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Intensifying Lung Cancer Classification Model Using Hybrid-Layer Convolutional Neural Network with Enhanced-CSO Weight Optimization Algorithm

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Abstract: In recent time the Lung Cancer disease is evolving as highly life-threatening disease for human beings, as per world-health organization the lung-cancer disease becoming second largest cause of deaths as compared to all other types of cancer. Although the prevailing available technology is striving to get more exposer in the area of medical science using Computer-Assisted Diagnosis (CAD) system, where image processing is playing crucial role for detecting the cancerous nodules in computer tomographic images. Augmenting the Machine Learning techniques with image processing algorithms is becoming more comprehensive examination of cancer disease in proposed CAD system. This paper is exhibiting the heuristic approach for lung cancer nodule detection, the purported model is predominantly categorized the foremost tasks, which are Image Enhancement, Segmenting ROI (Region of Interest), Features Extraction, Nodule Classification. In preprocessing, primarily the AMF filtering method is applied to eliminate the speckle noise in input CT image of LIDC-IDRI dataset through, and quality of input image is improved by applying Histogram Equalization technique with Contrast-Limited Adaptive approach. Secondly, in successive stage the Improved LevelSet (ILS) algorithm is used to segment the interest region (ROI). Furthermore, the third step of projected work is applied to extract the definite learnable Texture Features and Statistical Features from segmented ROI. Based on the extracted features in aforementioned stage are applied to pioneering improved Convolutional Neural Network CNN architecture with Hybrid-Layer to classify the lung cancer nodule is either benign or malignant. Principally this research is carried out by contributing to each stage of it, where novel concept of improved Hybrid-Layer Convolutional Neural Network (CNN) is employed by optimizing and selecting the optimal weight using the Enhanced Cat Swarm Optimization (ECSO) algorithm. The experimental result of proposed Hybrid-Layer CNN using weight optimization algorithm ECSO is achieved the accuracy of 93.5%, which is comparatively efficient with respect to existing model such as DBN, SVM, CNN, Hybrid-Layer: WOA, MFO, CSO. Moreover, this work provides conclusive decision on detected nodule is either benign or malignant.

Keywords: Computer Tomography (CT), Convolutional Neural Network (CNN), Preprocessing, Segmentation, Computer Assisted Diagnosis (CAD), Feature Extraction, Lung Cancer, Classification.

1. INTRODUCTION

In the present days the Lung carcinoma is the most life-threatening disease, as per WHO in 2018 it is reported that around 1.76 million patients are died only because of lung cancer disease across the world [1]. There are distinct medical examination techniques are in existence to detect the lung cancer in human body such as X-rays, CT scanning, and Biopsy. However, the symptoms of lung cancer patients are developing progressively less often fission, which is the perilous fact about the characteristics of this disease. The early-stage detection of lung cancer saves patents life with survival rate of 18% up to 5 years [2]. The prevailing medical examining systems are in demand of computed based technology to provide the accompanying solutions to detect the lung cancer in its early stage of disease, centered on this analysis the computer assisted diagnosis (CAD) is developing the standards in last two to three decades for providing computer-based solution as assistance to the radiologist and doctors [3] [4]. This paper is exhibiting the heuristic approach in cancerous nodules detection and classification of lung using computer assisted diagnosis (CAD) system, proposed ensemble model which comprises of novel Machine Learning based algorithm and Image Processing techniques to bring in a robust model to classify the nodules in to the category of benign or malignant . Lastly the intended model endorses the conclusive decisive analysis whether the patients is consisting of cancer disease or not. This proposed model is using the low-dose Computer Tomography (CT) images, since CT images are produced with high resolution images, these

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CT images entailing superfluous source of information in terms significant features as compared to X-rays images. The projected work encompasses the diverse steps in meeting the objectives of proposed model, firstly the image enhancement process is accomplished by employing AMF Filtering method for noise removal in input image and (CLAHE) histogram equalization technique is applied to input Computer Tomography (CT) images, which applied to improve the quality of input CT images, in second step the preprocessed CT images are endured to segment the ROI (Region of Interest), the suspected region in input CT images is segmented using improved LevelSet algorithm. The texture features and statistical features extraction in ROI is commenced in third step, which are highly significant features in the perspective of classification stage. The fourth step is of classification where the proposed work employing a Hybrid-Layer Convolutional Neural Network (HL-CNN) model with adapting optimal weight in HL-CNN. The scalability ratio at fully connected layer in CNN is very low, to suppress such sort of issue the proposed Hybrid Layer architecture is established. Correspondingly, in HL-CNN the enhanced-CSO empower the proposed model by reducing parametric overhead in the projected network. And finally, this research work is attaining the superior statistical analysis over the conventional model by computing Sensitivity, Specificity, Accuracy, Mean, Median, Standard Deviation, Worst and Best of analytical values.

Principal Contributions of this research papers: (i) Developing Hybrid-Layer Convolutional Neural Network (HL-CNN) architecture, (ii) Augmenting weight optimization method through enhanced Cat Swarm Optimization (ECSO) algorithm

2. Related Work

This section discussed various papers related to CAD system for disease diagnosis using Image Processing techniques and Machine-Learning model [5]. In present time computer aided diagnosis system offering the clearer technological assistance using varied kind images such as MRI, CT, X-rays, etc to diagnose the disease in different part of body [6] [7]. The concoction of image processing and machine learning algorithms create constructive path predicting and classifying the category of different class value in input data, the distinct classification model such as SVM, CNN, DBN and etc are applying in CAD system successfully for classification purpose [8] [9]. The CAD system also implemented to diagnose the Tumor inside the brain in MRI images [10], Breast Cancer using Histopathological Images [11] [12].

Teramoto A et al. 2017 [13], proposed a model to classify the lung cancer disease, by applying the filtering techniques such as gaussian filter and convolutional edge filter to microscopic images, which are trimmed and rebuild with the resolution 256 X 256 pixels to avoid the overfitting exertion. The authors introduced DCNN model to classify the lung cancer, this DCNN model contains 3-convolutional layers, 3-pooling layers and 2-fully connected layers. The proposed system succeeds to classify the distinct types of cancers and the accuracy of this model is assessed based on three-fold cross validation, 71% of cancer images are classified precisely.

Atefeh Nekouie and Mohammad Hossein Moattar, (2019) [14], the inadequacy revealing in clinical diagnosis for the reason of missing values in data are the challenges for diagnosis system. Author introduced enhanced machine learning methods such tensor factorization is applicable for predicting precise value against missing values, the adaptive modification using particle swarm optimization algorithm deciphering the missing value issue, additionally in this paper the proposed algorithm implements chaotic search method. The planned model implemented to estimate the missing values in incomplete database of Breast Cancer data, the tensor factor is applied to identify the numerical data values from large source of numerical data, and to conquer challenges of tensor such as class discrepancy are unraveled through implementing adaptive modification using particle swarm optimization algorithm. This work has employed Bayesian networks as classification model to learn the computational network for understanding complex relationships between the random variables. In due course, performance analysis of projected model used the metrics such as specificity, sensitivity, accuracy, and RMSE, and compared with distinct classification model, finally it is concluded that the proposed work has attained the outstanding result in all.

K.P. Baby Resma and Madhu S. Nair, (2018) [15], the segmentation technique is applied to separate the foreground region from background region in input images, the Kill-Herd Optimization algorithm implemented to recognize the optimal thresholding value which will maximize the efficacy of objective function. However, the proposed KHO algorithm is reducing time frame for computing the optimal threshold value. Evaluating the result of proposed technique with present Bio-inspired model using (MFO), (PSO), Bacterial-Foraging (BF) and GA based thresholding method has developed superior result.

Nivea Kesav and M.G. Jibukumar, (2021) [16], in order to address the issues such as architectural complexity and time for execution of CNN classification model, the researchers of this article have developed uncomplicated classification prototype by applying RCNN model with two channels in CNN. Primarily this work aims to build the low-complexity CNN architecture for classifying the tumors from MRI images, and productively the proposed framework has attained the accuracy of over 98%. In the view of reducing time for execution the proposed work continued with the same CNN framework to classify the tumor in MRI images, the 2-channel CNN is used to locate the fascinated region, in further stage the work is extracting the parametric features in MRI and these extracted features are used by RCNN, based on the trained RCNN network the proposed model efficaciously detect the tumor and average-confidence score is achieved around 99%. Correspondingly, this work is compared with standard fast-RCNN and faster RCNN model and conclusively it has been acknowledged that the proposed work has improved accuracy and it takes less execution time.

Schwyzer M, et al, (2018) [17], the Schwyzer and other researchers have developed an automated lung cancer detection system using artificial neural network. The input dataset containing ultra-low dose CT and PET images for around hundred patients, in which 50 percent of images are of normal patients and remaining 50 percent of cancer patients. The artificial neural network-based machine learning algorithm applied to PET images with ultra-low-doses, the ultra-low dose radiation is of 0.11 mSv is used. The applied efforts for screening lung cancer disease using ANN classifier accomplishes the sensitivity of 95.9 percent and 91.5percent and a specificity of 98.1 percent and 94.2 percent.

Nadakarni et al. (2019) [18], proposed early-stage detection of cancer disease using CT images in DICOM image format as input of Cancer Image Archive Database. The distinct image preprocessing techniques are applied to enhance input image quality, by applying Median Filtering, and Histogram Equalization techniques the quality of input image upgraded. Moreover, the grey-scale image is converted into binary form and applied the segmentation techniques to identify the interested portion of image. From the segmented portion of meaningful features are extracted such as eccentricity, area, and perimeter. Based on the extracted features, the proposed SVM classification technique classifies the given input image is cancerous or not and detected in its early stage with premier accuracy.

In Ayman E. et al. (2013) [19], authors projected model for predicting lung cancer nodules from LIDC-IDRI dataset of CT images, the convolution neural network classification technique is employed for lung cancer nodules detection. The provided input images are converted into stack encoder (SAE) for processing the input image, then by extracting significant features from input image the proposed model established CNN and deep-learning neural network classification model for detecting nodules whether it is benign or malignant. The proposed system achieves the accuracy of 84.32%.

Yu Guo et al.(2014) [20], authors proposed a system for prediction of lung cancer by applying CNN network. Initially the CT images are preprocessed by this model. However, the features extracted from CT scan images, then those features are trained by deep learning process for predicting the lung cancer disease and attained the conclusive decision on lung cancer disease prediction.

3. Methods and Materials

The lung cancer detection system is exhibited commendable performance by applying ensemble approach using image processing techniques and machine learning techniques. The projected work has used the Computer Tomography (CT) images as input to this CAD system. The collected images are in the form of DICOM format, the source of these CT images is LIDC-IDRI dataset [21], the collected CT scan images are accessible in the size of 512 X 512 pixels resolution. Consisting of cancerous nodules size of nodules ≥ 3mm and nodules ≤ 3mm, whereas the non-cancerous nodules ≥ 3mm. In CT image the header information of DICOM image format is consisting of patient's details, any such CT images can get the details about the particular patients. The anticipated Computer Assisted Diagnosis (CAD) system for lung-cancer nodule detection from CT-images is considered the major steps, the flow of enactment of proposed CAD system using proposed HL-CNN (ECSO) classification model is shown in Figure (1).

In the first step noise removal filter is applied and by applying novel CLAhe model the quality input image is improved. In the second step interested region is segmented by applying ELS algorithm. The third step is working on to extract the texture features and statistical features from suspected region of CT image, the features such Mean, Variance, Deviation, Entropy, Local Binary Pattern (LBP), (GLCM), and (GLRM) are extracted from ROI. The Fourth step is of classification which is applying Hybrid-Layer Convolutional Neural Network (HL-CNN), the projected model worked training dataset and validation dataset for computing performance measurement of the system.

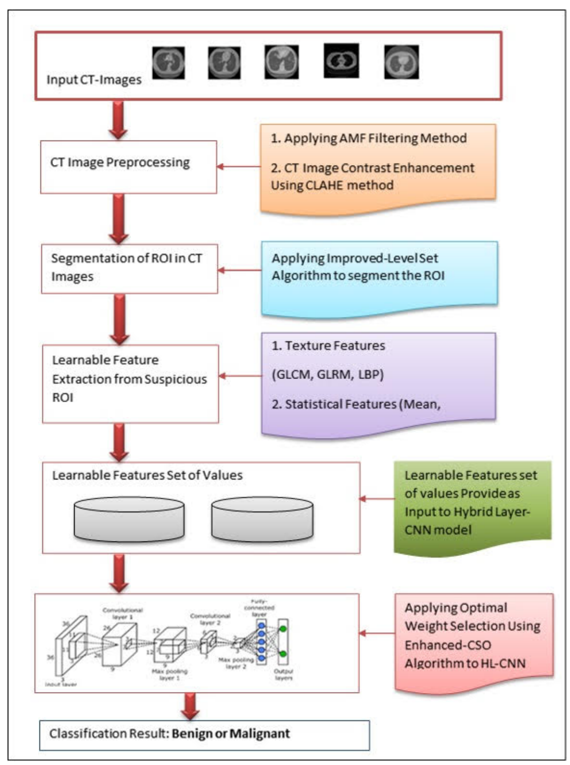

Figure 1. Block Diagram of proposed Computer Assisted Diagnosis system using HL-CNN Classification Model

A. CT Image Preprocessing

The scanned input CT image may contain the speckle and impulse noises in it, if these noises are persisted in the same can influence on the finishing accuracy of proposed system. Correspondingly, extensive use of filtering technique can degrade the quality of input image. The narrative approach of filtering technique such as Adaptive Median Filter (AMF) is fundamentally efficient to preserve the information of input image [22]. The later stage image preprocessing is working on to improve the contrast illumination in input images, the Contrast-Limited Adaptive Histogram Equalization (CLAhe) method which attains the quality in input CT image [23].

1) Applying Adaptive Median Filter for Image Denoising

The classical Median Filter [24] replaces the middle value with median value in the given frame of the input-image, although the noises in the input image is suppressed with the same uncorrected pixel values are replaced by median filter, which may cause to lead the disruption of the quality of input image. Thus, work on target specific region of image Adaptive Median Filtering technique is inevitably effective, this step of image denoising is applying advanced deterministic Adaptive Median Filtering method. Filtering technique select the window size from image W_z, the indication of noises are highlighted by point P_{xy} matrix, the projected filtering technique is handling two cases where a point $P_{xy} = 1$ which contains the noise. When $n > 0$ the neighbored having point signal calculates the median value of the selected window size, where n indicates the signal points.

$$Z_{xy} = \begin{cases} med(P(x,y)), & n\epsilon odd \\ (P_{med\_1}(x,y) + P_{med\_2}(x,y))/2, & n\epsilon even \end{cases} \tag{1}$$

In all of these P_{xy} is the point indicate that the grey value 0 and n represents number of points observed as 0, these two grey level points represents in the center of organizing.

When there are no pixels comprising of noise in the given image then further processing is interrupted, the obtained outcome is given to the final output of subsequent point of matrix is indicated by S_{xy}. Initially this denoising filter is processing with 3 X 3 matrix, the equation (2) concluding the particular for adaptive filtering technique.

$$S_{xy} = \begin{cases} l_{xy}, P_{xy} = 1, & n > 0 \\ m_{xy}, & else \end{cases} \tag{2}$$

Where mxy is the point of noise when median filter is applied and considered as point in image, now for binary sign in matrix the value of point is exchange from by 0 from 1 which replicate the noise dispersion in image point.

$$P_{xy} = \begin{cases} 0, & S_{xy} = l_{xy} \\ 0, & \end{cases} \tag{3}$$

The final outcome acquired as S_{xy}, then analyze for further binary mark points in P_{xy}. If there are any points present, then S_{xy} will be considered as original input image and over that same filtering technique is applied on it.

2) Applying (CLAhe) Contrast-Limited Adaptive Histogram Equalization model

The process of intensity distribution adaptation for improving image contrast is known as Histogram Equalization, the purpose of this HE method is to obtain the linear pattern in input image [25]. The conventional histogram equalization methods are applicable to the image globally, where the contrast is enhanced all over the image. However, this CLAhe method works on particular surfaces of the image, the circumstantial miniature region of image is preprocessed by applying CLAhe model [26]. The bigger value of histogram equalization is regulated through estimating the clip-point in every block [27].

To deal with histogram equalization is completely centered on the calculation of cumulative-distribution function (cdf), equation (4) defines function (cdf) which is sum of all probabilities lie down in its portion.

$$cdf(n) = \sum_{I=0}^{n} P(k) \tag{4}$$

The CLAhe model enhanced the contrast of image by setting up the clip point limit β as defined in equation (5).

$$\beta = \frac{P}{G}\left(1 + \frac{\alpha}{100} Max_{slope}\right) \tag{5}$$

In above equation (5), P is number pixels and G is grey levels in every region of image, α is indicating the clipping-factor in the range of (0-100), Max_{slope} corresponds to maximum slope of the transformation function.

Hence the quality of input image is improved by preprocessing steps, here and now the segmentation method is applied on preprocessed images.

B. Segmentation

The proposed Improved LevelSet segmentation algorithms is determined based upon the prevailing LevelSet Segmentation algorithm, where it computes the speed function using moving curve with curving-based velocities for separating the exterior region. The 3D curve is generated from the standard level set function,

$\Phi = (x, y, z) = 0$, primarily the level set function set as zero. However, the Signed Distance Function is defined in equation (6).

$$\phi = (x, y, z) = SDF \tag{6}$$

$$\phi_t + F|\nabla_t| = 0 \tag{7}$$

In above equation (7), F indicates the speed function accompanying with the moving curve in the given image for the build exterior region, the execution of speed function is based on the SDF value and the values of the curvature which distinguish the change of variation in the image.

The improved LevelSet segmentation algorithm is determined by obtaining the optimistic values of FC-Means and K-means algorithm, the experimental enhancement in proposed Level Set segmentation algorithm is producing superior result in segmenting suspected region of CT image.

$$\varphi_0(y, z) = -5\kappa(0.4 - [0.5(FC + KM)]) \tag{8}$$

The equation (8) corresponds to improved Level Set segmentation method FC is refers to F-C Means and KM refers to K-Means and is indicates the diasaco function, the standard energy function computes the internal and external energy in the presumed image. The length (ln) and area (α) of are calculated in equation (9) and (10) respectively.

$$ln = \int_I^{\delta} (\varphi_0) d_y d_z \tag{9}$$

$$a = \int_I^{H} (\varphi_0) d_y d_z \tag{10}$$

The Heaviside function $H(\varphi)$ is computed in equation (11),

$$= \begin{cases} 0, & \varphi_0 < 0 \\ 1, & \varphi_0 \geq 0 \end{cases} \tag{11}$$

Thus, enhanced level set segmentation method accomplishes the estrangement of suspected region in CT image.

C. Feature Extraction

The succeeding phase in CAD system is to extract the significant features from segmented region of CT image, the purported region of interest in CT image consisting certain gauging values which may use to classify the cancerous and noncancerous nodules. This paper is researching on statistical features and texture features to learn the system for training dataset [28] [29].

1) Statistical Features Extraction

The statistical features namely as Mean, Median, Mode, Entropy, Skewness, Kurtosis and Moment are extracted from suspected region of CT image, the size of statistical features is 1 X 7. The objectives of extraction these statistical features are exaggerate the premium quantifiable parameters for the stage classification to detect the nodules in CT image flawlessly. The perifissurally positioned nodules are challenging to detect through the texture pattern of CT images, in such circumstances the statistical values in distinct input image calculates the inevitable parameter to classify the nodules [30].

2) Texture Features Extraction

Texture features are the similar patterns which are comprising data point and those data points are coordinated in composition of consistent intermission. Texture features implies the physical elements and their existence in the form of shape, size, pixel-intensity, and contrast presentation. This research comprises of diverse texture feature extraction techniques are used to extract the momentous features such as LBP, (GLCM) , (GLRM), [31] [32]. The GLCM method is applied to distinguish the smoothness of an input CT-image by evaluating the links of pixel through precise values, further it will affirm the spatial linking in an input image by extracting statistical based texture features in image. The GLRM feature extraction technique support to signify the numerous clusters of objects which are going to be extract, GLRM deals with combined numerical, definite, and ordinal values of in input image with a random number of misplaced data value and enables the algorithm to categorize in pairs of conclusive outcomes. The LBP method allows to label the pixels of input image by calculating LBP code and confirming the threshold value of each neighboring pixels by contemplating the result in binary number. All the extracted features from statistical features and texture features are extended to the classification stage, the features values are applied to estimated neural network to train the proposed system for further lung cancer detection assignment.

D. Classification Using Hybrid-Layer Convolutional Neural Network (HL-CNN)

There are distinct popular classification techniques are implemented for various classification problems in image processing, moreover this paper presents a Hybrid-Layer approach of CNN for lung-cancer nodule detection [33]. The foremost challenges with conventional CNN techniques are Overfitting issues, gradient overflowing, and discrepancy in categorizing the output classes, so to overcome on these challenges in CNN architecture [34] [35] and traditional algorithm Cat-Swarm Optimization (CSO) [36] for weight optimization method the proposed classification techniques applying Hybrid-Layer approach with the tuning weight in CNN for improving accuracy by employing the Enhanced Cat-Swarm Optimization algorithm. The deep learning models have multiple layers which trained deeper knowledge in in any classification model and various activation function are applied in model to activate the neurons, the ReLu is one of the activation function used in this work [37].

1) Proposed Hybrid Layer CNN Model

In order to classify the lung cancer nodules from input CT images the proposed work is employing two set of Hybrid-Layer CNN model, this proposed CNN architecture is designed with three convolutional layer of kernel size 32, 32 and 64 respectively, the first and second convolutional neural layer is trailed with activation function ReLU and a pooling layer (max-pooling layer), the next layer of convolutional layer is connected wit fully-connected layer. Lastly the fully connected layer is connected with sigmoid layer which is nothing but thhe activation function that classify the detected nodules shown in Figure: (2).

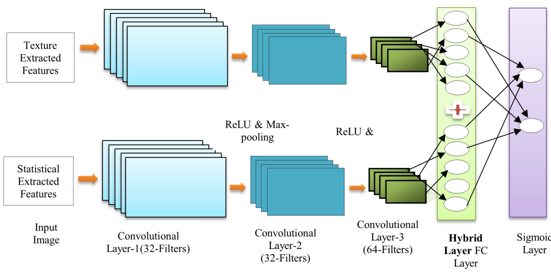

Figure 2. Hybrid-Layer Convolutional NN Architecture

The extracted features values from previous step are offered as input to this stage of classification, further these feature values q^{th} are pair with s^{th} layer, for the location of features p and r is defining the mapping function as $R^{s}_{p,r,q}$ in equation (12). The mapping function encompass the optimal weight factor W^{s}_{k} and bias function respectively, accordingly training the proposed Hybrid-layer CNN model the weight optimization model is applied to improve the accuracy using Enhanced Cat Swarm Optimization (ECSO).

$$R^{s}_{p,r,q} = W^{s^{T}}_{k} J^{s}_{p,r} + B^{s}_{k} \tag{12}$$

Here, the purpose of activation function is to increase the non linearity and activate the decedent neurons in CNN model is defined in equation (13), considering the use of pooling layer in CNN architecture extends support to lessening the overhead on the functioning of projected system, the max pooling technique is outwardly acceptable in this condition is defined in equation (14). The pool() pooling function estimating the feature values for neighboring location p and r for each feature map for all portrayed location $L_{p,r}$.

$$A^{s}_{p,r,q} = A(R^{s}_{p,r,q}) \tag{13}$$

$$O^{s}_{p,r,q} = pool(A^{s}_{p,r,q}) \forall (a,b) \epsilon L_{p,r} \tag{14}$$

However, the Loss function of CNN is to calculate considering the difference in input and output values with respect to aimed values while training period of CNN, Loss function is demonstrated in equation (15).

$$Loss = \frac{1}{Num} \sum_{t=1}^{d} PT(\varsigma, Y^{(t)}, OUT^{(t)}) \tag{15}$$

E. Proposed ECSO model for Weight Optimization

The weight optimization in neural network reduces parametric value and it promotes the network to trained in-depth measurable parameter [38]. The standard Cat Swarm Optimization algorithm is constant type of algorithm, this algorithm motivated from the characteristics of Cat. Cat is very alert when it is in resting mode, cat observe ingeniously the activities are taking place around it. As soon any movement is observed Cat track that very quickly for grabbing the food. Correspondingly, CSO algorithm revealed based on the natural activity of Cat for searching the food [39] [40]. The CSO model combined of two sub task which are seeking and tracing, in CSO model it obtains the fitness value, position of cat and flag value from every individual cat. The dimension of space search is indicated by DM for cat position, and in each dimension, cat maintains its own velocity. The obtained solution for cat delivers fitness value which indicates perfection of cat position, and lastly flag implies the mode of cat either it exists in tracing or seeking mode.

Steps followed by CSO algorithm:
Step-1: Preliminary setting up the lower level and higher-level value for solution encoding.
Step-2: The set of solution encoding are assigned in all dimension DM, with the definite velocity of cat under the range of defined level of velocity.
Step-3: The Mixture Ratio (MR) set for given number of cats, the cats are divided into the seeking mode and tracing mode.
Step-4: Assessment of fitness value performed for each cat, based on the optimal solution encoding position of cat is saved into the memory
Step-5: Correspondingly, cat searches for another best value, accordingly cat select the seeking mode or tracing mode.
Step-6: Algorithm checks for termination condition, if satisfies it stops its execution otherwise it run its execution in steps 3 to 5 till it reaches the termination condition.

1) Seeking Mode

The seeking mode is behavior of cat where cat is perceiving for objective, in seeking mode there are four imperative factors namely as (SMP: Seeking Memory Pool), which express the memory size search for each cat, Seeking Range for selected Dimension (SRD) defines change of rate of dimension for the designated portion. Count of Dimension to Change (CDC), this represents the number of dimensions to be reformed which are in the interval of [0, 1]. Moreover, Self Position consideration

(SPC) which is Boolean flag-value represents that the present position of cat will be considered for next recapitulation. If the flag is true, then it creates (SMP-1) number of candidates as SMP is to be assumes as the one of the current positions amongst all. The Steps are in seeking mode are shown below.

Step-1: Build n copies of SMP, which indicates the position of Cat_f.
Step-2: Randomly choose and add the positive value and negative value to the SRD dimension, which change the prior position of each copy, the new position will be presented in the below equation (16).

$$CnDM_{New} = (SRD \times RnD + 1) \times CnDM_{Old} \quad (16)$$

Here, n indicates number of cats, DM represents the dimension, Rnd is the random number in the interval of [0, 1], $CnDM_{New}$ shows the present position of cat and $CnDM_{Old}$ represents the old position of cat.
Step-3: Compute the Fitness value (FS) for all positions of cat.
Step-4: select the random point of candidate whose fitness value is optimal for the current position of Cat_f, the probability of selecting all candidates point when fitness value is similar at all position then position value to be set as 1.

$$C_x = \frac{|FS_x - FS_{Best}|}{FS_{max} - FS_{min}} \quad where \quad 0 < x < y \quad (17)$$

If the objective function obtains the minimum fitness values, then $FS_{best} = FS_{max}$ otherwise the $FS_{best} = FS_{min}$

2) Tracing Mode

The tracing mode is based on the tracing behavior of cats; the equal velocity is assigned to each cat for moving in all dimensions. Further the velocity of cat is updated for next step in this algorithm, the tracing mode establish the function in the following steps.
Step-1: The present velocity of cat for all dimension is updated as as per equation (18).
Step-2: The moment velocity is reaching to the maximum limit, or it is exceeding the higher limit then it is set as to be the maximum limit of velocity.

$$VC_{i,d} = VC_{i,d} + Rn_1 C_1 (P_{best,d} - P_{i,d}) \quad (18)$$

Step-3: The Enhanced ECSO updating the position of candidate Cat_f in equation (19)

$$P_{i,d} = P_{i,d} + VC_{i,d} \quad (19)$$

Consequently, the proposed enhanced CSO model is employed to acquiring the optimal weight for hybrid layer CNN architecture.

4. Result Analysis and Discussion

he proposed lung cancer nodule detection system tested on the LIDC-IDRI dataset, the source of dataset is accessible online: https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI [21]. This projected CAD system is developed a Hybrid-Layer Convolutional Neural Network architecture with improved Level Set segmentation technique and Enhanced Cat-Swarm Optimization algorithm in PYTHON environment using PyCharm Community Edition 2020.3.5 x64 IDE. The performance metrics evaluation for proposed HL-CNN (ECSO) is computed the result and compared with standard methods such as SVM [41], CNN [41]. Correspondingly, this work has melded Hybrid-Layer architecture of CNN with distinct weight optimization techniques and developed the model for the same such as HL-CNN (WOA) [42], HL-CNN (MFO) [43], and HL-CNN (CSO) [44]. The implication of Hybrid layer in CNN is to train the low-level longitudinal features and in hybrid architecture the activation function produces 2-dimenssial matrix features from 1-dimensional data through reshaping.

It is observed that the 2-dimensional matrix input are admirable to learn deeper features. Correspondingly, implementation of Enhanced-CSO algorithm established new velocity control functions design in the current optimization positions to adapt the velocity for searching optimal weight velocity profusely. The Inference of proposing novel weight optimization algorithm is to reduce the overhead of attribute correction function and reduce the loss, eventually HL-CNN (ECSO) improves the accuracy.

A. Experimental Output

The consequence of experimental processes such as image preprocessing and extracting the region of interest ROI through segmentation technique on sample input images is shown in the Figure (3). The first column shows the input CT images from LIDC-IDRI dataset, second column includes the preprocessed images, third column shows marked edges segmented ROI and the last column comprised of suspicious nodules regions produced in implementation environment. The diverse features are collected from suspicious region of CT image, the collected feature values are accessible for Hybrid-CNN model for training purpose.

B. Performance Analysis

The performance metrics evaluation of HL-CNN (ECSO) model is calculated and substantially compared with the prevailing model by adapting the training-testing percentage of dataset in the range of 50-50, 60-40, 70-30, 80-20, and 90-10. To measure the performance analysis metrics of Hybrid-layer CNN (ECSO) proposed model computed to determine the Accuracy, Specificity, Sensitivity and Precision. Based on confusion matrix procedure the performance of classification model is measures the metrics of Accuracy, Specificity, Sensitivity, Precision and ROC curve by getting precise values of dataset established on True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN).

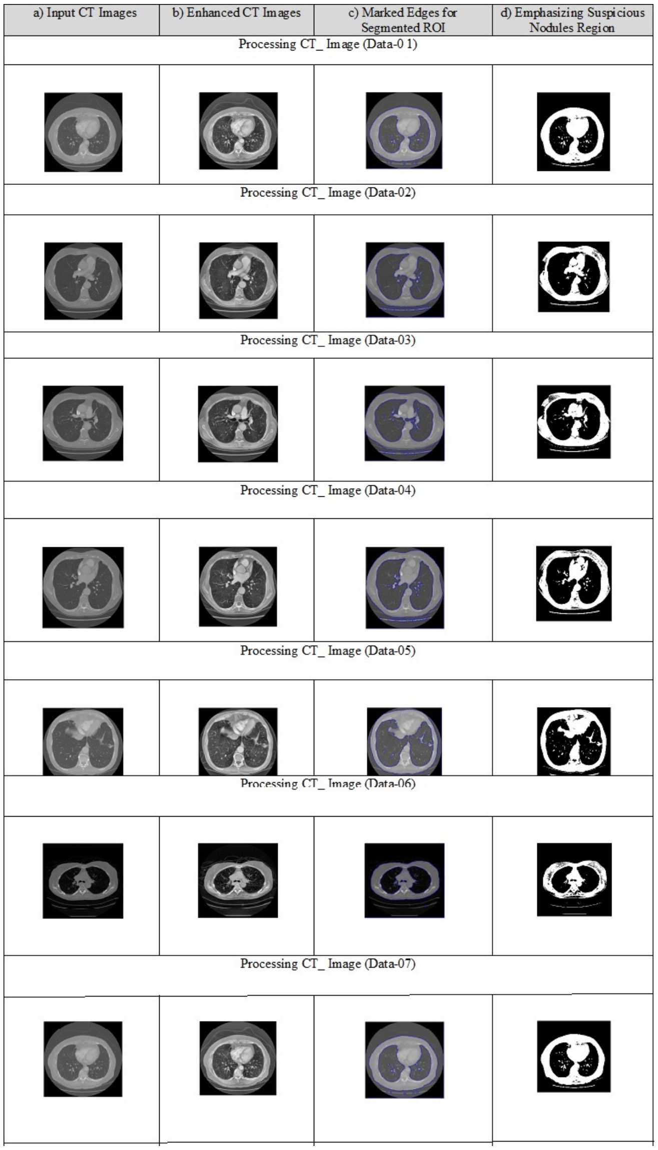

Figure 3. Output generation in proposed CAD model: a)CT Image samples from LIDC_IDRI Dataset, b) Output of Preprocessing stage, c) Output of Segmentation steps d) Emphasizing suspicious Nodules in CT images

1) Accuracy

The computed accuracy of HL-CNN (ECSO) classification model is compared with the standard models such as SVM [45], CNN [45], HL-CNN (WOA) [42], HL-CNN (MFO) [43], and HL-CNN (CSO) [44] by varying the training percentage in 50%, 60%, 70%, 80%, and 90%. The obtained accuracy calculated are determined using equation (20), and results are as shown in Table 1.

$$Accuracy(ACC) = \frac{TP + TN}{TP + TN + FP + FN} 100\% \qquad (20)$$

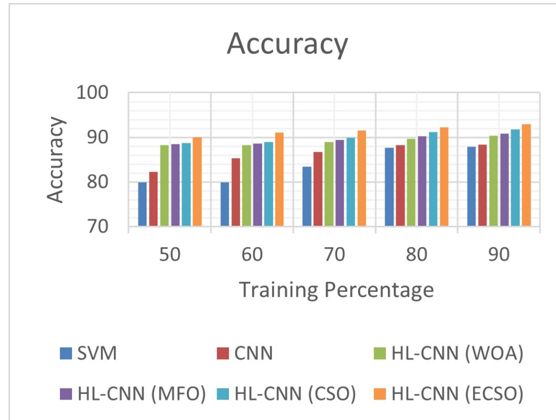

Figure 4. Accuracy analysis of proposed model comparison with conventional models.

Classifier Model	Accuracy				
	Training Percentage (%)				
	50	**60**	**70**	**80**	**90**
SVM	79.87	79.87	83.43	87.71	87.9
CNN	82.31	85.27	86.79	88.29	88.42
HL-CNN (WOA)	88.24	88.28	89.01	89.66	90.38
HL-CNN (MFO)	88.52	88.61	89.44	90.22	90.86
HL-CNN (CSO)	88.72	88.91	89.88	91.18	91.83
HL-CNN (ECSO)	90.07	91.08	91.51	92.28	93.5

TABLE I. Evaluation of Accuracy with conventional models

The results of proposed HL-CNN (ECSO) model in terms of accuracy are evaluated and represented in graphical analysis in Figure (4). The standard SVM classification model is a simple approach using kernel is consequential in nature, hence the maximum accuracy achieve by SVM is only 87.9% even with 90 th training percentage dataset. The second classifier is standard CNN approach, the CNN model engenders the intelligent neural network which helps to learn the pixel-based reflectance in the input image, that reduces the loss in classification and improve the accuracy in CNN compared to SVM. The first part of experimentation conducted to improvise the accuracy through modifying architecture of CNN by applying hybridization using two similar set CNN, the intent of to employ a Hybrid-Layered CNN architecture is to enhance the region proposal network in CNN model, and to substantiate the manifestation of artifacts more accurately by calculating the loss function. The second part research is to recognize the superior weight optimization algorithm, the purpose of to recognize better algorithm is to reduce the overhead of attribute correction function and ultimately to improve the accuracy in

2) Specificity

The specificity computes the probability that examine the true negative test value amongst all noncancerous cases from dataset. The HL-CNN (ECSO) model attains the higher specificity in contrast all other standard model, the obtained result of specificity by changing the training percentage are shown in Table (2), the specificity assessment is performed using equation (21).

$$Specificity(SPC) = \frac{TN}{(TN + FP)} 100\% \tag{21}$$

Classifier Model	Specificity				
	Training Percentage (%)				
	50	**60**	**70**	**80**	**90**
SVM	79.76	80.87	84.62	85.64	86.57
CNN	82.77	83.08	85.15	86.28	86.69
HL-CNN (WOA)	83.77	84.99	88.45	89.77	90.35
HL-CNN (MFO)	84.77	88.43	89.57	91.19	91.45
HL-CNN (CSO)	88.19	91.59	92.48	93.51	94.53
HL-CNN (ECSO)	94.05	95.09	96.13	96.62	97

TABLE II. Evaluation of Specificity with conventional models

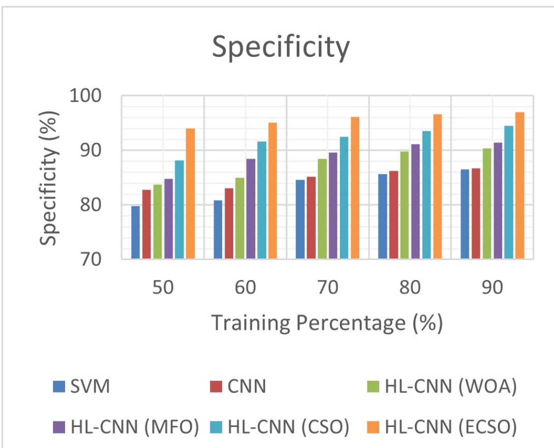

Figure 5. Specificity analysis of proposed model comparison with conventional models

3) Precision

The precision corresponds to the actual positive predicted values amongst all predicted positive values, precision implies excellence in prediction system and proposed system well marginally ahead in comparison with traditional classification models. The result of Precision is shown in Table (4), the calculation of Precision is performed using equation (23).

$$Precision(PR) = \frac{TP}{(TP + FP)} 100\% \tag{22}$$

The analytical evaluation of proposed HL-CNN (ECSO) classification model is exhibited in Figure (7), the graphical representation of proposed approach is compared with other standard and hybrid architecture models such as SVM [45], CNN [41], HL-CNN (WOA) [42], HL-CNN (MFO) [43], and HL-CNN (CSO)[44]. The clearly it is seen that the proposed model attains good quality in precision.

Classifier Model	Precision				
	Training Percentage (%)				
	50	**60**	**70**	**80**	**90**
SVM	88.97	89.7	89.74	90.53	90.66
CNN	90.48	91.06	91.15	91.19	91.81
HL-CNN (WOA)	91.45	91.72	92.48	93.51	94.53
HL-CNN (MFO)	92.62	93.65	94.54	94.61	95.22
HL-CNN (CSO)	93.02	94.04	94.95	95.32	95.56
HL-CNN (ECSO)	94.45	95.49	96.13	96.81	97.05

TABLE III. Evaluation of Precision with conventional models

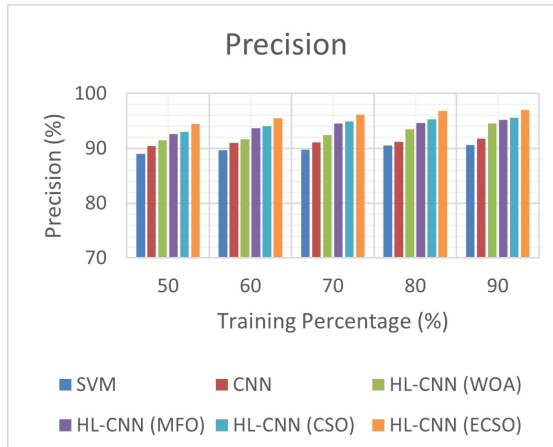

Figure 6. Precision analysis of proposed model comparison with conventional models

4) AUC-ROC Curve

The AUC-ROC result analysis evaluates the performance of proposed HL-CNN (ECSO) model and compared the AUC-ROC with standard CNN and SVM in Figure (8), the performance evaluation is conducted at different epoch's levels. The value of AUC (Area under Curve) of ROC (Receiver Operating Characteristics Curve) demonstrates the relation between TPR (True Positive Rate) and FPR (False Positive Rate), the proposed model attains the AUC value of ROC curve is 0.997 shown in figure (8).

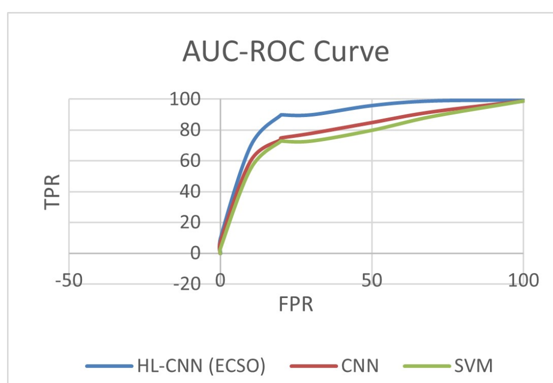

Figure 7. ROC Curve for Classification Models

However, the AUC-ROC curve area for CNN is 0.945 and SVM is 0.932 respectively, which implies that the proposed model is more robust system as compared to other traditional classification model.

5. Conclusion

The intent of this research is to develop a heuristic model for lung cancer nodule detection, the intended Computer Assisted Diagnosis system has principally categorized in major task, which are Image Enhancement, Segmenting ROI, Extracting learnable Features, and Classification. In image enhancement, Adaptive Median Filtering method applied to reduce the Speckle and Gaussian noises from input CT images, further step of image preprocessing applied CLAhe method to enrich the image contrast by processing histogram equalization technique on tiny region that is tiles of CT image. Subsequent step of proposed work segments the ROI using Improved LevelSet (ILS) Segmentation method which drove the moving curves and surfaces with curvature-based velocities for separating the suspected region. In the phase of feature extraction, the measurable feature values are extracted using Statistical Features (such as Mode, Median, Mean, Entropy, Skewness, Kurtosis and Moment) and Texture Features (like GLRM, GLCM and LBP features). The extracted feature values are offered as input to proposed Hybrid-Layer CNN (ECSO) classification model, the modeled hybrid layer CNN classifier worked with two analogous set of CNN for improving the efficiency. Moreover, proposed Enhanced Cat-Swarm Optimization (ECSO) algorithm employed to opt the best optimal weight in CNN classification model and conclusively the proposed HL-CNN (ECSO) achieves the accuracy of 93.5%, specificity of 97%, Sensitivity of 93.2% and Precision of 97.05% as shown in Table no. (1), (2), (3), and (4) respectively; which is explicitly producing superior results when it is compared along with the hybrid Layer architecture of HL-CNN (WOA), HL-CNN (MFO), HL-CNN (CSO) and standard SVM and CNN models.

6. Funding or Conflicts of Interests

The authors of this research paper hereby declare that, we do not have any known competing financial interests or personal affairs that could have appeared to influence the work reported in this paper.

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