Helix (2021) 11 (5): 11-19

https://doi.org/10.29042/2021-11-5-11-19

# Detection of Lung Cancer in CT scans via Deep learning and Cuckoo Search Optimization and IOT

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**Received: 6th August 2021, Accepted: 18th September 2021, Published: 30th October 2021**

## Abstract
Radiologists spend a lot of time and effort sifting through CT scans to find cancerous lung lesions. Using image processing techniques, a new diagnostic tool for medical purposes, the suggested method is applied In order to implement the proposed system, there are two steps. Optimization and deep learning are used to detect lung cancer in the early stages. In the second step, data is transferred from the MATLAB to the authorised PC using ThingSpeak. After a database search, the CT image is pre-processed using a median filter to remove background noise. Next, the Otsu-Thresholding approach segments the image together with the Cuckoo scan, and the feature extracts identify the illness size and location. Finally, the segmented image is sent to a deep learning system, which determines whether or not it contains anything normal or abnormal. ThingSpeak, MATLAB's IoT cloud, receives the final parameters. The suggested technique additionally measures and compares current system outcomes with various PSNR, correlation, precision, specificity, sensitivity, and MSE metrics.

***Keywords:*** *Lung Cancer, Image, Deep learning, CAD, Cuckoo, MATLAB, Otsu, Thingspeak*

## Introduction
The medical business is currently looking to gain a significant edge as the number of Internet-of-of-things (IoT) users expands significantly through the usage of wearables, tablets, and virtual reality applications. For example, biomedical imaging methods include x-rays (controller scans), sound (ultrasounds), magnetic (controller), and radiation for processing and communication of unmatched data on the current condition of an organ or tissue (nuclear medicine). However, due to the rising complexity and urgency of processing the data generated by these instruments, capital and resources are becoming increasingly scarce. Medical research relies heavily on the use of biomedical images. To convey information that is not obvious or implicit in the field, clinicians used techniques such as ultrasonic, electrical and radiography. Imaging technology is essential for medical devices. The entire patient's body as a molecular type, including ultrasound, anatomy, ophthalmology, and dermatology, plays a vital role in the treatment of patients.

Visualizing internal organs and tissues for the purposes of biological, scientific, and organ-and-tissue research is known as biomedical imaging. Images of the skin's anatomy and physiology are regularly sent to libraries in order to uncover flaws in medical representation. Instruments like RAI, RI, and ULTROS are frequently employed in the field of radiology. Consider a piece of machinery. Non-invasive information about a patient's internal organs can be obtained through a variety of medical imaging techniques. By overcoming these restrictions and incorporating more digital IoT (Internet of Things), edge computing technology is increasingly succeeding in biomedical imaging. In the medical field, pictures and procedures are used to create internal anatomical images for the development and usage of tissues and organs. Medical networks' increased computing power and Internet of Things (IoT) capabilities will allow providers to access patient data in real time, which is a key goal of this initiative.

Early detection methods for lung cancer are becoming more common in other nations. Low-dose CT users' death rate has fallen considerably after three rounds of mandatory screening. These measures necessitate an abnormally high number of CT scans performed by radiologists. Even well-versed physicians sometimes have difficulty spotting nodules. The number of CT scans performed for scientific purposes puts a heavy burden on radiologists. Preventive and early warning treatments are increasing in number, therefore scientists are investigating computerised solutions that reduce working conditions for doctors, improve diagnostic accuracy, and minimise medical expenditures.

## Literature Review

A real-coded GA is used by some researchers to alter the image's grey intensity transformation.. This algorithm's fundamental flaw is that it requires the user to spend a significant amount of time reviewing each image, making it time consuming. Based on an objective criterion, a similar technique was employed. The photo's proportional edges count and the intensity curve's clumping are both noteworthy. As a result, each approach has its own advantages and disadvantages, and each is best suited for a particular noise distribution. For the most part, there is no single method for improving photos that can deal with a wide range of noise distributions.

An important metric in medical imaging is the signal-to-noise ratio (SNR or CNR). Hardware (phased array coils, low noise preamplifiers, and so on), imaging optimization, and post-processing (signal averaging, directional filtering) have all been tried in various ways to improve the SNR or CNR imagery in MR scans. Images when the SNR is quite low and some resolution loss is acceptable can be enhanced using the techniques presented thus far. There has been limited success in applications where Image SNR is moderate and maintaining resolution is a primary concern. We are creating a more general method (a GA approach) that can be customised to arbitrary imagery shapes without just taking geometry into account, which encompasses most medical imaging approaches in general and MR or EMR imagery in particular. Using a modified CNR as an objective criterion, the findings were compared to quick and adaptable approaches for enhancing contrast in another application. The use of GA to enhance tomographic pictures in various imaging modalities is becoming well-documented.

Another technique was developed by Eberhart and Kennedy in 1995. The optimum solutions are being sought by each particle, which has its own memory and an adjusted velocity in relation to its neighbours. Differences in the structure of the PSO mean that it is more likely to be detected at a local level, making it easier to detect. PSO particles, on the other hand, have the ability to remember and influence the other particles. As a result, faster convergence is possible when using this algorithm characteristic. Different from the PSO algorithm, chromosomes communicate with each other in the GA algorithm.

Vitorino Ramos et al have provided "a way to design creative procedures on these topics." These images were created as a result of an optimization and compositional dilemma "Genetic techniques for clustering small colour patches using evolution Means that clustering approaches Genetic algorithms in an unrestricted manner." Despite the availability of numerous types of segmentation, and the time required and 'only then can a segmentation-algorithm manage multiple frames, there is no general algorithm that can operate well for all photographs. Additionally, photos must be quickly segmented. Despite years of research, completely automated segmentation is still necessary for in-depth image analysis. The picture segmentation process includes a number of adaptive processes, such as GA. Some examples are: ant-colony improvement, clustering, and ringing, Simulation of clusters, neural and self-adaptive networks, and regularization. Because genetic algorithms (GAs) are "capable of missing local optimal solutions to attain global optimum and of obtaining an optimal solution rapidly from a broad search field," they can manage these issues. There have been some effective applications of genetic algorithms to image segmentation, but none of them have been able to address the problem completely.

## Research Methodology

The cuckoo scan CT image optimization technology is used to find the lung cancer. Here is a more in-depth look at the proposed strategy in Figure 1.
The first step is to look at the CT scans associated with lung cancer. CT pictures typically contain low-frequency noise. A medium filter is needed to get rid of the noise pre processing. With Otsu's thresholding technique, the median filter output picture is divided into PSO and CSO, which are currently being considered as well as PSO and CSO that have already been implemented.

In order to determine whether or not the image is normal or abnormal, the image is first segmented and labelled in deep neural networks. To remove tumours or cancer, local binary pattern structure extraction (LBP) is performed. A segmented image's properties are measured and sent to the authorised user via ThingSpeak.

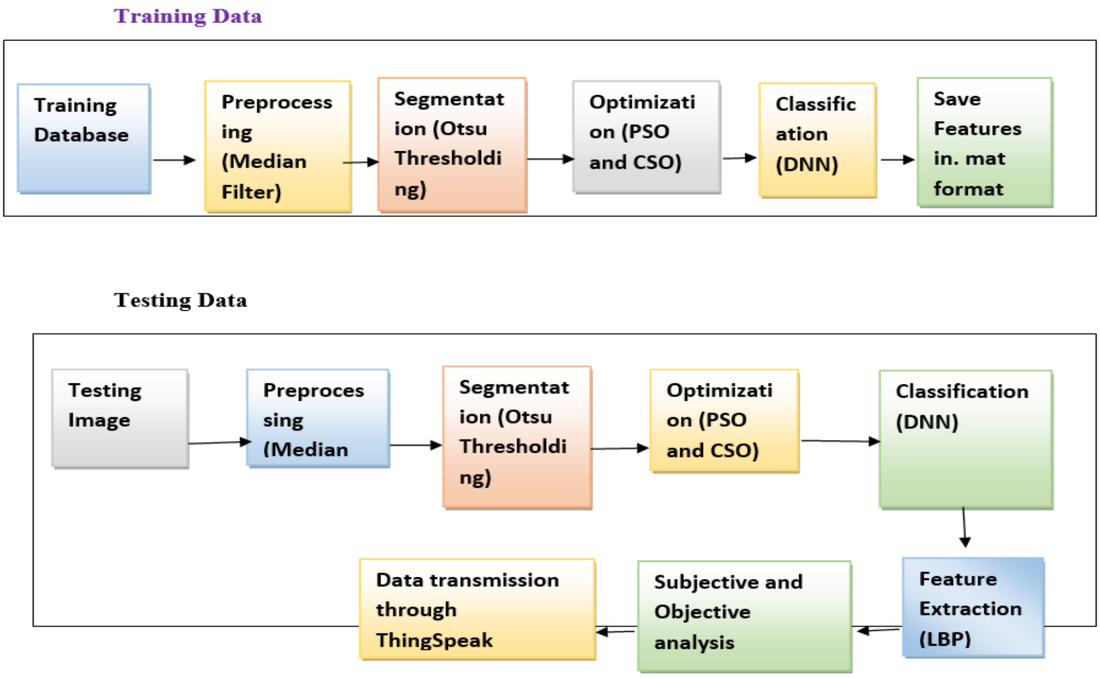



**Fig 1: Block diagram of proposed method**

## Results and Discussion

Optimisation and image processing have played a major role in engineering and technology in many fields, including computer science, medicine, and astronomy. Magnetic resonance imaging (MRI) and the analysis of astronomical information necessitates the use of digital cameras and new gadgets, such as Google Glass and self-driving cars, that require a substantial number of processing stages such as picture transfer and distortion correction. Digital images are mostly created through a series of intermediate phases. Incorporating traditional methods of image augmentation is determining whether or not a simulated image is adequate for the task at hand. As a result, the amount of change in a photograph cannot be accurately quantified. To establish whether or not the final image is acceptable, it must first be sketched and then evaluated by the artist. As a result, genetic techniques and metaheuristic algorithms have been used to replace human inspections and the creation of fake images. It is possible to create superior image neutralizations and computations using the approaches of metaheuristic and genetic algorithm.

Lung cancer can be detected using a variety of optimization techniques, including as article swarm optimization and genetic algorithms. However, because of their own flaws, the new optimization approaches are unable to accurately diagnose cancer. Each imaging mode has its own characteristics and different values of intensity. Owing to different grey levels the single approach of optimization functions to detect illnesses in multiple images like MRI & CT. Some of the drawbacks of existing methods are-The optimization techniques yield less precise images, Fast time for delivery is missing and one method of optimization alone is not used to diagnose neoplasms in multiple medical imaging

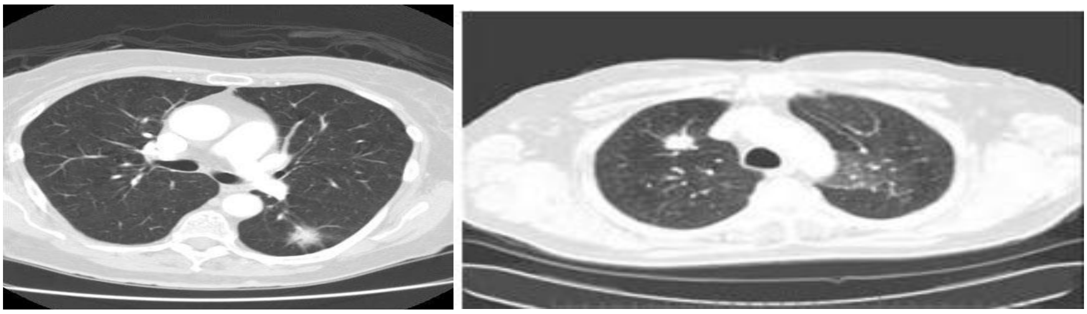
Hence a hybrid optimization is suggested for various imaging types for disease detection.

An initial malignancy such as lung cancer is discovered using a cuckoo search algorithm in CT medical pictures with MATLAB and the attributes collected are communicated to doctors with Stuff say. The database was used to obtain the images of CT scans showing lung cancer. The Cuckoo Search Algorithm (CSA) principle can be used to solve the thresholding problem, which is referred to as an optimization problem in this procedure.

The simulation Existing and proposed results methods are shown below.

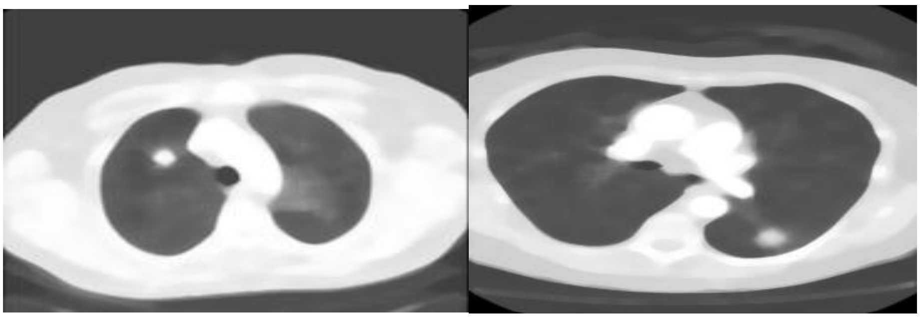
## EXISTING METHOD RESULTS

**Particle Swarm Optimization Algorithm for Detection of lung cancer in CT image:** Fig 2 & Fig 3 display the input and median filter output of pictures of CT lung cancer. The low frequency noise of the CT image is usually less distortion. The input image is stored in medium filter to reduce noise and distortion from the CT image.



**(a) Input Image 1** **(b) Input Image 2**

**Fig 2 (a) and (b): Input CT Lung Images**



**(a) Image 1** **(b) Image 2**

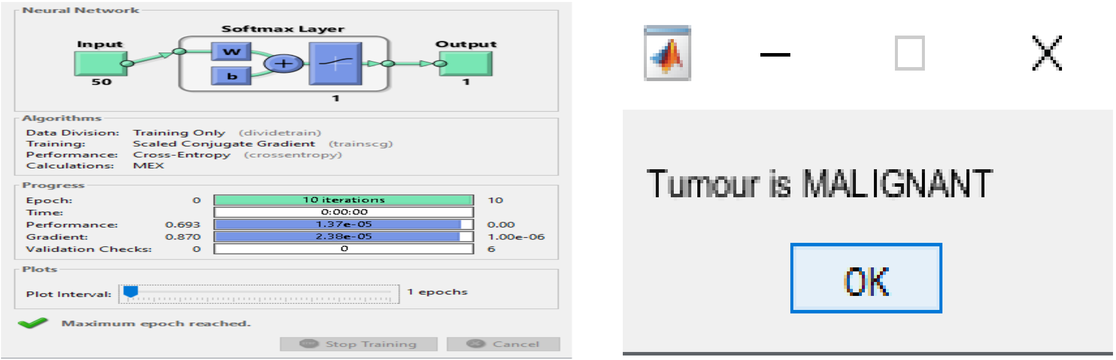
**Fig 3 (a) and (b): Median filter output**

The output image of the CT filter is segmented using an Otsu threshold and an optimization technique for tumour detection. In the beginning, the CT image is segmented using only the simple Otsu threshold, which maximises the segmented class's absolute class variance.

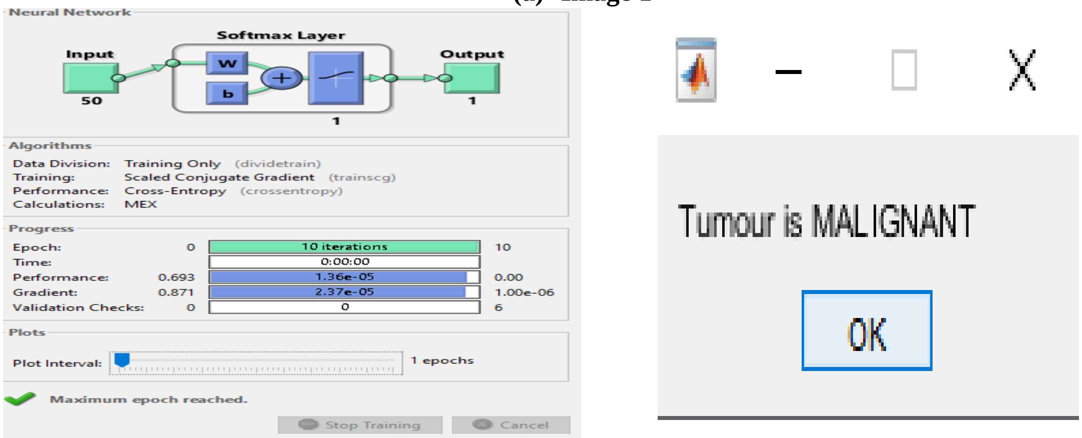
**(a) Image 1** **(b) Image 2**

**Fig 4 (a) and (b): Segmented output images by PSO**

After partitioning the image, a deep classification is implemented where the specified image is classified as normal or abnormal when a message is shown as "Tumour is MALIGNANT or Tumour is BENIGN ".




**(a) Image 1**




**(b) Image 2**

**Fig 5 (a) and (b): Classification and Processing output images by Swarm Optimization Algorithm**

After classification, the picture is extracted by feature. The extraction function extracts the features of a file. The local binary pattern is used as extraction of features in this work.

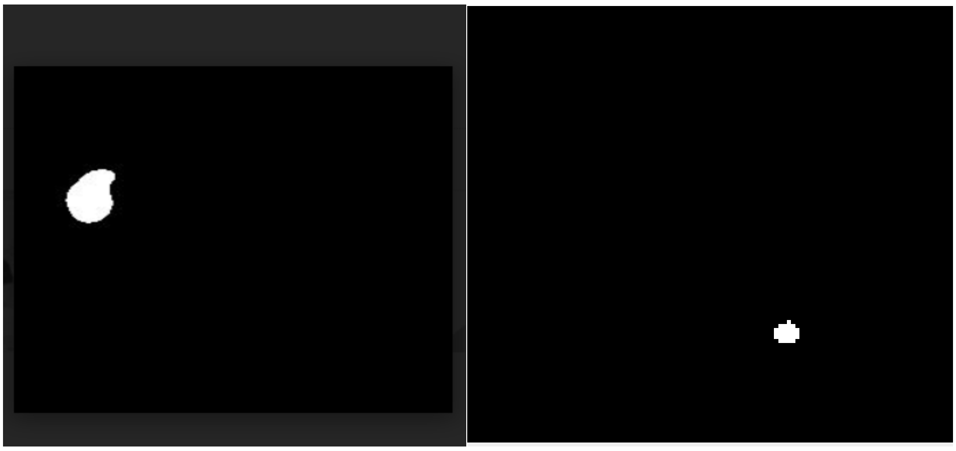
The Statistical attributes obtained from the particle swarm optimization method is shown in Table1.

**Table 1: Attributes Obtained from Existing Method**

| PARAMETERS | IMAGE 1 | IMAGE 2 |
|---|---|---|
| **MSE** | 0.186241 | 0.204916 |
| **PSNR** | 22.7293 | 21.8993 |
| **Specificity(%)** | 97.18 | 99.98 |
| **Sensitivity(%)** | 92.21 | 92.01 |
| **Accuracy (%)** | 93.55 | 92.22 |
| **Entropy** | 0.61014 | 0.65007 |

## PROPOSED METHOD RESULTS

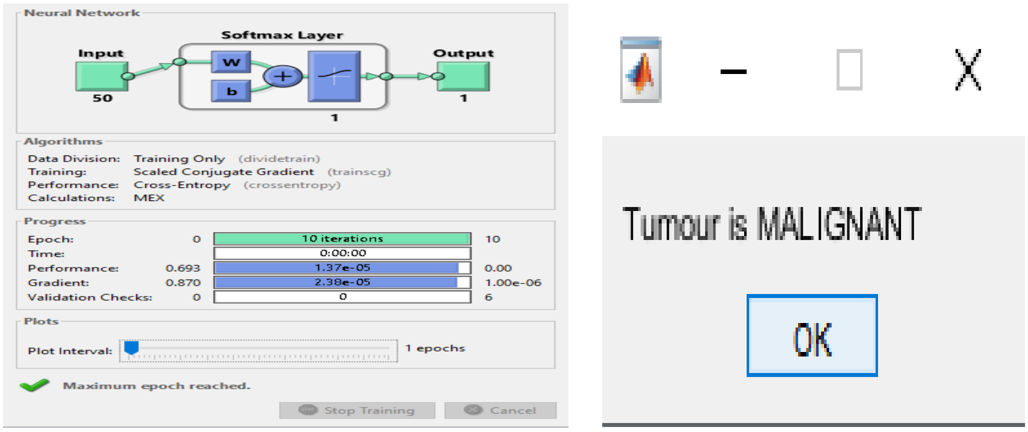
**Cuckoo Search Algorithm for detection of lung cancer in CT image:** CT lung cancer media output representations are shown in Fig 6 & Fig7. The Otsu threshold and an optimization technique are used to segment the tumour in CT scans. First, a basic Otsu threshold is used to optimise the segmented classes, called "all class variance," in the CT picture. Cuckoo optimization analysis can improve the threshold technique's results. The optimization approach used by cuckoos follows a pattern found in the avian world. It's a way of thinking. The cuckoo, for example, does not lay eggs in its own nest but instead uses those of other birds. Host birds tear down or depart the nest if they are aware of the cuckoo egg, pi = (pi1, pi2... pid) pi=1, 2,.... N.



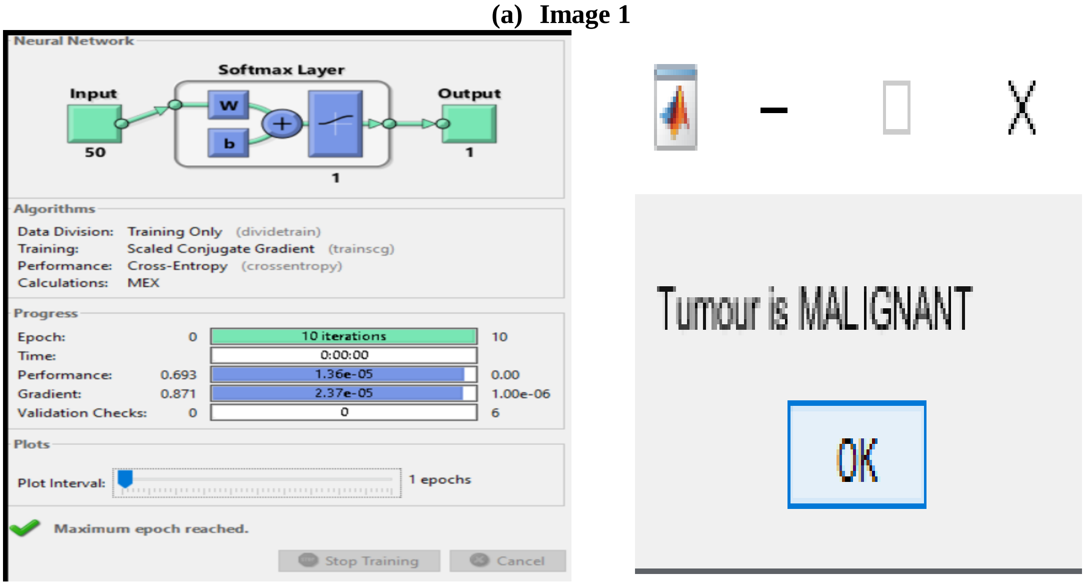
(a)Image 2 (b)Image 2

**Fig 6: Segmented output images by CSO**

After partitioning, the image is categorised as a deep sample, where the given image is normal or abnormal by showing a code as "Tumour is MALIGNANT or Tumour is BENIGN "




**(a) Image 1**




**(b)Image 2**

**Fig 7 (a) and (b): Classification and Processing output Images**

After classification, the picture is extracted by feature. The extraction function extracts the features of a file. This work uses the local binary pattern as an extraction tool.
The statistical attributes obtained from the cuckoo search optimization method is shown in Table 2.

**Table 2: Attributes Obtained from Proposed Method**

| PARAMETERS | IMAGE 1 | IMAGE 2 |
|---|---|---|
| MSE | 0.171994 | 0.154226 |
| PSNR | 43.4205 | 44.3676 |
| Specificity(%) | 95.4899 | 96.0148 |
| Sensitivity(%) | 96.5211 | 96.5834 |
| Accuracy (%) | 95.3551 | 95.4793 |
| Entropy | 0.610136 | 0.650074 |

**STATISTICAL ANALYSIS:** The below table shows the obtained attributes of PSO and CSO for Lung cancer detection in CT image.

**Table 3: Comparative Results of PSO & CSO for detection of Lung cancer**

| PARAMETERS | IMAGE-1 | | IMAGE-2 | |
|---|---|---|---|---|
| | PSO | CSO | PSO | CSO |
| MSE | 0.186241 | 0.171994 | 0.204916 | 0.154226 |
| PSNR | 22.7293 | 43.4205 | 21.8993 | 44.3676 |
| Specificity(%) | 97.18 | 95.4899 | 99.98 | 96.0148 |
| Sensitivity(%) | 92.21 | 96.5211 | 92.01 | 96.5834 |
| Accuracy (%) | 93.55 | 95.3551 | 92.22 | 95.4793 |
| Entropy | 0.61013 | 0.61014 | 0.65007 | 0.650074 |

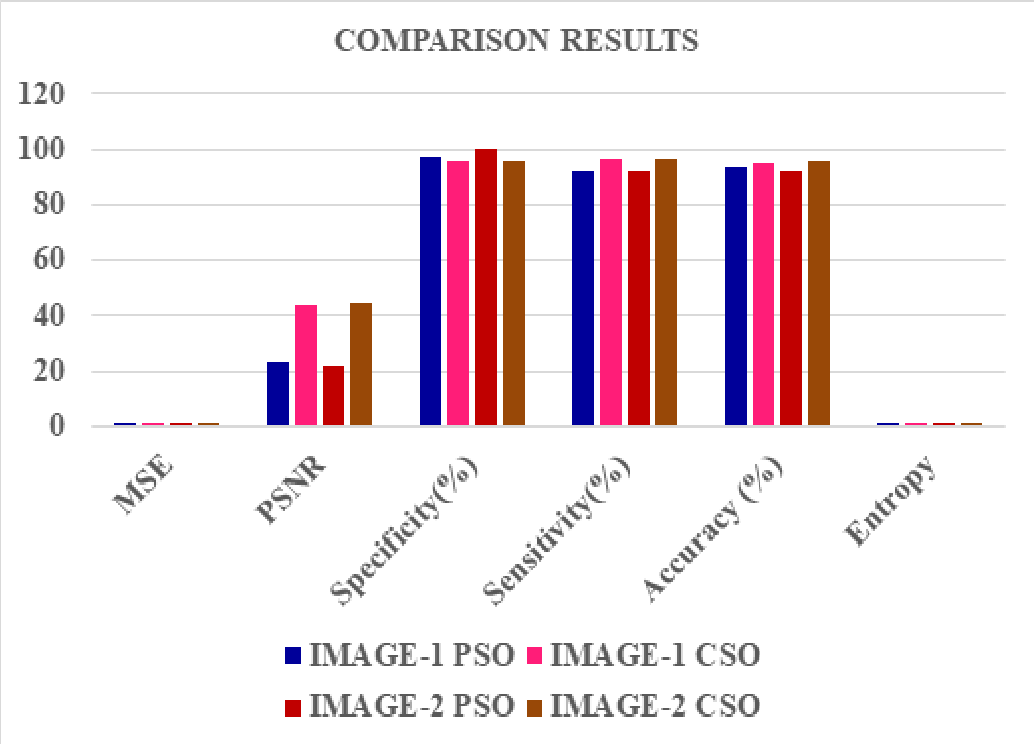



**Fig 8: Comparison Results**

The following map indicates the easiest way to achieve the lowest MSE i.e., 0.171994 for image 1 and 0.154226 for image 2 both high PSNR i.e., 43.4205 for images 1 and 44.3676 for images 2 and high precision i.e. 95.3551 percent for images 1 and 95.4793 for image 2.

Finally the result obtained is provided as a graph in the ThingSpeak and is only shared with the approved workers. The following figure shows the common ThingSpeak plots.

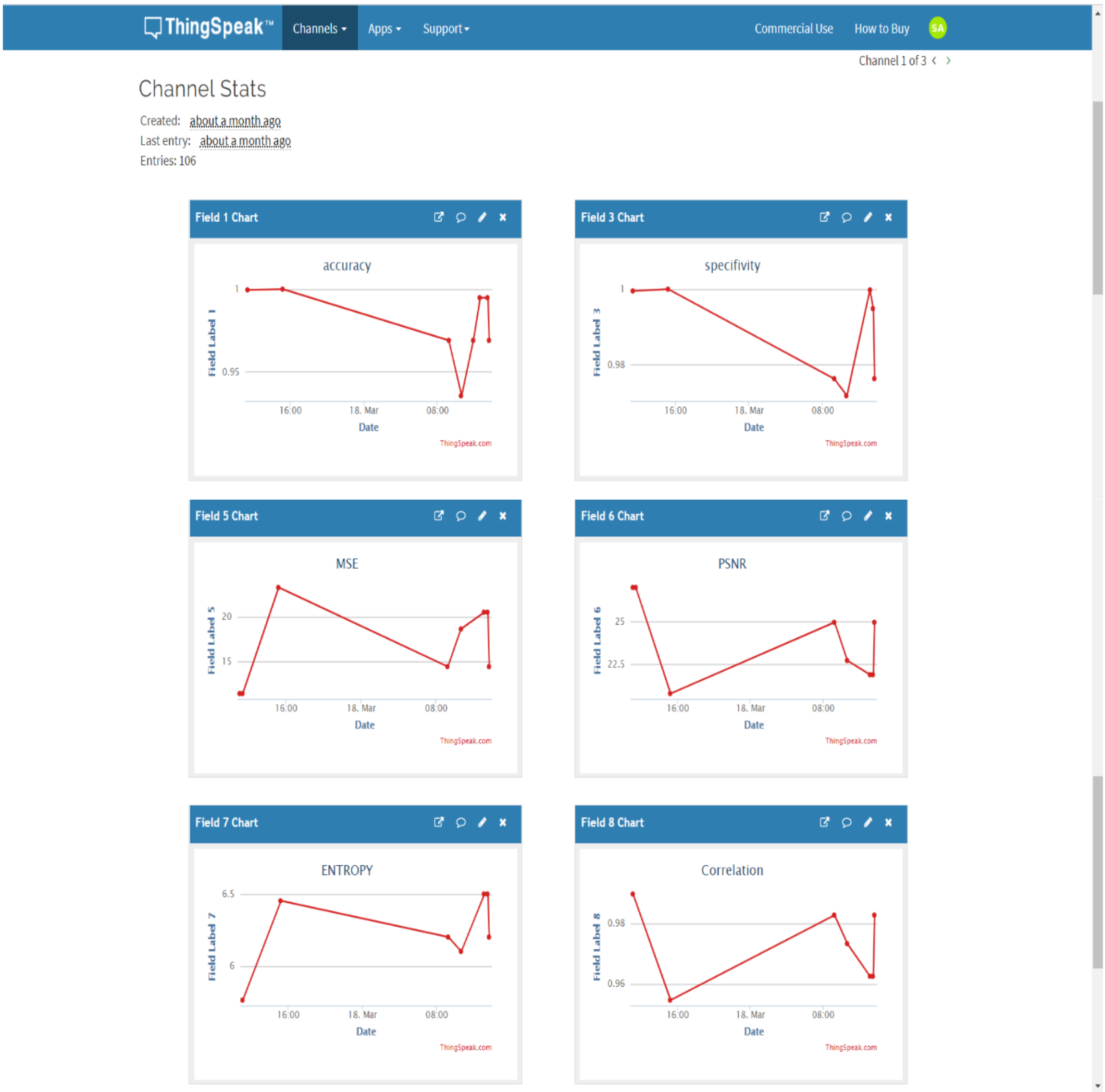



**Fig 9: Data Transmission through ThingSpeak**

## Conclusion

CT scan images from the collection are the first step in this project. To remove noise from the scanned images, they are subjected to a medium-filter analysis. There is an inherent optimization for cuckoos in the filtered videos, with the focus on tumour or disease explicitly segmented. The segmented image identifies areas where lung cancer has been found. Current technologies of swarm optimisation are typically referred to by various parameters such as PSNR, MSE, precision, accuracy, sensitivity, and other similar terms. Finally, Stuff Talk transmits the criteria it has gathered to physicians or radiologists.

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