary electron emission with a Poisson distribution and a mean response value, this expression is utilized. Because a Poisson distribution’s mean and variance are the same, the image-dependent term is considered to have a standard deviation if it is assumed that the noise has a variance of one.

2.5.5 Quantization noise

Quantization noise is the effect of representing an analog continuous signal with a discrete number (digital signal). The rounding error is referred to as quantization noise. The quantization noise is nearly random (at least for high resolution digitizers) and is treated as a noise source.

The SNR is given as

$SNR_{dB} = 20\log_{10}(P_{max} - P_{min})/\ \sigma_n$

Where σ_n = Standard deviation of noise, when input is full amplitude sine wave SNR becomes

SNR = 6n+1.76dB

Where n is number of bits. Quantization noise obeys the uniform distribution. That is why it is referred as uniform noise

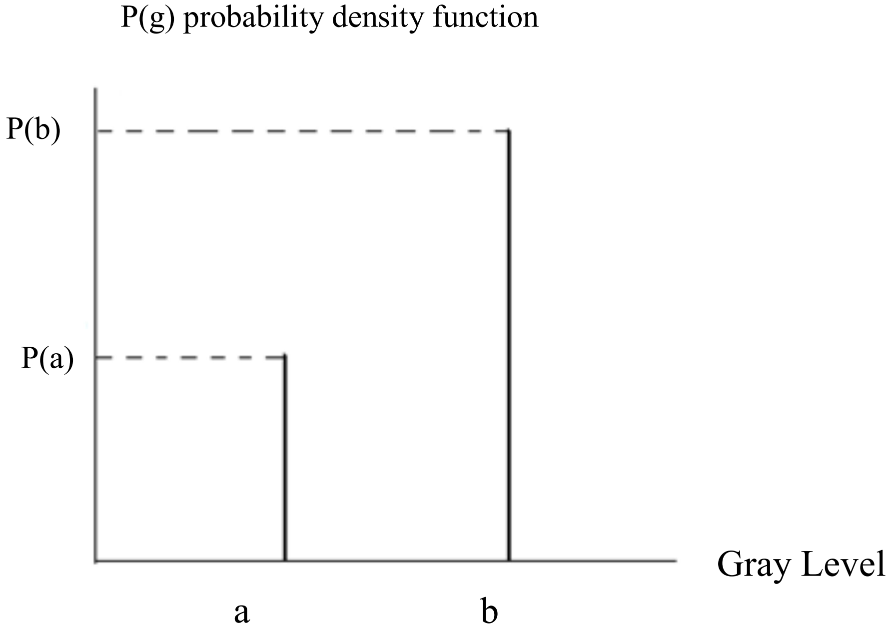


Fig 2.5.5 Quantization noise

2.5.6 Shot noise

The dominant noise in the brighter parts of an image from an image sensor is typically that caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level. This noise is known as photon shot noise. Shot noise has a root-mean-square value proportional to the square root of the image intensity, and the noises at different pixels are independent of one another. Shot noise follows a Poisson distribution, which except at very high intensity levels approximates a Gaussian distribution. In addition to photon shot noise, there can be additional shot noise from the dark leakage current in the image sensor; this noise is sometimes known as "dark shot noise" or "dark-current shot noise".. Dark current is greatest at "hot pixels" within the image sensor. The variable dark charge of normal and hot pixels can be subtracted off (using "dark frame subtraction"), leaving only the shot noise, or random component, of the leakage. If dark-frame subtraction is not done, or if the exposure time is long enough that the hot pixel charge exceeds the linear charge capacity, the noise will be more than just shot noise, and hot pixels appear as salt-and-pepper noise.

2.5.7 Film grain

The grain of photographic film is a signal-dependent noise, with similar statistical distribution to shot noise. If film grains are uniformly distributed (equal number per area), and if each grain has an equal and independent probability of developing to a dark silver grain after absorbing photons, then the number of such dark grains in an area will be random with a binomial distribution. In areas where the probability is low, this distribution will be close to the classic Poisson distribution of shot noise. A simple Gaussian distribution is often used as an adequately accurate model. Film grain is usually regarded as a nearly isotropic (non-oriented) noise source. Its effect is made worse by the distribution of silver halide grains in the film also being random.

2.5.8 Periodic Noise:

A common source of periodic noise in an image is from electrical or electromechanical interference during the image capturing process.An image affected by periodic noise will look like a repeating pattern has been added on top of the original image. In the frequency domain this type of noise can be seen as discrete spikes. Significant reduction of this noise can be achieved by applying notch filters in the frequency domain. The following images illustrate an image affected by periodic noise, and the result of reducing the noise using frequency domain filtering. Note that the filtered image still has some noise on the borders. Further filtering could reduce this border noise, however it may also reduce some of the fine details in the image. The trade-off between noise reduction and preserving fine details is application specific. For example, if the fine details on the castle are not considered important, low pass filtering could be an appropriate option. If the fine details of the castle are considered important, a viable solution may be to crop off the border of the image entirely.

2.6 IMAGE DE-NOISING:

Image de-noising is very important task in image processing for the analysis of images. One goal in image restoration is to remove the noise from the image in such a way that the original image is discernible. In modern digital image processing data de-noising is a well- known problem and it is the concern of diverse application areas. Image de-noising is often used in the field of photography or publishing where image was somehow degraded but needs to be improved before it can be printed. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. There are two types of noise removal approaches (i) linear filtering (ii) nonlinear filtering.

Linear Filtering: Linear filters are used to remove certain types of noise. These filters remove noise by convolving the original image with a mask that represents a low-pass filter or smoothing operation. The output of a linear operation due to the sum of two inputs is the same as performing the operation on the inputs individually and then summing the results. These filters also tend to blur the sharp edges, destroy the lines and other fine details of the image. Linear methods are fast but they do not preserve the details of the image.

Non-Linear Filtering: Non- linear filter is a filter whose output is not a linear function of its inputs. Non-linear filters preserve the details of the image. Non-linear filters have many applications, especially removal of certain types of noise that are not additive. Non-linear filters are considerably harder to use and design than linear ones.

2.6.1 Different types of linear and non-linear filters:

2.6.1.1 Mean Filter:

The mean filter is a simple spatial filter. Mean filter acts on an image by smoothing it. The mean filter is a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighbouring pixel values including itself. This process is repeated for all pixel values in the image. By doing this, it replaces pixels that are unrepresentative of their surroundings. The window is usually square but it can be of any shape.

$$\begin{pmatrix} 8 & 4 & 7 \\ 2 & 1 & 9 \\ 5 & 3 & 6 \end{pmatrix}$$

This provides a calculated value of 5. The centre value is 1, in the pixel matrix and it is replaced with this calculated value 5. Median Filter: Median filter is a simple and powerful non-linear filter which is based on order statics, whose response is based on the ranking of pixel values contained in the filter region. It is easy to implement method of smoothing images. The median filter also follows the moving window principle similar to the mean filter. A 3*3, 5*5, or 7*7 kernel of the pixels is scanned over pixel matrix of the entire image. In this filter, we do not replace the pixel value of the image with the mean of all neighbouring pixel values; we replace it with the median value. Median filtering is done by, first sorting all the pixel values from the surrounds neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value.

123	125	126	130	140
122	124	126	127	135
118	120	150	125	134
119	115	119	123	133
111	116	110	120	130

Neighbourhood values: **115,119,120,123,124,125,126,127,150**

Median value = 124

2.6.1.2 Adaptive Filter:

Adaptive filter is performed on the degraded image that contains original image and noise. The mean and variance are the two statistical measures that a local adaptive filter depends with a defined mxn window region.The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image. The wiener2 function applies a Wiener filter (a type of linear filter) to an image adaptively, tailoring itself to the local image variance. Where the variance is large, wiener2 performs little smoothing. Where the variance is small, wiener2 performs more smoothing. Another method for removing noise is to evolve the image under a smoothing partial differential equation similar to the heat equation which is called anisotropic diffusion.

2.6.1.3 Wiener Filter:

The main aim of this technique is to filter out noise that has corrupted the signal. It is kind of statistical approach. For the designing of this filter one should know the spectral properties of the original signal ,the noise and linear time-variant filter whose output should be as close as to the original as possible. The Wiener filter minimizes the mean square error between the estimated random process and the desired process. Weiner filter are characterized by following:

1. Assumption: Signal and additive noise are stationary linear with known spectral characteristics or known autocorrelation and cross-correlation.
2. Requirement: the filter must be physically realizable.
3. Performance criterion: minimum mean –square error. The orthogonality principle implies that the Wiener filter in Fourier domain can be written as follows:

2.6.1.4 Max and Min Filter:

Minimum and maximum filters, also known as erosion and dilation filters, respectively, are morphological filters that work by considering a neighbourhood around each pixel. From the list of neighbour pixels, the minimum or maximum value is found and stored as the corresponding resulting value. Finally, each pixel in the image is replaced by the resulting value generated for its associated neighbourhood. If we apply max and min filters alternately they can remove certain kind of noise, such as salt-and-pepper noise very efficiently.

2.6.1.5 Midpoint Filter:

The midpoint filter simply computes the midpoint between the maximum and minimum values in the area encompassed by the filter.

2.6.1.6 Alpha- trimmed mean Filter:

Alpha-trimmed mean filter is windowed filter of nonlinear class; its nature is hybrid of the mean and median filters. The basic idea behind filter is for any element of the signal (image) look at its neighbourhood, discard the most atypical elements and calculate mean value using the rest of them. Alpha you can see in the name of the filter is indeed parameter responsible for the number of trimmed elements.

Alpha-trimmed mean filter algorithm:

a) Place a window over element.
b) Pick up elements.
c) Order elements.
d) Discard elements at the beginning and at the end of the got ordered set.
e) Take an average — sum up the remaining elements and divide the sum by their number.

2.7 THRESHOLDING:

Thresholding is a procedure of transforming an input grayscale image into a binarized image, or image with a new range of gray level, by using a particular threshold value. The goal of thresholding is to extract some pixels from the image while removing others. The purpose of thresholding is to mark pixels that belong to foreground pixels with the same intensity and background pixels with different intensities.

Threshold is not only related to the image processing field. Rather threshold has the same meaning in any arena. A threshold is basically a value having two set of regions on its either side, that is, above the threshold or below the threshold. Any function can have a threshold value. The function has different expressions for below the threshold value and for above the threshold value. For an image, if the pixel value of the original image is less than or below a particular threshold value it will follow a specific transformation or conversion function, if not, it will follow another.

Threshold can be global or local. Global threshold means the threshold is selected from the whole image. Local or adaptive threshold is used when the image has uneven illumination, which makes it difficult to segment using a single threshold. In that case, the original image is divided into sub-images, and for each sub-image a particular threshold is used for segmentation.

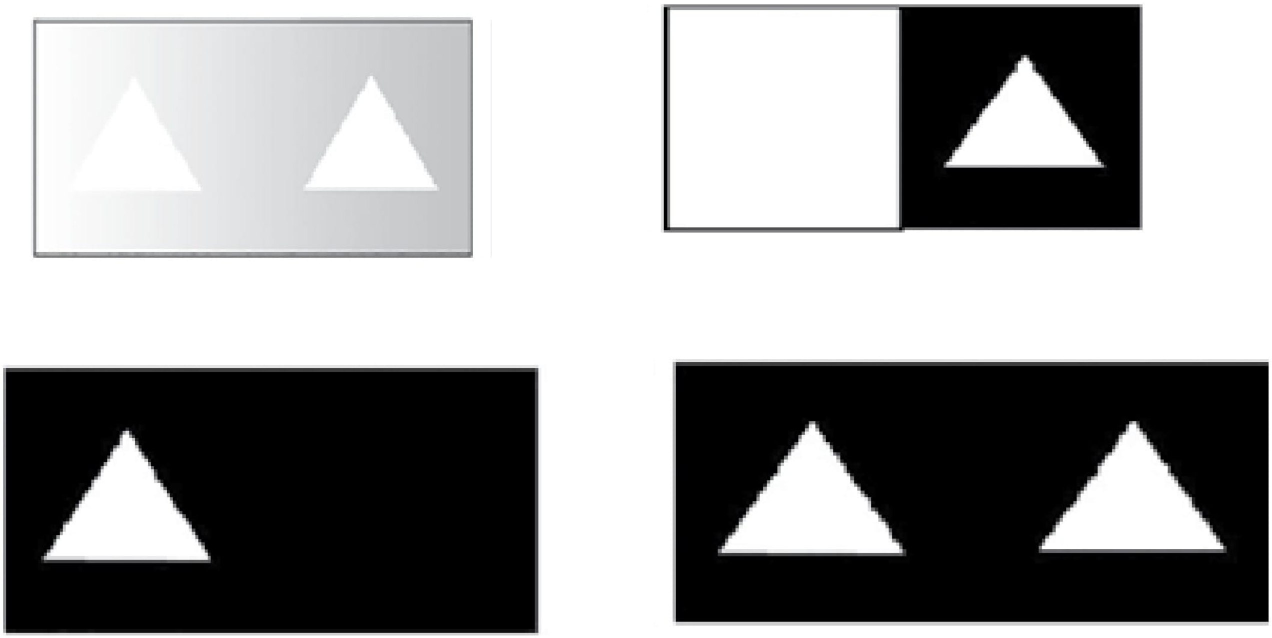


Fig 2.7 Original image to Threshold Image

2.7.1 Conversion of Gray Scale Image to Binary Image:

A gray scale (or gray level) image is simply one in which the only colours are shades of gray. The reason for differentiating such images from any other sort of colour image is that less information needs to be provided for each pixel. A gray scale image has a certain number (probably 8) bits of information per pixel, hence, 256 possible grey values. A binary image has only two values for each pixel, 0 and 1 corresponding to black and white (or vice versa).

This conversion is done due to the following advantages

- Easy to acquire: simple digital cameras can be used together with very simple frame stores, or low-cost scanners, or thresholding may be applied to grey-level images.
- Low storage: no more than 1 bit/pixel, often this can be reduced as such images are very amenable to compression (e.g. run-length coding).
- Simple processing: the algorithms are in most cases much simpler than those applied to grey-level images.

Fig 2.7.1 Conversion of Gray Scale Image to Binary Image

CHAPTER 3
IMAGE SEGMENTATION

3.1 IMAGE SEGMENTATION:

Image segmentation is the process of breakdown of digital image into image segments. Image segmentation is the method helps to better analysing of digital image. Image segmentation method is used to locate the boundaries of image. Every pixel in the image is allocated to one of a number of these categories. Image segmentation is the process of assigning a label to every pixel in an image in such way that pixels with the label share certain characteristics. It is mainly used to locate objects and boundaries like lines and curves in the images. In semantic segmentation is basically used for more accurate view of an image. Segmentation is an important stage of the image recognition system, because it extracts the objects of our interest, for further processing such as description or recognition. Segmentation of an image is in practice for the classification of image pixel.

Cancer has long been a deadly illness. Even in today's age of technological advancements, cancer can be fatal if we don't identify it at an early stage. Detecting cancerous cell(s) as quickly as possible can potentially save millions of lives. The shape of the cancerous cells plays a vital role in determining the severity of the cancer. we might have put the pieces together – object detection will not be very useful here.

Fig 3.1 Segmentation

We will only generate bounding boxes which will not help us in identifying the shape of the cells. Image Segmentation techniques make a massive impact here. They help us approach this problem in a more granular manner and get more meaningful results.

3.2 SEGMENTATION USING WATERSHED:

A watershed is a transformation defined on a greyscale image. The name refers metaphorically to a geological watershed, or drainage divide, which separates adjacent drainage basins. The watershed transformation treats the image it operates upon like a topographic map with the brightness of each point representing its height, and finds the lines that run along the tops of ridges. There are different technical definitions of a watershed. In graphs, watershed lines may be defined on the nodes, on the edges, or hybrid lines on both nodes and edges. Watersheds may also be defined in the continuous domain. There are also many different algorithms to compute watersheds. Watershed algorithms are used in image processing primarily for object segmentation purposes, that is, for separating different objects in an image. This allows for counting the objects or for further analysis of the separated objects. The algorithm based on the concept of “immersion”. Each local minima of a gray-scale image I which can be regarded as a surface has a hole and the surface is immersed out into water. Then, starting from the minima of lowest intensity value, the water will progressively fill up different catchment basins of image (surface) I. Conceptually the algorithm then builds a dam to avoid a situation that the water coming from two or more different local minima would be merged. At the end of this immersion process, each local minimum is totally enclosed by dams corresponding to watersheds of image (surface).

The watershed transform has been widely used in many fields of image processing, including medical image segmentation, due to the number of advantages that it possesses: it is a simple intuitive method, it is fast and can be parallelized and an almost linear speedup was reported for a number of processors up to 64 and it produces a complete division of the image in separated regions even if the contrast is poor, thus avoiding the need for any kind of contour joining. It is appropriate to use this method to segment the high-resolution remote sensing image.

3.2.1 Watershed implementation methods:

3.1 Distance Transform Approach

3.2 Gradient method

3.3 Marker Controlled Approach

3.2.1.1 Distance Transform Approach:

A tool used commonly in conjunction with the watershed transform for segmentation is the distance transform. It is the distance from every pixel to the nearest nonzero-valued pixel. The distance transform can be computed using toolbox function bwdist, whose calling syntax is D=bwdist (f) A binary image can be converted to a gray level image, which is suitable for watershed segmentation using different DT. However, different DT functions produce different effects. Euclidean DT has a higher possibility of “salt and pepper” over segmentation. City Block DT has a higher possibility of over segmentation for the components in the image.

The reason is that City Block DT propagates to the neighbourhood in the shape of diamond. Chessboard DT has a better pruning effect due to its square shape propagation. It can effectively remove the jaggedness formed in the Euclidean DT and avoid the components over segmentation caused by City Block DT.

3.2.1.2 Gradient method

The gradient magnitude is used to pre process a gray-scale image prior to using the watershed transform for segmentation. The gradient magnitude image has high pixel values along object edges and low pixel values everywhere else. Watershed transform would result in watershed ridge lines along object edges. There is a problem of over segmentation in this method. The topological gradient provides a global analysis of the image then the almost unwanted contours due to the noise added to a given image can be significantly reduced by our approach. The experimental results show that the over segmentation problem, which usually appears with the watershed technique, can be attenuated, and the segmentation results can be performed using the topological gradient approach. Another advantage of this method is that it splits the segmentation process into two separate steps: first we detect the main edges of the image processed, and then we compute the watershed of the gradient detected.

3.2.1.3 Marker Controlled Approach:

Direct application of watershed transform to a gradient image can result in over segmentation due to noise. Over segmentation means a large number of segmented regions. An approach used to control over segmentation is based on the concept of markers. A marker is a connected component belonging to an image. Markers are used to modify the gradient image. Markers are of two types internal and external, internal for object and external for boundary. The marker-controlled watershed segmentation has been shown to be a robust and flexible method for segmentation of objects with closed contours, where the boundaries are expressed as ridges. Markers are placed inside an object of interest; internal markers associate with objects of interest, and external markers associate with the background. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbours.

3.3 EROSION AND DILATION:

3.3.1 Erosion:

The erosion of a binary image f by a structuring element s (denoted $f \ominus s$) produces a new binary image $g = f \ominus s$ with ones in all locations (x, y) of a structuring element's origin at which that structuring element s fits the input image f, i.e. $g(x, y) = 1$ is s fits f and 0 otherwise, repeating for all pixel.

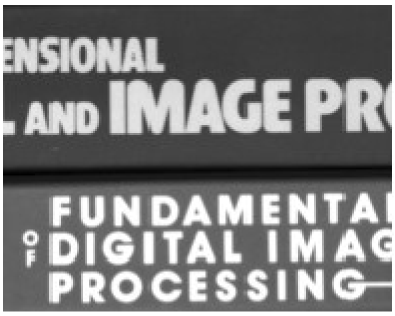


Fig 3.3.1.1 greyscale image to binary image by thresholding

Fig 3.3.1.2 Erosion: a 2x2 square structuring element

Erosion with small (e.g. 2×2 - 5×5) square structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. The holes and gaps between different regions become larger, and small details are eliminated.

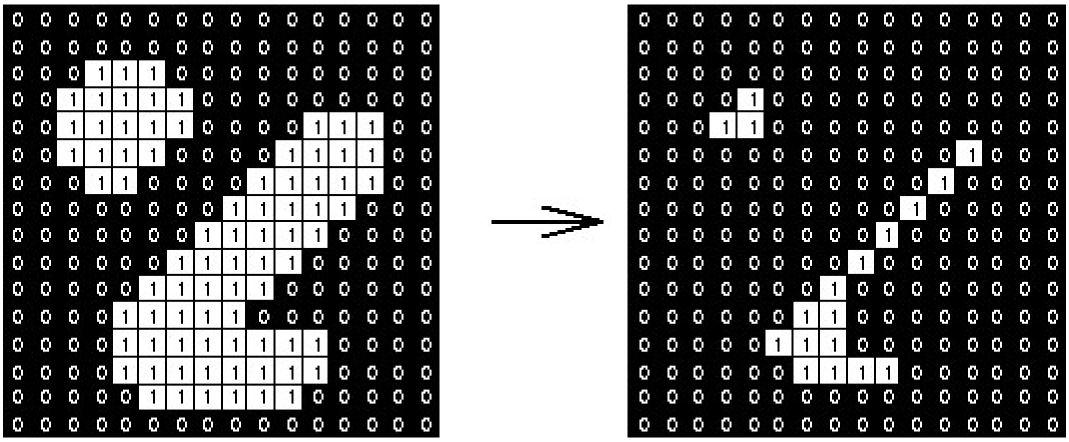


Fig 3.3.1.3 Erosion: a 3x3 square structuring element

Larger structuring elements have a more pronounced effect, the result of erosion with a large structuring element being similar to the result obtained by iterated erosion using a smaller structuring element of the same shape. If s_1 and s_2 are a pair of structuring elements identical in shape, with s_2 twice the size of s_1, then

$$f \ominus s_2 \approx (f \ominus s_1) \ominus s_1. \longrightarrow \quad 1$$

Erosion removes small-scale details from a binary image but simultaneously reduces the size of regions of interest, too. By subtracting the eroded image from the original image, boundaries of each region can be found: $b = f - (f \ominus s)$ where f is an image of the regions, s is a 3×3 structuring element, and b is an image of the region boundaries.

3.3.2 Dilation:

The dilation of an image f by a structuring element s (denoted $f \oplus s$) produces a new binary image $g = f \oplus s$ with ones in all locations (x, y) of a structuring element's origin at which that structuring element s hits the input image f, i.e. $g(x, y) = 1$ if s hits f and 0 otherwise, repeating for all pixel coordinates (x, y). Dilation has the opposite effect to erosion -- it adds a layer of pixels to both the inner and outer boundaries of regions.

Fig 3.3.2.1 Binary image to a 2x2 square structuring element

The holes enclosed by a single region and gaps between different regions become smaller, and small intrusions into boundaries of a region are filled in.

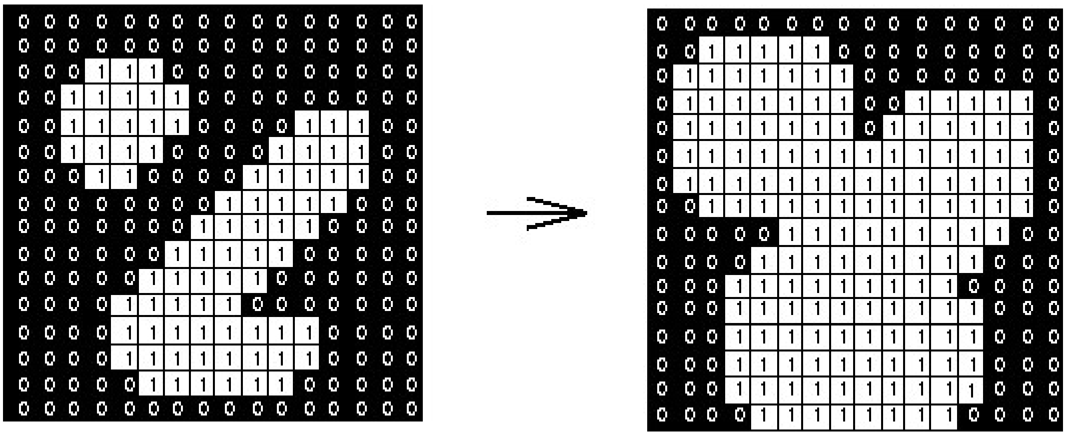


Fig 3.3.2.2 Dilation: a 3×3 square structuring element

Results of dilation or erosion are influenced both by the size and shape of a structuring element. Dilation and erosion are *dual* operations in that they have opposite effects. Let f^c denote the complement of an image f, i.e., the image produced by replacing 1 with 0 and vice versa. Formally, the duality is written as

$$f \oplus s = f^c \ominus s_{rot} \longrightarrow 2$$

where s_{rot} is the structuring element s rotated by 180°. If a structuring element is symmetrical with respect to rotation, then s_{rot} does not differ from s. If a binary image is considered to be a collection of connected regions of pixels set to 1 on a background of pixels set to 0, then erosion is the fitting of a structuring element to these regions and dilation is the fitting of a structuring element (rotated if necessary) into the background, followed by inversion of the result.

3.4 K-MEANS ALGORITHM

The K-means clustering algorithm computes centroids and repeats until the optimal centroid is found. It is presumptively known how many clusters there are. It is also known as the flat clustering algorithm. The number of clusters found from data by the method is denoted by the letter 'K' in K-means.

In this method, data points are assigned to clusters in such a way that the sum of the squared distances between the data points and the centroid is as small as possible. It is essential to note that reduced diversity within clusters leads to more identical data points within the same cluster.

3.4.1 Working of K-Means Algorithm

The following stages will help us understand how the K-Means clustering technique works-

Step 1: First, we need to provide the number of clusters, K, that need to be generated by this algorithm.

Step 2: Next, choose K data points at random and assign each to a cluster. Briefly, categorize the data based on the number of data points.

Step 3: The cluster centroids will now be computed.

Step 4: Iterate the steps below until we find the ideal centroid, which is the assigning of data points to clusters that do not vary.

4.1 The sum of squared distances between data points and centroids would be calculated first.
4.2 At this point, we need to allocate each data point to the cluster that is closest to the others (centroid).
4.3 Finally, compute the centroids for the clusters by averaging all of the cluster's data points.

K-means implements the Expectation-Maximization strategy to solve the problem. The Expectation-step is used to assign data points to the nearest cluster, and the Maximization-step is used to compute the centroid of each cluster.

When using the K-means algorithm, we must keep the following points in mind:

It is suggested to normalize the data while dealing with clustering algorithms such as K-Means since such algorithms employ distance-based measurement to identify the similarity between data points.

Because of the iterative nature of K-Means and the random initialization of centroids, K-Means may become stuck in a local optimum and fail to converge to the global optimum. As a result, it is advised to employ distinct centroids' initializations.

3.4.2 Implementation Of K Means Clustering Graphical Form

STEP 1: Let us pick k clusters, i.e., K=2, to separate the dataset and assign it to its appropriate clusters. We will select two random places to function as the cluster's centroid.

STEP 2: Now, each data point will be assigned to a scatter plot depending on its distance from the nearest K-point or centroid. This will be accomplished by establishing a median between both centroids.

STEP 3: The points on the line's left side are close to the blue centroid, while the points on the line's right side are close to the yellow centroid. The left Form cluster has a blue centroid, whereas the right Form cluster has a yellow centroid.

STEP 4: Repeat the procedure, this time selecting a different centroid. To choose the new centroids, we will determine their new center of gravity, which is represented below:

STEP 5: After that, we'll re-assign each data point to its new centroid. We shall repeat the procedure outlined before (using a median line). The blue cluster will contain the yellow data point on the blue side of the median line.

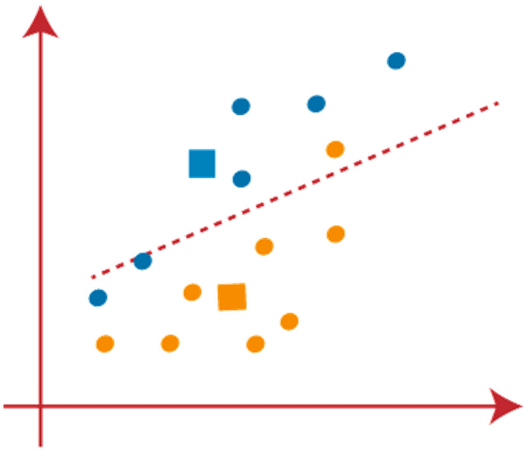


Fig 3.4.2.1 Applying Centroid

STEP 6: Now that reassignment has occurred, we will repeat the previous step of locating new centroids.

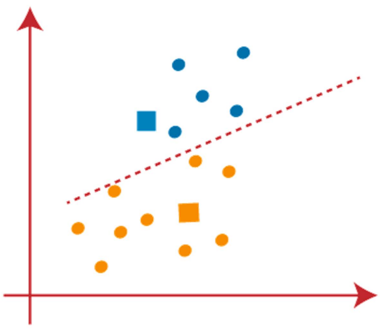


Fig 3.4.2.2 Reassignment occurred

STEP 7: We will repeat the procedure outlined above for determining the center of gravity of centroids, as shown below.

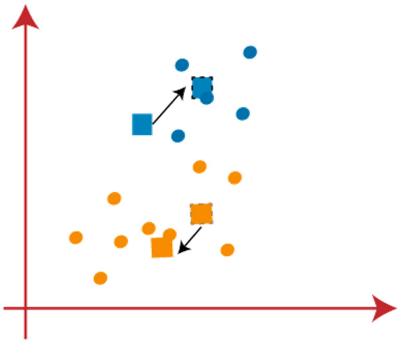


Fig 3.4.2.3 Repeating the Procedure

STEP 8: Similar to the previous stages, we will draw the median line and reassign the data points after locating the new centroids.

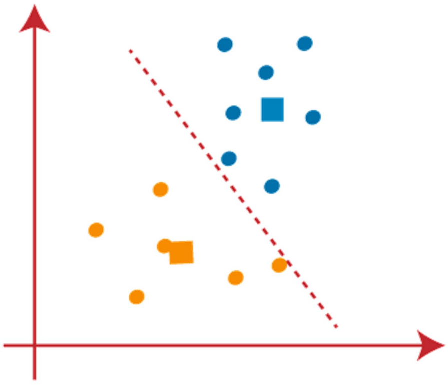


Fig 3.4.2.4 Reassign the data points

STEP 9: We will finally group points depending on their distance from the median line, ensuring that two distinct groups are established and that no dissimilar points included In a single group

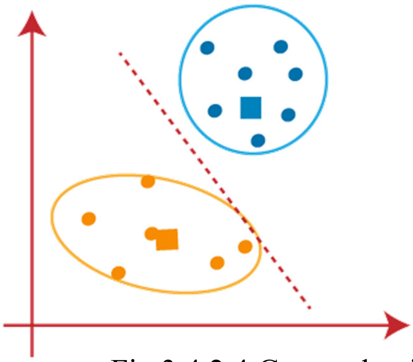


Fig 3.4.2.4 Grouped points depending on their distance from the median

The final Cluster is as follows:

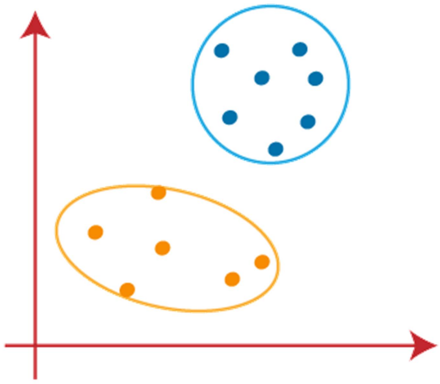


Fig 3.4.2.5 Final Clusters

3.5 EDGE DETECTION

Edge detection is a technique of image processing used to identify points in a digital image with discontinuities, simply to say, sharp changes in the image brightness. These points where the image brightness varies sharply are called the edges (or boundaries) of the image.

Fig 3.5.1 Edge detection

It is one of the basic steps in image processing, pattern recognition in images and computer vision. When we process very high-resolution digital images, convolution techniques come to our rescue. Let us understand the convolution operation (represented in the below image using *) using an example-

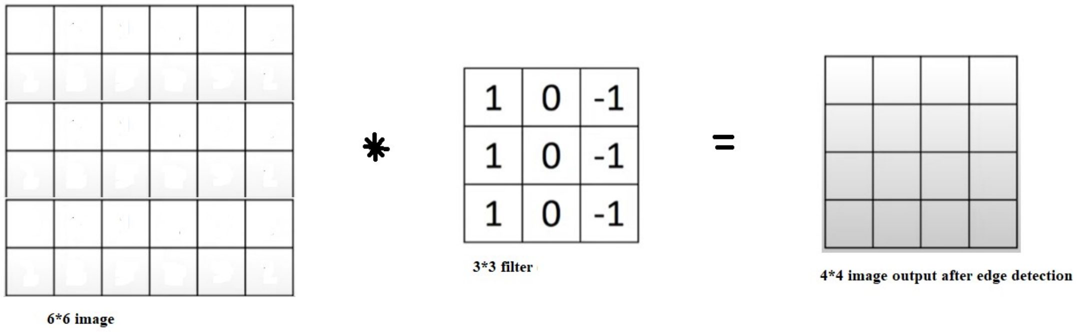


Fig 3.5.2 Prewitt Filter

For this example, we are using 3*3 Prewitt filter as shown in the above image. As shown below, when we apply the filter to perform detection on the given 6*6 image (we have highlighted it in purple for our understanding) the output image will contain ((a11*1) + (a12*0) + (a13*(-1))+(a21*1)+(a22*0)+(a23*(-1))+(a31*1)+(a32*0)+(a33*(-1))) in the purple square. We repeat the convolutions horizontally and then vertically to obtain the output image.

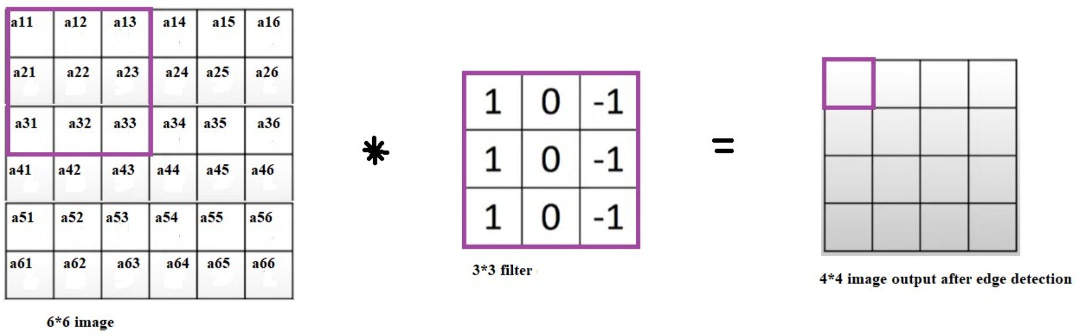


Fig 3.5.3 Prewitt Filter

We would continue the above procedure to get the processed image after edge-detection. But, in the real world, we deal with very high-resolution images for Artificial Intelligence applications. Hence we opt for an algorithm to perform the convolutions, and even use Deep Learning to decide on the best values of the filter.

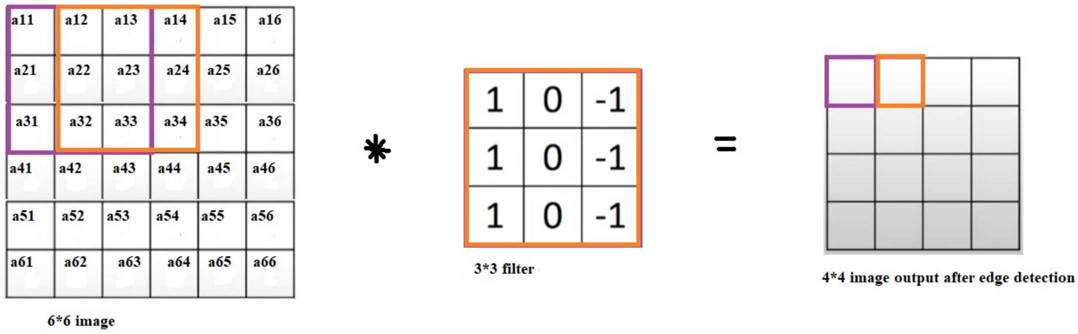


Fig 3.5.4 Prewitt Filter (2)

3.5.1 Methods of Edge Detection

There are various methods, and the following are some of the most commonly used methods-

- Prewitt edge detection
- Sobel edge detection
- Laplacian edge detection
- Canny edge detection

3.5.1.1 Prewitt Edge Detection

This method is a commonly used edge detector mostly to detect the horizontal and vertical edges in images. The following are the Prewitt edge detection filters-

$$G_x = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \qquad G_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

Prewitt filter for vetical edge detection **Prewitt filter for horizontal edge detection**

Fig 3.5.1.1 Prewitt Edge detection

3.5.1.2 Sobel Edge Detection:

This uses a filter that gives more emphasis to the centre of the filter. It is one of the most commonly used edge detectors and helps reduce noise and provides differentiating, giving edge response simultaneously. The following are the filters used in this method-

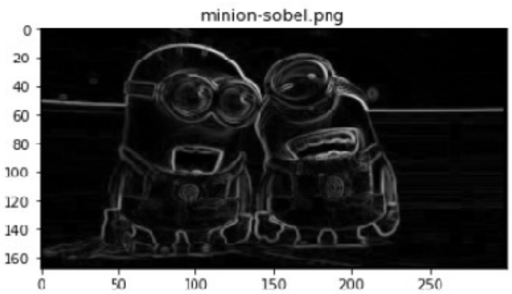
$$G_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \qquad G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Sobel filter for vertical edge detection **Sobel filter for horizontal edge detection**

Fig 3.5.1.2 Sobel Edge detection

The following shows the before and after images of applying Sobel edge detection-

original minion image



minion image after applying sobel edge detector

Fig 3.5.1.2.1 Sobel Edge detection output

3.5.1.3 Laplacian Edge Detection

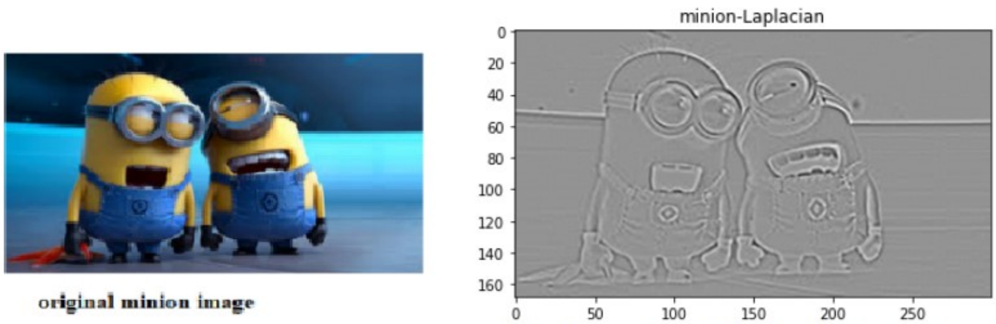
The Laplacian edge detectors vary from the previously discussed edge detectors. This method uses only one filter (also called a kernel). In a single pass, Laplacian detection performs second-order derivatives and hence are sensitive to noise. To avoid this sensitivity to noise, before applying this method, Gaussian smoothing is performed on the image.

−1	−1	−1
−1	8	−1
−1	−1	−1

0	−1	0
−1	4	−1
0	−1	0

Fig 3.5.1.3 Laplacian Edge detection

The above are some of the commonly used Laplacian edge detector filters that are small in size. The following shows the original minion image and the final image after applying Gaussian smoothing (GaussianBlur() method of cv2) followed by Laplacian detection-



original minion image

minion image after applying Laplacian edge detection

Fig 3.5.1.3.1 Laplacian Edge detection output

3.5.1.4 Canny Edge Detection

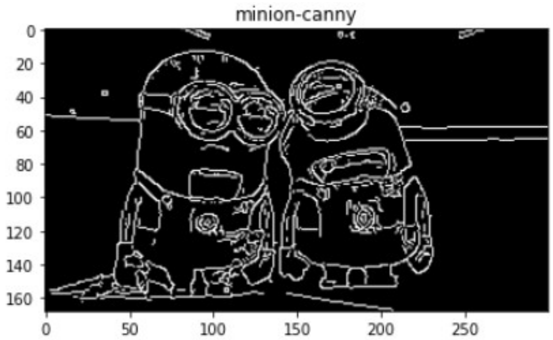
This is the most commonly used highly effective and complex compared to many other methods. It is a multi-stage algorithm used to detect/identify a wide range of edges.

- Convert the image to grayscale
- Reduce noise – as the edge detection that using derivatives is sensitive to noise, we reduce it.
- Calculate the gradient – helps identify the edge intensity and direction.

- Non-maximum suppression – to thin the edges of the image.
- Double threshold – to identify the strong, weak and irrelevant pixels in the images.
- Hysteresis edge tracking – helps convert the weak pixels into strong ones only if they have a strong pixel around them.

The following are the original minion image and the image after applying this method.

original minion image



minion image after applying canny edge detection

Fig 3.5.1.3 Canny Edge detection output

3.6 SCALE INVARIANT FEATURE TRANSFORM

SIFT, or Scale Invariant Feature Transform, is a feature detection algorithm in Computer Vision SIFT helps locate the local features in an image, commonly known as the 'key points' of the image. These key points are scale & rotation invariant that can be used for various computer vision applications, like image matching, object detection, scene detection etc. We can also use the key points generated using SIFT as features for the image during model training. The major advantage of SIFT features, over edge features or hog features, is that they are not affected by the size or orientation of the image. SIFT key points of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of key points that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalised Hough transform. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence.

Object recognition using SIFT features Given SIFT's ability to find distinctive key points that are invariant to location, scale and rotation, and robust to affine transformations (changes in scale, rotation, shear, and position) and changes in illumination, they are usable for object recognition. The steps are given below.

First, SIFT features are obtained from the input image using the algorithm described above.

These features are matched to the SIFT feature database obtained from the training images. This feature matching is done through a Euclidean-distance based nearest neighbour approach. To increase robustness, matches are rejected for those key points for which the ratio of the nearest neighbour distance to the second-nearest neighbour distance is greater than 0.8. This discards many of the false matches arising from background clutter. Finally, to avoid the expensive search required for finding the Euclidean-distance-based nearest neighbour, an approximate algorithm called the best-bin-first algorithm is used. This is a fast method for returning the nearest neighbour with high probability, and can give speedup by factor of 1000 while finding nearest neighbour (of interest) 95% of the time.

Although the distance ratio test described above discards many of the false matches arising from background clutter, we still have matches that belong to different objects. Therefore, to increase robustness to object identification, we want to cluster those features that belong to the same object and reject the matches that are left out in the clustering process. This is done using the Hough transform. This will identify clusters of features that vote for the same object pose. When clusters of features are found to vote for the same pose of an object, the probability of the interpretation being correct is much higher than for any single feature. Each key point votes for the set of object poses that are consistent with the key point’s location, scale, and orientation. Bins that accumulate at least 3 votes are identified as candidate object/pose matches.

For each candidate cluster, a least-squares solution for the best estimated affine projection parameters relating the training image to the input image is obtained. If the projection of a key point through these parameters lies within half the error range that was used for the parameters in the Hough transforms bins, the key point match is kept. If fewer than 3 points remain after discarding outliers for a bin, then the object match is rejected. The least-squares fitting is repeated until no more rejections take place. This works better for planar surface recognition than 3D object recognition since the affine model is no longer accurate for 3D objects.

In this project, authors proposed a new approach to use SIFT descriptors for multiple object detection purposes. The proposed multiple object detection approach is tested on aerial and satellite images.

SIFT features can essentially be applied to any task that requires identification of matching locations between images. Work has been done on applications such as recognition of particular object categories in 2D images, 3D reconstruction, motion tracking and segmentation, robot localization, image panorama stitching and epi-polar calibration. Some of these are discussed in more detail below.

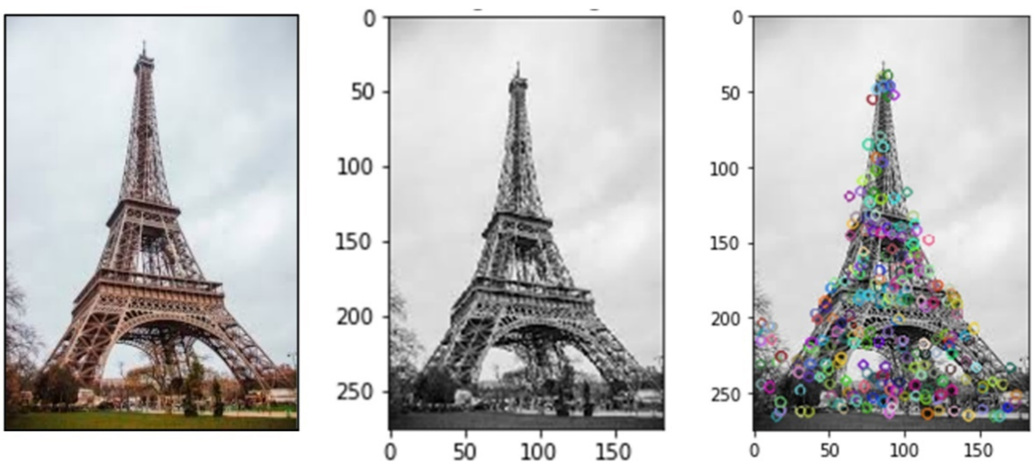


Fig 3.6 SIFT transformation

CHAPTER 4

RESULTS AND CONCLUSION

4.1 RESULTS

Implementing the following steps the cancer cells are identified. “Fig. 4.1 shows cancerous lungs CT scan image which was collected from Cancer Imaging Archive (CIA) database. The various experiments/processes proposed in the above sections for the lung cancer detection were implemented using PYTHON MACHINE LEARNING, which is necessary and suitable for better classification of the stage of cancer and accuracy in the process of prediction using segmentation. “Fig. 4.2 and Fig 4.3” illustrates the pre-processing output results and “Fig. 4.4, 4.5, 4.6, 4.7”vshows the segmentation results. “Fig. 4.8” reveals the tumour cell detection.

The accuracy of the proposed model to detect the lung cancer stage is highlighted based on these results shown under.

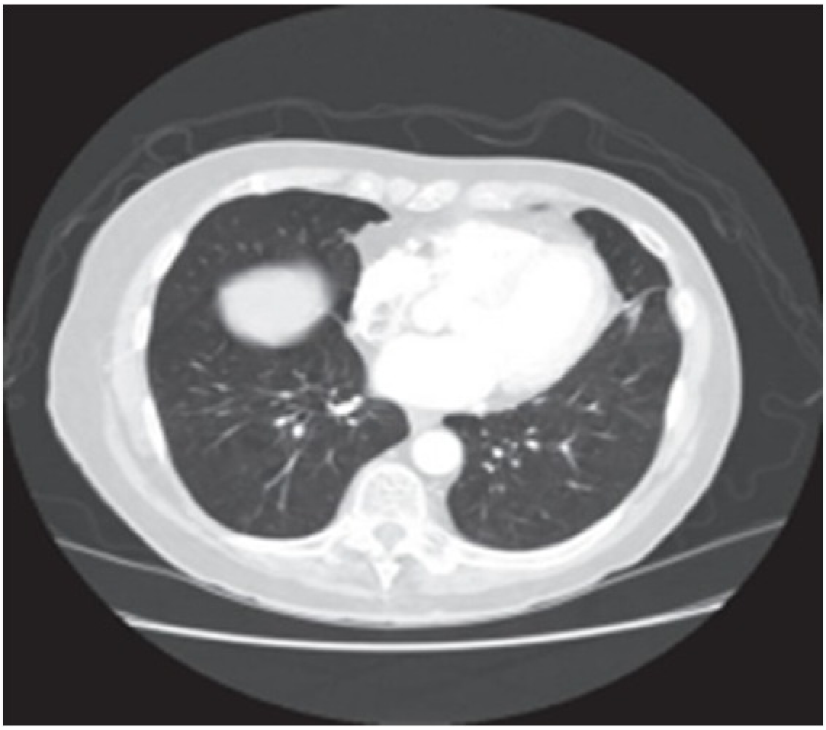


Fig. 4.1 Original Image

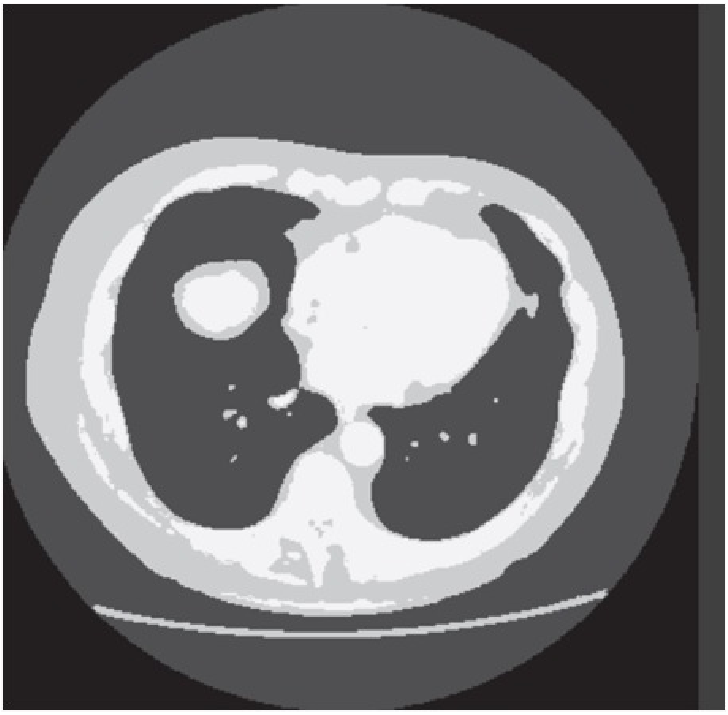


Fig. 4.2 K-Means Image

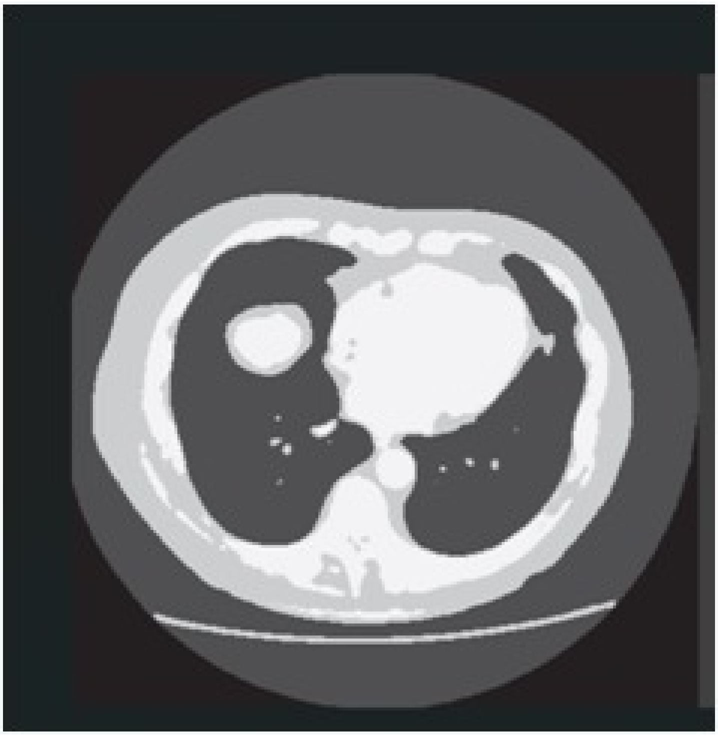


Fig. 4.3 Median Filter Image

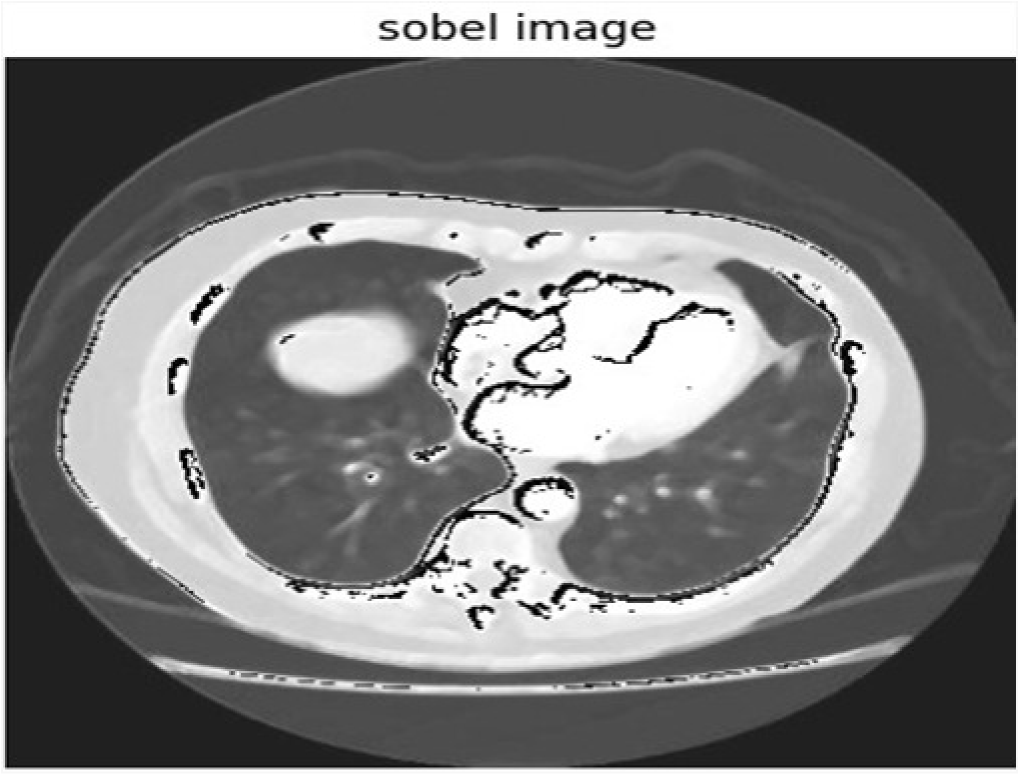


Fig. 4.4 Sobel Image

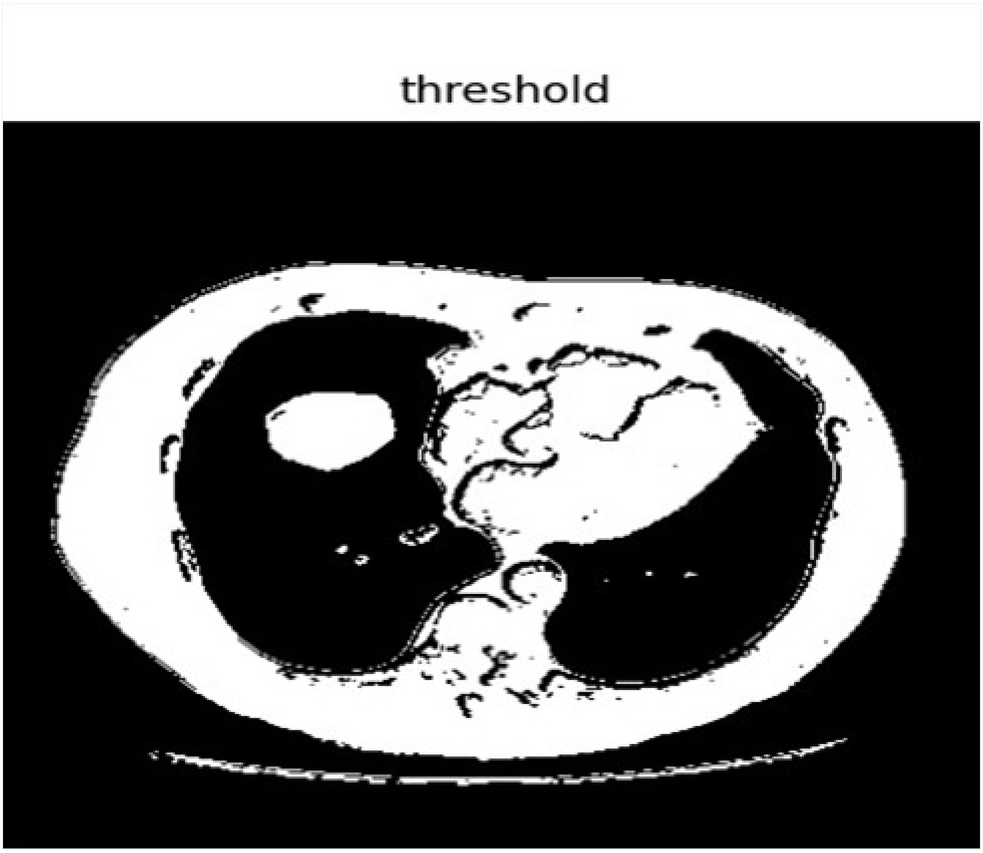


Fig. 4.5 Threshold Image

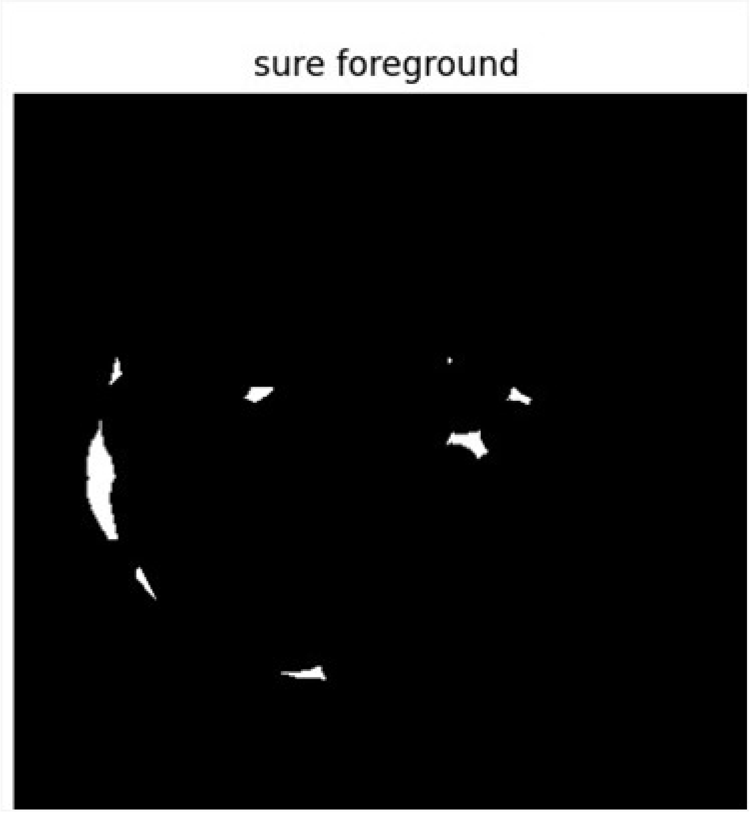


Fig. 4.6 Sure Foreground

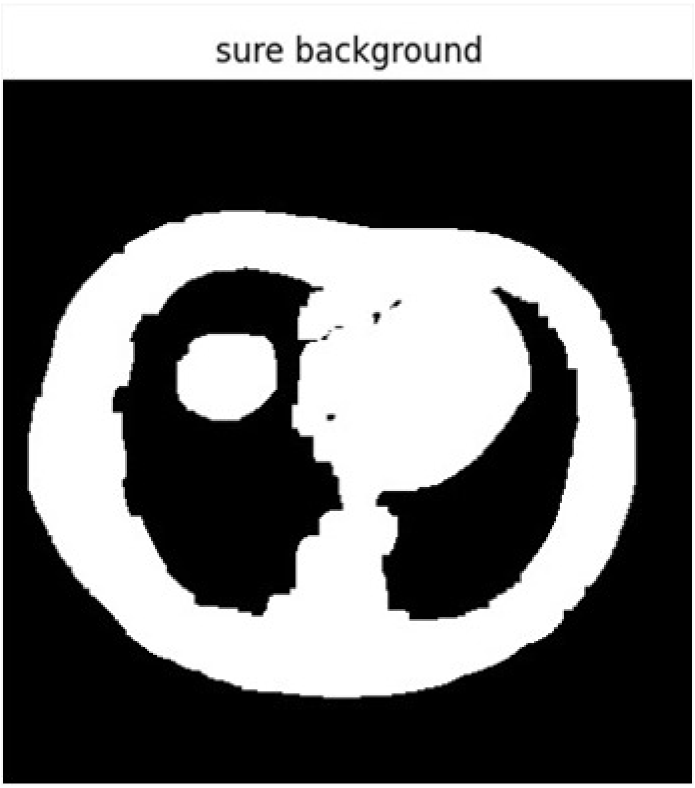


Fig. 4.7 Sure Background

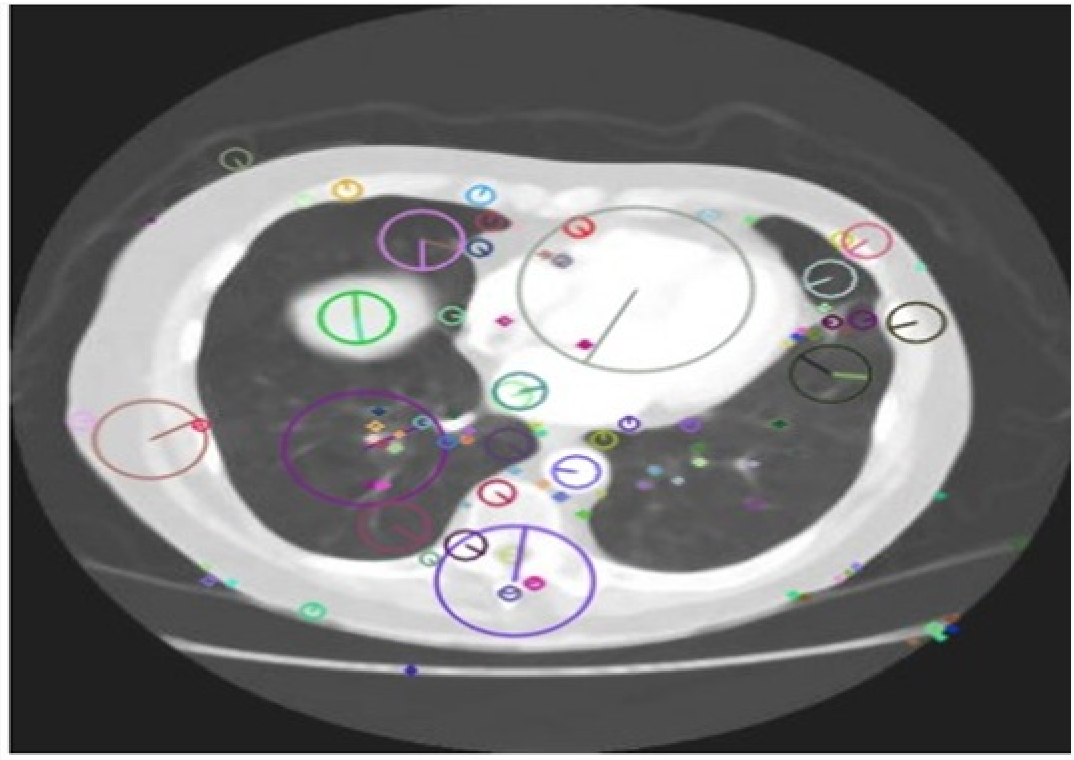


Fig. 4.8 SIFT Image

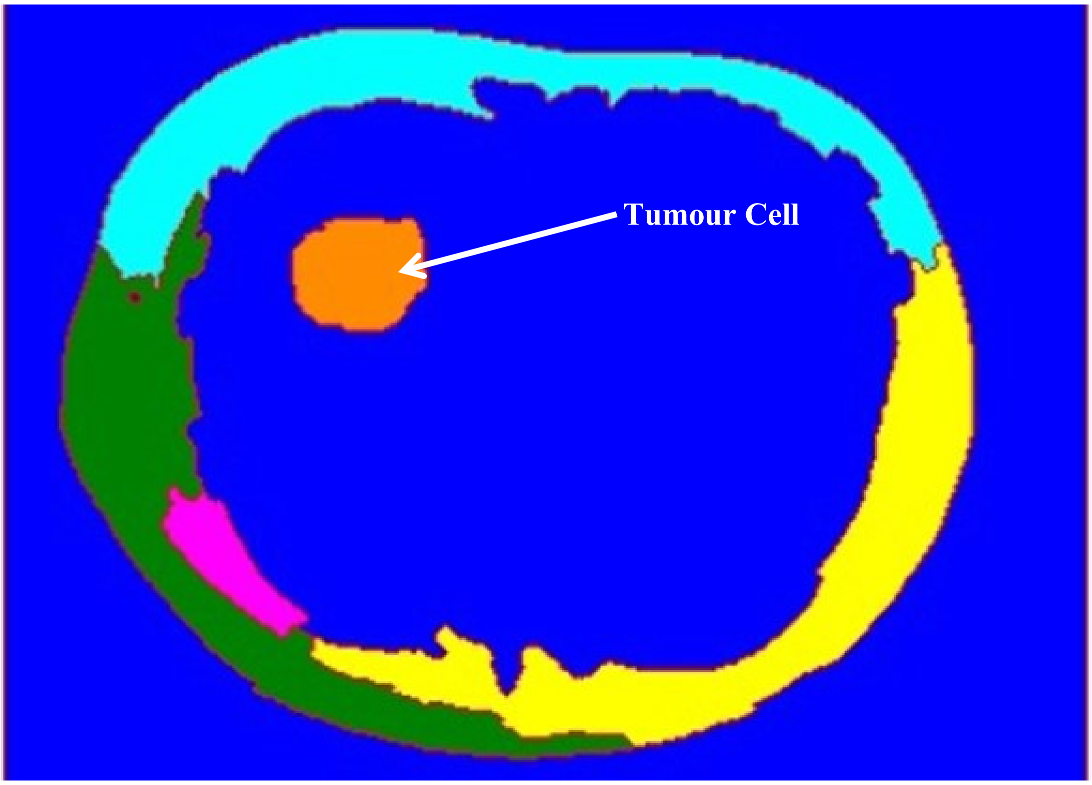


Fig. 4.9 Watershed Applied Image

4.1 CONCLUSION:

The project is based on detection of lung cancer by Machine Learning algorithms. In this project a medical CT image has been considered and this image has been pre-processed to increase the quality. Noise from the image has been removed using median filter and then the image is segmented into various sub groups called image segments which helps in reducing the complexity of the image to make further processing of the image simple, then watershed algorithm has been applied to the image. The project has successfully identified the tumour cell.

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