EMPOWERING LUNG CANCER PREDICTION: THE ENHANCED ARTIFICIAL BEE COLONY OPTIMIZATION (EABC) APPROACH

Dr.A.Sathishkumar Professor / BME

Erode Sengunthar Engineering College Perundurai – Tamilnadu Mail id : sat090579@gmail.com

Dr.P.Dhanasekaran Professor / CHEMICAL

Erode Sengunthar Engineering College Perundurai – Tamilnadu Mail id : <u>dhanasekaran.p69@gmail.com</u>

ABSTRACT

The fundamental objective of lung cancer diagnosis is to streamline the testing procedures. It is accomplished by integrating a variety of techniques for performing image pre-processing, feature extraction, and classification utilising a bio-inspired methodology. To minimise The distortion in the unprocessed picture input, filtering is used. To discover the area of concern, segmentation is used. To learn more around the impacted sections, the feature selection is carried out. To locate the corresponding features on the needed image while maintaining suspicion, the bio-inspirational search method is used. The algorithms developed by this research will be very helpful to radiologists and doctors in identifying the areas of the lungs that are impacted by cancer. There are several tests that may be used to detect cancer in a lung image, and one of these methods is suggested to locate the cancer-affected area. Using image clustering based on image intensity, locate the areas of the lung pictures affected by cancer. The pre-processing, contrast enhancement, and segmentation processes used in this work. When the detection is not made at the proper moment, the problem's complexity rises. Due of the aforementioned circumstance, lung cancer monitoring systems typically employ the Enhanced Artificial Bee Colony Optimization (EABC) technique, which describes how the target's picture may vary for many potential solutions of the object. This study addresses the issues of object detection, noise reduction, segmentation, feature extraction, and calculating the accuracy level.

Keywords: Enhanced Artificial Bee Colony Optimization (EABC), Marker-Controlled Watershed, Artificial Neural Networks

1. INTRODUCTION

In the human body, cancer causes aberrant cells to proliferate out of control. Normal cells in a human organism grow, divide, and die in a planned manner. The cancerous cells in carcinoma do not die; rather, they grow and spread rapidly. It causes an odd buildup of cells that spreads out of control. Cancer is the most prevalent cause of death worldwide. The WHO estimates that

carcinoma caused 7 million fatalities in 2015 or 13 percent of all deaths. By 2030, it is predicted that this disease will be responsible for 13.1 million fatalities. At that point, curative treatment is no longer practical. The most dangerous form of cancer, both in industrialised and developing nations, is lung cancer. Lung cancer is becoming more common in emerging nations as a result of rising lifespan expectation, urbanisation, and adoption of western lifestyles. Therefore, the foundation of lung cancer control continues to be the long- term outcome of cancer patients and early lung cancer diagnosis. Due to scarce resources and inadequate health systems, the majority of cases are discovered at a later stage. In order to expedite referral for diagnosis and treatment, it is vital to implement awareness programmes on early indications and symptoms.

2 RELATED WORKS

A suggested Adaptive Switching Median Filter by J. Aalavandan et al (ASMF). This procedure modifies the Switching Median Filter procedure (SMF). This method involves two stages for noise removal. In the first step, locate the noisy place. Here, thresholding values are used to create a binary image. wherein the binary image's values of 0 and 1 designate noise-free and noisy pixels, respectively. ASMF is used to reduce noise at the second stage. This suggested solution provides the optimum performance while keeping important and edge features, according to performance measurements. This approach is capable of eliminating salt and pepper sounds.

A technique to eliminate instinct noise by a min-max filter and midway filter was put forth by Sreedevi, M. et al. [5]. The min-max filter is used to locate the dimmest points in the image and minimise salt noise; it is also used to locate the brightest areas and reduce pepper noise. The midpoint between minimum and maximum values is determined using the midpoint algorithm. This method is applied on every image pixel that has been damaged. For noise density levels up to 70%, the suggested method produces superior results. Another aspect of study has a decision-based strategy that has been implemented in place of the traditional or enhanced way to reduce impulsive noise.

3 PROPOSED METHODOLOGY

Three crucial processes are included in the proposed Enhanced Artificial Bee Colony Optimization (EABCO) for the design and development of a lung cancer detection system.



Figure 3.1. Proposed Lung Cancer Detection

Utilizing feature extraction and image enhancement, pre-processing is done. Segmentation and the 5-level HAAR wavelet processing technique are the next steps in the extraction procedure. Finally, lung cancer picture categorization is followed by extraction, and the entire process is implemented in MATLAB. Collecting the lung CT image is the first step in the lung cancer detection paradigm. The LIDC-IDR [8] image collections, which are saved as pictures and accessible using MATLAB, are where the lung CT scans are gathered from. Because CT scan images have little noise, they are ideal for use in the detecting process. The attained CT scan images are saved in JPEG/PNG format after being made clearer by removing some minor noise. While processing the lung diagnostic, the procedure also reduces misrepresentation. The 512×512 pixel resolution is used to capture the input images.

3.1 ADAPTIVE HISTOGRAM EQUALIZATION FOR IMAGE ENHANCEMENT

It applies AHE, an extension of the traditional Histogram Equalization (HE) procedure, to improve the input CT scan images. This procedure enhances the contrast of the images and is suitable for enhancing local contrast in images using adaptive histogram equalization precise

manner with pixel noise removal. According to the limited surrounding area of the image, each pixel is enhanced, and then HE is applied. There is a potential of noise amplification and boundary region artefacts when employing adaptive histogram [6].

Using the function, the Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to pictures to combat the occurrence of artefacts. While operates on discrete, or tile- based, portions of the image, histeq functions throughout the full image. While employing CLAHE, they act on a tiny portion of images, considerably enhancing the source image, as opposed to using HE, which often works on the complete regions. The contrast of each tile is increased, making it so that the histogram of the production

zone almost exactly resembles a quantified histogram. After the equalisation procedure has been completed, the adjacent tiles are combined using a bilinear exclamation to eliminate boundaries that were artificially created. This strategy also amplifies noise in order to reduce contrast, particularly in cases of homogeneous landscapes.



Figure 3.2.(A) Original Image (B) Original Image with Histogram Equalization (HE)

3.2 RESPIRATORY IMAGE SEGMENTATION

To obtain more comprehensive information on the chosen lung image, the procedure of image segmentation is used to divide the image into segments. The primary goals of segmentation are to make visual representation more understandable and to facilitate quick and efficient analysis. Typically, the segmentation procedure separates the images into main areas and objects. The end product of the segmented objects divides the entire image into a number of recognisable sections. The segmentation process uses the watershed method with marker control, and is described in the steps below.

Step 1: Computing a picture whose dark areas are taken into account as segmentation objects. Step 2: To discover the connected blocks of pixels within recognised objects, markers are employed in the foreground determination procedure.

Step 3: Using background markers, the undesirable portion of the image is identified.

Step 4: The image's segmentation makes it simple to distinguish between the marked locations in the foreground and background.

Step 5: Locate the watershed transform segmentation area of the image.



Figure 3.3 : Segmenting Images with Watershed Transformation

3.3 FEATURE DISCOVERY THROUGH 5-LEVEL HAAR WAVELET TRANSFORMS

In order to identify the distinct components, the lung image typically has additional texturing information. The quality of matching the database photos to the extracted lung image pattern is improved by using a noiseless extraction approach. To do this, a five-level HAAR wavelet transform is used to decompose the image. The following are the techniques to extracting features utilising the 5 layers of Wavelet transform using HAAR:

Step 1: On the input lung picture, do 5 level decomposition for 2D DWT with HAAR.

Step 2: The division details during the level 4 and level 5 processes provides the lung image's feature vectors..

Step 3: The lung imaging code's obtained feature vectors are in binary format. Step 4: Store the lung image's binary code in the database.

3.4 ELEVATED ARTIFICIAL BEE COLONY OPTIMIZATION (EABC) IN LUNG CANCER PROGNOSTICATION

The situation of the food resource issue is a potential optimization solution in the Artificial Bee Colony (ABC) algorithm [15, 16]. The calibre of the solution that goes along with a food source is proportional with its quantity. There are as many employed and onlooker bees as there are potential solutions to the problem at hand.

Three very important control parameters in basic ABC are the amount of food sources, which is equivalent to the number of observers or hired bees (SN), the permissible value, and the number of optimum cycles. The honeybee colony's rate of recruitment indicates how quickly it decides on and makes public a newly discovered food source. The development and survival rate of the bee colony will be

determined by how quickly the best resource is discovered and used. A thorough case analysis of the current issue and an effective implementation of the suggested technique are crucial.

3.5 ENHANCED ARTIFICIAL BEE COLONY (EABC) OPTIMIZATION.

By bring together an adaptive method of lung cancer detection, the ABC algorithm is improved in the research work that is being suggested. In this, the population of solutions is first produced at random and changes over time in an adaptive manner. Taken from each person in the current population, the following statistics represent The median number of people of the position of future generations' food sources:

Set the initial population of solutions xi, G in the first step. Declare pol as a variable by initialising it to 0. For (i=0; ilung images; i++) in step two

Step 3: lung images = (int) (pol/lung images) + 0.5; Step 4: lung images = int pol= pol+ lung images[i][D].

Step 5: Even with controlled demographic aspect when the number of lung photos is equal to half the size of a bee colony.

Step 6: Next, carry out the actions listed in stages three through ten of the pseudocode for the ABC optimization method.

3.6 Dataset Description

The Lung Image Database Consortium was created by the National Cancer Institute (NCI) or LIDC, which uses the images gathered in other research facilities (7–9). The LIDC's job is to

(a) develop an image database as a freely accessible online resource for research into, instruction in, and evaluation of CAD techniques for CT-based detection of lung cancer and diagnosis, as well as (b) the development of this database to strengthen the link between 3D, time-sensitive, compulsively pulverised fact and the explanation of CAD techniques for lung nodule identification and arrangement. As a result, the LIDC is assured to make three categories of objects stand out:

Step 1: Nodules that are less than 3 mm in diameter, regardless of their histology. Step 2: Uncertain nodules with a diameter of less than 3 mm

Step 3: Nodules with a diameter of under 3 mm.

Step 4: Non-nodules and nodules that are less than 3 mm in size they are obviously harmless (i.e., strongly hardened) were specifically omitted from marking.

The study of the simulation uses almost 100 lung pictures. These selected lung images are utilised to assess the performance of the suggested EABC.

4 EXPERIMENTAL RESULTS

Utilizing the MATLAB programme, this research project was constructed and designed. The LIDC open repository is where the lung imaging database is gathered. The processes of picture pre-processing, separation, and feature abstraction are carried out with the use of an image processing toolbox. The suggested EABC-based lung cancer detection system uses its functionalities.

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Figure 3.4 Example Image 1: The Entire Lung Cancer Detection Process (A) shows the unique picture with the histogram equalised (B) shows a dilated gradient mask (C) shows an improved image with Gabor filters (D) shows an image without borders (E) shows a potential cancerous area indicated by a green boundary.

The suggested EABC-based approach can identify Nodules in the lungs that measure 3 mm or less, making it possible to identify lung nodules even in their earliest stages. As a result, it offers the capability for early lung cancer diagnosis, considerably increasing patient survival rates. Using the EABC optimization technique, this distinguishes between malignant and non-cancerous candidate nodules. Using CT pictures with a high level of sensitivity and a manageable false positive per image, number, an autonomous system can be set up for the early lung cancer detection. As a result, the technology will no longer postpone the radiologist's diagnosis. On the other hand, the suggested system can detect lung nodules with a diameter of less than 3 mm, meaning it can do so even when the nodules are still in the early stages.

4.1 PERFORMANCE EVALUATION METRICS

FERR, or False Error Rate: The ratio of negatives that are accurately classified as malignant versus noncancerous or vice versa is measured. Comparison of lung imaging feature extraction performance based on sensitivity, specificity, and accuracy using five distinct ways When compared to the other four approaches, it is practical to conclude that the five-level HAAR wavelet transform provides accurate results for the feature extraction of the lung picture. The worst scenario is carried out by DWT. In terms of feature extraction, the two level HAAR transform is placed second. It has been found that segmenting images allows for a more precise observation of the visual information in more detail.



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In comparison to the other four approaches, the suggested five-level HAAR wavelet transform yields more accurate results for lung image extraction. The worst scenario is carried out by DWT. The HAAR transform with two stages comes in second place for feature extraction. The details of the image information can be examined more precisely when the photos are segmented further.

4.2 OPTIMIZATION OF CLASSIFICATION ACCURACY

The performance of lung cancer identification in CT scan pictures is optimised in this study work using the bio inspirational based method. The fitness value of the EABC optimization and the capacity to more accurately identify the region of interest considerably reduce the uncertainty in the determination of the lung nodules.

Parameters	ANN	ABC	EABC
Root Mean Square Error	24.9	9.06	8.13
Peak Signal to Noise Ratio	45.6	31.09	83.10

Table 1 Result of the Proposed Method EABC with the other Two Existing Approaches

The two measures utilised to compare the proposed algorithm with existing algorithms are the RMSE and the PSNR. The RMSE value of the suggested EABC method is significantly lower than those of the two other current algorithms. ABC and ANN When compared to ANN and ABC approaches, the suggested EABC exhibits higher PSNR values.

5. CONCULSION

In order to detect CT scan images showing lung cancer early, modifying images is used in this study to improve the pulmonary scan images' quality used as input. The time it takes to complete the entire process has also significantly decreased. Focused pictures make it straightforward to identify abnormal lung nodules or tissues. The critical difficulties in this research are lung imaging accuracy and quality. Comparing the proposed methodology to the other current methodologies, the results are more encouraging. A comparison of normality and abnormality is made based on the general characteristics of the photographs. The most important characteristics for an accurate comparison of A particular percentage of the lung cancer images was produced utilising EABC optimization and more properly categorises the likelihood of lung nodules for cancer as a percentage.

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