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RESEARCH ARTICLE

A Novel Technique for Classifying Lung Lesions using Convolutional Neural Network Optimization Techniques

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ABSTRACT

World-wide cancer is the disease with the highest recurrence rate. Lung cancer is the most fatal of all cancer kinds. Lung cancer claims millions of lives each year. Early disease detection is extremely important for cancer patients. The survival rate increases when this disease is accurately predicted. But with the current techniques, accurate lung cancer detection is time-consuming and of utmost importance. The ability to examine genes and their relationships to various diseases, such as lung cancer, has been demonstrated by the accessibility of current technologies. The hybrid approach is suggested as a solution to this problem. The identification of cancer in CT scans is addressed in this study using a hybrid strategy that combines a whale optimisation algorithm and CNN classification. With the use of this technique, doctors can accurately identify lung nodules at an early stage.

Keywords: Optimization; Classification; Lung Cancer; Nodules; Convolutional Neural Network, Whale Optimization Algorithm (WOA); Discrete Wavelet Transform (DWT); Genetic Algorithm

INTRODUCTION

Lung cancer is a frequent cancer condition that can be treated quite successfully with an early [1] diagnosis. According to ACS (American cancer Society), in the year 2018 approximately 14% are lung cancer out of all cancer types [2].The use of image processing techniques and pattern recognition technologies to automatically recognise lung cancer from CT scans reduces human error and speeds up diagnosis [3]. In this study, CT images are examined using pipeline analysis to identify malignant tumours using image processing techniques. The first stage uses image contrast improvement and a noise drop to enhance the quality of CT pictures and the contrast of problematic spots in the image. In order to diagnose lung lesions accurately and effectively, a hybrid technique is suggested in this paper. The suggested method uses convolutional neural network to classify whether the detected section is cancerous or not, genetic algorithms as a segmentation method to precisely identify genes (lung nodule).

LITERATURE REVIEW

Ananya Choudhury et al. suggested a multi-objective genetic method for lung cancer segmentation in 2019 [4]. The genetic algorithm used in this method performs multi-level thresholding, and the connected component methodology is employed for classification. In this study, classification accuracy was measured in terms of true positives and false negatives, but segmentation accuracy was left out. Ammar Odeh et al. [5] suggested an early detection technique for lung cancer using genetics in 2017. In this study, the authors' accuracy was 84%. In 2017 Kamil Dimililer et.al [6] proposed a strategy for lung lesion detection using DWT. In this method DWT (Haar) is used for segmentation and extracted 4 output different images which are represented in vertical, horizontal, diagonal and approximation. Finally, all the images are processed through techniques like erosion and subtraction to extract the cancer area. By this method authors obtained 89% accuracy.

Mukesh Chandra Arya et al. [7] suggested a method in 2016 to use DWT to identify bulk tissues in chest X-ray images. By using this technique, the authors' accuracy was 86%. Manasee Kurkure et al. [8] suggested a method for identifying and categorising lung cancer in 2016. This approach uses a Nave Bayesian classifier for classification, a Genetic Candidate Group search for segmentation, and a clever edge detector. By using this technique, the authors' accuracy was 82%. This technique segments using the Canny edge detector. Due to its extensive computations and the fact that the canny detector doesn't conduct a decent operation for rotational regularity, it consumes extra computation time. All of the approaches that the authors have suggested have lower accuracy due to flaws including bad directionality, slow processing, lengthy computations, and complex computations. In order to address all of the shortcomings of the existing approaches listed above, a dynamic method for lung cancer identification in CT images is proposed in this study. CNN(Convolutional Neural Network) is utilised for feature extraction, and a genetic algorithm is used for segmentation.

METHODOLOGY

This method uses the CNN optimisation technique to identify and predict lung cancer from CT scans. The proposed method's processing methods are shown in Fig. 1. The lung cancer CT scan is initially read from the database. The captured image typically has minimal noise, and since direct noise removal runs the risk of reducing quality, processing techniques are used to eliminate the noise. A nonlinear digital filter called the median is used to cut down on noise.The Genetic method is then used to process the augmented image through segmentation. The segmented image is then processed using the feature extraction method. The CNN classifier is then given the retrieved image to determine whether the lung nodule is benign or cancerous.

Image Acquisition

The process of getting a digital image from a database is known as image acquisition. Typically, several scanners like MRIs and CTs are used to capture the images. The CT scanner produces the CT image. Through a process called computed tomography, each pixel in cross-sectional scans is given meaning [9]. This scan serves as a painless, non-invasive diagnostic technique. Additionally known as CAT, or computerised axial tomography.

Preprocessing

Pre-processing is the technique applied to images data to enhance the image. It lessens undesirable distortions and improves the characteristics of the image that are important for processing. The size of the pixel neighbourhood can be used to classify pre-processing methods. Image enhancement uses these techniques. Enhancement operations use sub-images of corresponding values and nearby image pixels. The noise and distortion are reduced during enhancement, which raises the quality of the image. The median filter is used in many bio-medical applications to reduce noise.

Median Filtering

Impulse and salt & pepper noise can be found in the collected CT images. The delicate details are hidden by these disturbances. By preserving the borders in an image, the median filter decreases impulsive, salt-and-pepper noise [10].

Segmentation

It extracts objects and boundary features. A challenging problem in medical images is to segment regions with boundary between object (Regions of Interest) and background [11]. To rectify this problem numerous segmentation methods have been proposed by researchers.

Classification

It is the process of removing data classes from a multiband raster image is referred as. To create topical maps, use the raster that results from image categorization after the first one. There are two types of classification: supervised and unsupervised, depending on the expert and computer's cooperation during categorization[12]. CNN, or supervised classification, is employed in this work. In order to characterise aimage, it makes use of spectral markings obtained from training examples.

Clustering

Clustering is a popular strategy to separate a significant amount of data from a small number of meetings [13]. When using k-means to cluster data, a large amount of data is split up into a large number of separate pieces and then joined into disparate groups [14]. There are two distinct phases in K-means. It leads the centroid of k in phase 1 and collects individual points from the cluster that is closer to the centroid in phase 2. One of the most widely used strategies for describing the separation of the closest centroid is Euclidean separation. The following equations are used to do the clustering.

$$D = || m(p, q) - C_n || \quad (1)$$

$$C_n = \frac{1}{n} \sum_{p \in C_n} \sum_{q \in C_n} m(p, q) \quad (2)$$

Where D is Euclidean distance and n is number of clusters

Segmentation by Genetic Algorithm

Using probabilistic techniques, GA is one form of optimisation strategy that is inspired by biological development. The concepts of "Natural Selection" and "genetic Inheritance" are used. John Holland first created this algorithm in 1975.GA is particularly suitable for challenging problems where minimal consideration is given to the fundamental research domain. A genetic algorithm maintains a population of competing solutions for the present problem and drives it forward by repeatedly applying numerous stochastic administrations. It uses stochastic operators to solve optimisation problems with workable solutions, applying these operations repeatedly to a set of feasible answers.
The GA algorithm is linked with many targets. It is connected to numerous stages, such as

The analogy between chromosomes and pixels.
To carry out segmentation and feature extraction
The valid fitness function is calculated by summing all the individual objects in the group sum. For certain hurdles, it is difficult to delineate the fitness function.GA operates based on the characteristics with Selection, mutation, crossover, and recombination.

Algorithm

- Generate initial population
- If the candidate is not best then
- Generate new population using descendant functions.
- Calculate each candidate fitness function.
- Return to the best solution (candidate).

Feature Extraction

Feature extraction is the process of breaking down and condensing a large initial set of images into smaller, easier to manage groups. Therefore, this method can make the further processing of the images simpler. The fact that these enormous datasets have a lot of parameters is their most crucial feature. These parameters require numerous calculation origins in order to be processed. The best feature from those large datasets can then be obtained by the selection and combination of variables, effectively reducing the data volume. Two well-known features, DWT, are used in this study for feature extraction, which is explained below.

Discrete Wavelet Transform (DWT)

Wavelet transform is a useful tool for a variety of image processing tasks and is used in many areas, including feature extraction, pattern identification, coding, and picture compression. A frequency domain approach is the wavelet transform. In this method, a function known as a wavelet is utilised in place of sine and cosine functions (such as Fourier transform). When a wavelet transform is used, the wavelet function keeps its shape but is moved along with the signal, compressed, and opened during the displacement, enclosing the entire signal.
This technique can produce varied resolutions for low- and high-frequency ranges, unlike the short-time Fourier transform.

Classification by CNN

A CNN typically consists of the convolutional layer, the pooling layer, and the fully connected layer. Each layer performs a different function. Each convolution neural network has two stages: a feed forward stage and a backward stage for training. The first process once the features enter the network is the point multiplication between each neuron's input and variables, followed by the application of convolution operations in each layer. From the literature, it is observed that using CNN models improves the diagnosis system performance [13].Optimising the weights of any CNN layer is the key goal here. The recommended optimisation algorithm (GA) exhibits appropriate advancements regarding the best CNN training.

This approach generated initial weight for convolution neural network by the operation of selection, crossover, and mutation. It utilised the global optimisation and [14] survival of fittest features of genetic algorithms. Learning performance after enhancement is superior to that of a conventional convolution neural network. Simulated results show that the genetic algorithm and convolution neural network combination technique has a greater classification accuracy than conventional convolution neural network and support vector machine. Fig. 2 illustrates a straightforward lung cancer diagnosis using standard CNN. The convolution layer in Fig. 2 analyses the output of the neurons that are input-connected to the local area. The calculation is done by multiplying the weights of each neuron by the activation mass, which is the region to which they are linked. The pooling layer's primary function is to subsample the input image in order to lessen the computational burden, memory requirements, and the number of parameters (over fitting). The neural network becomes less sensitive to image displacement (regardless of position) when the size of the input image is reduced.

Proposed Whale Optimization Algorithm (WOA) based CNN

Meta-heuristics are being used more and more frequently lately in a variety of applications. For the cross-entropy loss, for example, is one of these applications[15]. Several different types of meta-heuristic algorithms have been developed in recent years. Whale optimisation algorithm (WHO) is a brand-new meta-heuristic approach that Mirjalili and Lewis introduced in 2016 [16]. The bubble net hunting technique of humpback whales served as an inspiration for the whale optimisation algorithm. For certain applications, although being new, it produces good results [17-21]. In order to increase the effectiveness of the procedure, this algorithm is used to minimise cross-entropy loss for images of lung cancer. The whale optimisation method is used in this work to identify cancer in cancer photos.The primary goal of this exercise is to maximise the weights of each CNN layer. The suggested optimisation algorithm demonstrates appropriate advancements regarding the best CNN training.

The WOA is a brand-new stochastic optimisation technique that was inspired by how whales hunt [16]. WOA uses a random population collection of candidate solutions, like any evolutionary approach, to search for the problem's global optimal (maximum or minimum) answer. Until the optimum value is satisfied, the algorithm keeps updating and improving the answer depending on its structure. The WOA rules' approach to developing and updating the solution is the fundamental distinction between it and other meta-heuristic techniques. The WOA is modelled after the whale's trap and attack hunting technique; the usage of bubbles in spiral movements around the prey with which the trap is built is referred to as "bubble-net feeding behaviour". Fig. 3depicts the bubble-net feeding process' behaviour.

Fig-4 makes it obvious that the humpback whale initially blows bubbles around its meal. The whale's spiral motion is used to carry out this procedure. It then attacks the prey. The WOA's primary contributor is made up of this process. An optimised techniques of CNN with the help of WOA is shown is figure 5. According to mathematics, the explained generated bubble-net system is defined as follows:

Mathematical Model

Bubble-net feeding is a unique behaviour that can only be observed in humpback whales. In whale optimization algorithm (WOA) the spiral bubble-net feeding maneuver is mathematically modeled in order to perform optimization. WOA simulated hunting behaviour with random or the best search agent to chase the prey. WOA uses a spiral to simulate bubble-net attacking mechanism of humpback whales.

Encircling Prey

Current best candidate solution is assumed to be closes to target prey and other solutions update their position towards the best agent

$$\vec{D} = |\vec{C}.\vec{X}_{best}(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_{best}(t) - \vec{A}.\vec{D} \quad (2)$$

Where t indicates the current iteration, \vec{A} and \vec{C} are coefficient vectors, \vec{X}_{best} is the position vector of the best solution, and \vec{X} indicates the position vector of a grey wolf

$$\vec{A} = 2\vec{a}\vec{r_1} - \vec{a} \quad (3)$$

$$\vec{C} = 2\vec{r_2} \quad (4)$$

Where $\vec{r_1}, \vec{r_2}$ are random vectors in [0, 1].

Bubble-net attacking method (exploitation phase)

In order to mathematically model the bubble-net behaviour of humpback whales, two approaches are designed as follows

1. Shrinking encircling mechanism

This behaviour is achieved by decreasing the value of \vec{a} . a is decreased from 2 to 0 over the course of iterations.

2. Spiral updating position

$$\vec{D}' = |\vec{X}_{best}(t) - \vec{X}(t)|$$
$$\vec{X}(t+1) = \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}_{best}(t) \quad (5)$$

l is a random number in [-1, 1]

Search for prey

Humpback whales search randomly according to the position of each other

$$\vec{D} = |\vec{C}.\vec{X}_{rand}(t) - \vec{X}(t)| \quad (6)$$
$$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{A}.\vec{D} \quad (7)$$

Algorithm

```
Step1: Initialize the whales population Xi (i= 1, 2, ..., n)
Step2: Calculate fitness of each search agent
     X{best} = the best search agent
Step3: while(t < maximum number of iterations)
         for each search agent:
           Update a, A, C, land p
           if(p<0.5):
             if(|A|<1):
               Update current agent by eq. (1)
             else:
               Select a random agent X{rand}
               update current agent by eq (7)
           else:
             update search agent by eq (5)
         end-for
         Check if any search agent goes beyond the search space and amend it
         Calculate fitness of each search agent
         Update X_{best} if there is a better solution
          t = t+1
       end-while
Step4: return X{best}
```

Dataset Description

LIDC (The Lung Image Database Consortium) database has been used to attest to and analyse the suggested method: The Lung Image Database Consortium image collection (LIDC-IDRI) consists of diagnostic and lung cancer screening thoracic computed tomography (CT) scans with marked-up annotated lesions. It is a web-accessible international resource for development, training, and evaluation of computer-assisted diagnostic (CAD) methods for lung cancer detection and diagnosis. Initiated by the National Cancer Institute (NCI), further advanced by the Foundation for the National Institutes of Health (FNIH), and accompanied by the Food and Drug Administration (FDA) through active participation, this public-private partnership demonstrates the success of a consortium founded on a consensus-based process. Seven academic centers and eight medical imaging companies collaborated to create this data set which contains 1018 cases. Some examples of the LIDC databases are shown in figure 6.

Implementation Results

On an Intel Core i10-4790K processor with 32 GB of RAM and two NVIDIA GeForce GTX Titan X GPU cards with scalable link interface (SLI), experimental simulations are done using Matlab R2017® software. To evaluate the system performance, the suggested simulations are put into practise on LIDC database for lung cancer.10% of the data are used as the validation set, while 70% are used as the training set. As test sets, the remaining 20% are used.

The 80/20 rule is a division known as the Pareto principle. Approximately 80% of the 20% of causes result in effects. They are chosen at random to determine which images should be used for the training, validating, or testing part. To be fair all of the dataset images underwent image processing and are scaled to 640480. The WOA approach is used to train the proposed CNN. Since the radius and number of neuron cells differ in the experiment shown (Fig. 7), the learning rate varied between 0.2 and 0.9. Additionally, practically all the training pixels will be included in the prototype neurons.

The ideal situation is to choose a neural network with the least number of neurons. According to [22], the performance ratio can be used to choose an appropriate learning rate. Fig-8 demonstrates how the performance ratio and training duration will both rise as the learning rate rises. Even though performance ratio is important, a learning rate of 0.9 is used in order to trade off performance ratio and training time. LIDC database are used as the most relevant database to vouch for the suggested strategy, as previously explained. The proposed network is trained over 30,000 iterations. to produce an accurate and independent analysis of the images. After 60 iterations of the training phase, the final results are described using the mean values. Three performance metrics that are outlined below are used to demonstrate how well the suggested system performed.

For the purpose of detecting lung cancer, various research projects have been developed. Each of these approaches has its own challenges and drawbacks. It is impossible to use every one of these techniques. Thus, three techniques have been chosen for [23] comparison with our suggested method. Automatically extracted descriptors from this method are used for a fair comparison. For this comparison, some deep learning-based systems are also used, including XG Boost and Random Forest [24], Multi-resolution patch-based CNNs [25], 3D Convolutional Neural Networks [26]. A performance comparison between the proposed system and the mentioned approaches is shown in Table 1. framework is affected by employing the WOA optimisation method. The distribution of classification performance from the previous table is displayed as a bar chart in Fig. 7 for further understanding. The excellent effectiveness of the proposed method for the diagnosis of lung cancer regions is demonstrated by experimental findings.

CONCLUSIONS

A novel method for the detection of lung cancer is put forth in this research. The suggested approach employs a meta-heuristicconvolutional neural network optimisation strategy based on back propagation to train the biases and weights of the network. To do this, a lung cancer validation method that comprises a streamlined measured error between the reference and the system output is taken into consideration for the proposed optimised CNN. In this study, the whale optimisation algorithm—a recently developed algorithm—is used to reduce the error rate of the Convolutional neural network's learning stage. The proposed approach is known as CNN+WOA.

The proposed method is then put to the testing using images from two well-known database, namely LIDC (The Lung Image Database Consortium), and it is contrasted with three other well-liked categorization techniques. Final findings demonstrate the suggested system's accuracy superiority over the compared classifiers.

Conflict of interest statement: Authors state no conflict of interest.

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Table 1: Comparison among state-of-the-art Lung Cancer detection Methods

S.No	Method	Performance Metric		
		Sensitivity	Specificity	Accuracy
1.	Proposed CNN+WOA	0.94	0.91	0.91
2.	XG Boost and Random Forest	0.85	0.61	0.78
3.	Multi-resolution patch-based CNN	0.91	0.89	0.64
4.	3D Convolutional Neural Networks CNNs	0.86	0.77	0.89

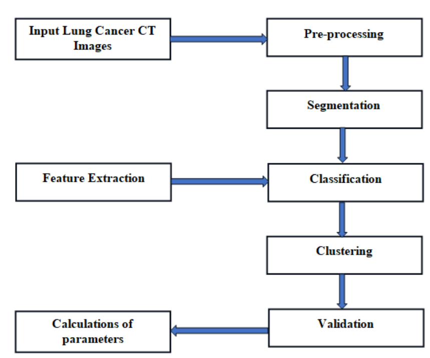


Fig. 1: Proposed Model

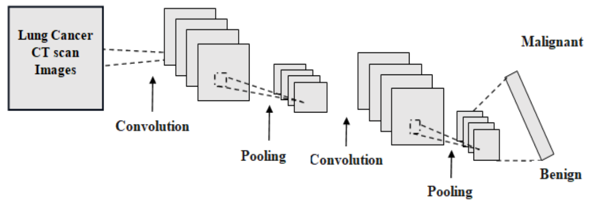


Fig. 2: A simple lung cancer detection using ordinary CNN

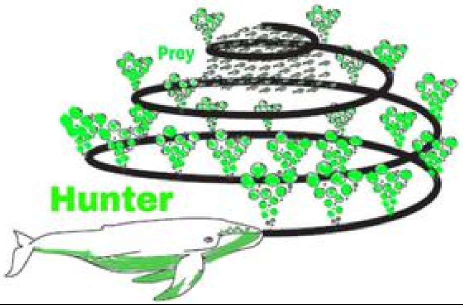


Fig. 3: Bubble-net feeding behaviour of humpback whales.

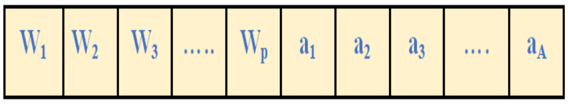


Fig. 4:The WOA search agent vector assignment on CNN

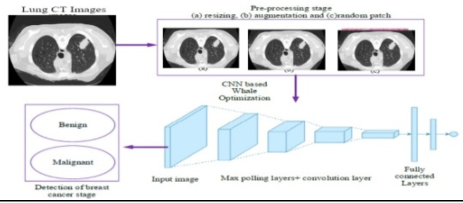


Fig 5: The WOA based CNN

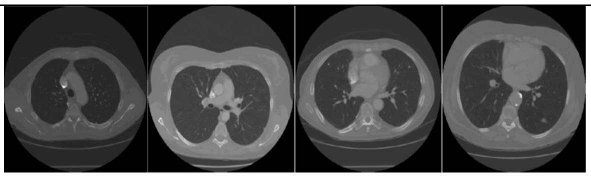
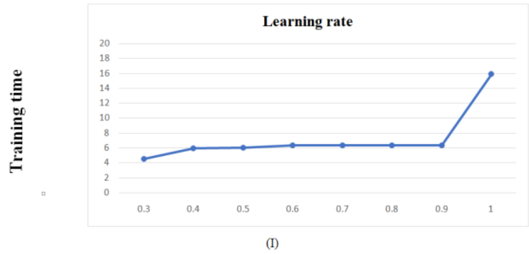


Fig 6: Some examples of the LIDC databases



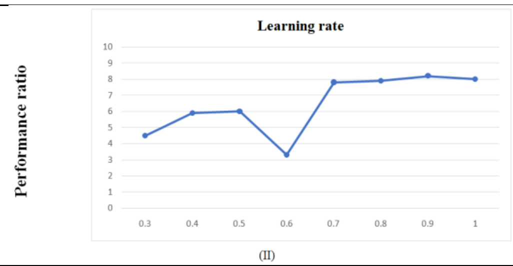


Fig-7: (I) learning rate vs. training time, (II) learning rate vs. performance ratio

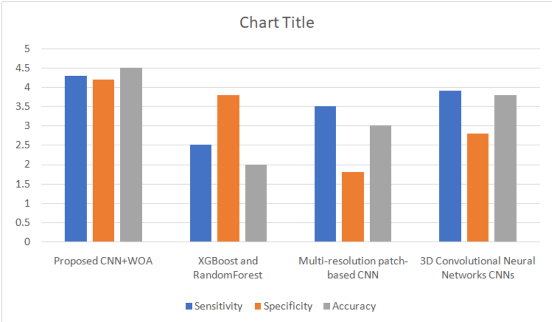


Fig. 8: Distribution of classification performance of the methods for lung cancer detection