A Novel Approach for Small Object Detection in Medical Images through Deep Ensemble Convolution Neural Network

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***Abstract*—Small objects detection in medical image becomes an interesting field of research that helps the medical practitioners to focus on in-depth evaluation of diseases. The accurate localization and classification of objects face tremendous difficulty due to lower intensity of the images and distraction of pixel points that vary the decision on identifying the shape, structure etc. In many real-time cases, detection and classification of tiny objects in the medically treated images becomes mandatory. The proposed system is designed in the same criteria in which the semantic segmentation of tiny objects in the medical images is considered. The system design focused on implementing the model for different kinds of human organs such as lung and liver. The axial CT or PET images of Lung and Liver are considered as the prime input for the given system. Detection of tiny objects in the CT-PET images, segmenting it from the background and classification of segmented part as Tumor or Nodule is discussed. The preprocessed images are feature extracted after the morphology segmentation that determines the structural features of the tiny object being segmented. The feature vectors are nothing but the feature points from Kaze feature extraction and Morphology segmented image. These two inputs are fetched to the Deep ensemble Convolution neural network (DECNN) to obtain the dual classification results. Performing the quantitative measurements to evaluate the decision making system for nodule or tumor class is determined. The performance measure is done using accuracy, precision, recall and F1Score.**

***Keywords*—Medical image processing; convolution neural network; lung tumor detection; early prediction; image enhancement**

I. Introduction

Lung cancer becomes the most commonly occurring life threatening disease that needs to be detected and diagnosed in the early stages [1]. Most common lung cancers are detected using the Chest X-rays or CT images, rarely using the MRI images in the early stage itself because of the problems it causes in the normal activities of the body [2]. Since many lung cancers have higher chances of spreading it towards the liver, it is mandatory nowadays, the screening of lung and liver with high accuracy is focused. In recent days the test named Low Dose CT scan (LDCT) [3] has been used to detect lung cancer and liver cancer. Lung cancer is more frequent with people with smoking habits and unhealthy habitual changes. In the case of early prediction the treatment of lung cancer is likely to be successful.

1) Lung and liver tumor: [4] Nearly 40% of patients with lung cancer have higher chances of metastasis to the neighborhood organs such as the liver. Metastasis is a kind of process held in the body, which migrates the cancer cells from one place to another. Cancer cells break away from the primary tumor and start to travel through the lymph channels or blood and affect the other organs. Hence early detection of tumor cells is highly important. Lung cancer cells migrate to other organs such as lymph nodes, the brain, the bones and the adrenal glands.

2) Stages of tumor: [5] Lung tumors are classified based on different stages as non-small cell, and small cell lung cancer. The early stage of non-small cell or NSCLC is also represented as carcinoma in Situ or CIS. Small cell tumor cancers are treated through radiation therapy or surgery.

3) Role of medical imaging: [6] There are almost six imaging modalities followed in screening the human organs. At each stage of the cancer it is required to screen, test and diagnose the cancer with accurate information. X-Rays, Computed Tomography(CT), Ultrasound(US), Magnetic resonance imaging (MRI) and Single photon emission Computed tomography(SPECT) and photon emission tomography(PET) [7] and optical imaging etc. The goal of the medical images is to produce a higher resolution to diagnose cancer cells properly. Determining the semantic objects present in the lungs are focused. Due to motion artifacts many noise factors interrupt the medical image being recorded accurately. Removal of noise from the images is an important task. Semantic segmentation of medical images are helpful in identifying the nature of abnormality occurring in the organs such as Lungs, liver etc. These lesions need to be treated in the early stage to stop the further transmissions. Considering Lung and Liver in the presented study, a comprehensive system model is created with Deep Ensemble Convolution neural network (DECNN).

The presented paper is organized as detailed background study in Section II, followed by methodology in Section III. Discussion on problem statement in the existing systems and selection of software tool is discussed in Section IV. System design architecture is discussed in Section V. Followed by results and discussions in Section VI.

II. Literature Survey

Systematic detection of lung cancer using Lung CT images is discussed with the presented system [8]. The model focused on image enhancement, segmentation process using binary lung mask etc. TCIA dataset images are considered for evaluation. The improved CT images are preprocessed and segmented with thresholding concept. The obtained mask is further fused with the ground truth to identify the tumor area alone. Further by using Support vector machines (SVM) algorithm the segmented area is classified. Image noise removal and its importance are clearly discussed in the paper.

The present paper [9] discuss the malignly detection of Lung CT images. Comparative study of one or more lung dataset is utilized such as LIDC, IDRI and LUNA16 are considered. Further the proposed approach uses two different architecture for evaluation such as U-Net architecture and VGG net is considered. The Multi-path 3D architecture used to classify the nodule and malignant part of the Lung images. The system achieved the accuracy of 95.6% and also the system suggested improving the further classification by improving the parameters considered.

Multi-resolution residual connected lung tumor detection system is discussed in [12]. The percentage system uses TCI open source lung tumor data set that consists of large count of lung patients and the CT images details helpful in analyzing the multi-resolution oil futures that impacts the prediction of lung tumor. Accessing system multistate convolutional neural network architecture is used to detect the lung tumor with multi resolution spectrum.

The present system discusses in detail about the clinical study and their impacts on lung tumor detection systems [13]. Epidemic growth receptor based decision tree model is discussed to detect the lung tumor without ignoring the residual factors that create similarity results. The author presented a system and discussed in detail on cell growth and its impact on lung tumor.

Knowledge based collaborative systems are required in many lung tumor detection systems in which each patient has unique problems and health records that impact the decision making process of tumor diagnosis [14]. The present system has developed a robust collaborative approach using ResNet-50 architecture. Most of their effects occurring because the present system is evaluated using a back propagation network. The presented knowledge based extraction method achieved the accuracy of 95.7% and the model training accuracy is achieved with 91.6% with ResNet-50 architecture.

Deep convolutional neural network architecture combined with artificial neural networks that create an impact on analyzing the lung tumor detection systems [15]. Most neural network architectures are less time consuming since the training and testing data will be formulated with the given configuration. The maximum of thousand approx. is allowed with the artificial intelligence networks in which the maximum accuracy will be achieved at any point of time with the given iteration. The present system uses a light DC data set for the analysis of lung cancer prediction. Study is helpful in understanding the basic concepts that associated with the lung tumor detection systems. [16] Object tracking is discussed in the present paper. Small objects tracking using particle filter is focused with the present system. Based on energy accumulation, target trajectory process is done. The experimental results show the better signal to noise ratio with images of complex background.

III. Methodology

The proposed methodology is focused on incorporation of image processing techniques and deep learning algorithms to evaluate the lung tumor and liver tumor detection system. [1] The systematic approach uses the tuned layers of convolution neural networks to identify a tiny object present in the screening image as a tumor or nodule. In the aspect of image processing, the segmentation works on extracting the semantic object present in the test image through image processing techniques. To determine the class of the segmented objects, the features such as shape and size are required. Tumors larger than three centimeters are represented as masses. Pulmonary lung nodules are very common and they are identified clearly in many chest X-Rays. In case of lung or liver tumor, the early prediction is feasible if the system is able to detect the tiny nodes present in the medical images. The smaller nodule can also be developed into cancerous as it may appear in the early stage, detection of tiny objects that are less than nodule also focused.

1) Data collection: The lung images are collected from IQ-OTH/NCCD cancer patient’s dataset and the Liver images are collected from TCIA publicly available dataset. The images are converted from DCM format to JPEG format. The images are labeled with respect to their age and patient name. The dataset modalities are completely differing from each other. The model created here utilize common Deep ensemble Convolution neural network (DECNN) only, whereas the primary processing steps varies separately for both Lung and Liver separately.

IV. System Design

The problem statement behind the small objects detection in medical images is lack of accuracy in low quality images like medical images [8], obtaining the accuracy, improving the precision in identifying the broken pixels of the objects. MATLAB is helpful in working out the detailed portions of the image through the image processing toolbox. The reason behind the selection of System tools is that MATLAB has numerous benefits over technical computing. Implement and test your algorithms easily. Develop the computational codes easily., Debug easily, Use a large database of built in algorithms, Process still images and create simulation videos easily, Symbolic computation can be easily done, Call external libraries and Perform extensive data analysis and visualization. Hence for image analysis, the system tool of MATLAB is more apt. using convolution neural network toolbox the improved DECNN structure is formulated.

V. Design Architecture

A. System Architecture

Fig. 1 shows the system architecture of proposed system using DECNN with BlobNet, in which the initial model creation is clearly depicted. The creations of model using training images are further tested with performance using the randomly selectable test images. The purpose of the Model created here is to provide fast and accurate segmentation of Semantic small object in the medical image as well as classify the object as tumor or nodule based on structural features.

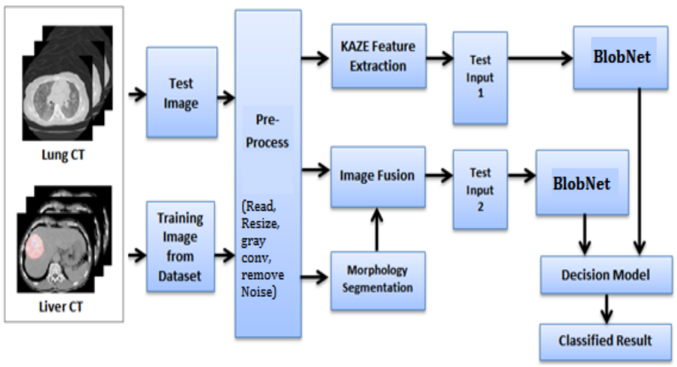

Fig. 1. System Architecture of the Proposed System DECNN with BlobNet.

B. Preprocessing

The input dataset is collected from TCIA and IQ-OTH/NCCD website, contains the [7] Lung CT images with detected Lung nodules and Lung tumor as well, also the IQ-OTH/NCCD dataset contains the Liver Tumor or Normal CT images of various patients. The input images are preprocessed before fetching it into the feature extraction stage. The input test image is read, resized into a common matrix for ease of handling. The processed image data is further applied to morphology image segmentation where the image is dilated, open and closed by the binary morphology operations.

C. KAZE Feature Extraction

The upgraded picture input is additionally prepared with KAZE highlight extraction method. Element descriptors are needed to be tuned in a manner the special pixel guides need toward be removed from the information test picture through non-straight space. For distinguishing central focuses, we figure the response of scale-normalized determinants of the Hessian at different scale levels. For multi-scale feature acknowledgment, the formula is given below.

$$\mathbf{L}_{\mathbf{Hessain}\,=\,\mathbf{p}^2}\,[LxLy\text{-}Lxy] \tag{1}$$

Differential heads ought to be normalized concerning scale, since by and large the assembly of spatial auxiliaries decay with scale. Where Lx, Ly go about as the flat subsidiary and vertical subordinate in the second request individually. The descriptor searches the exceptional focuses and applies to every one of the sifted pictures from the non-straight space. The finder reaction at different levels is being followed if there should be an occurrence of article following modules.

D. Image Fusion

The preprocessed image is further fused with the reference image through gradient mapping [10]. The fusion is required to highlight the tumor portion alone. The fused image with color mapped image is fetched to the DECNN model to make the pattern matching score with the trained dataset of lung and liver separately. MATLAB toolbox utilizes a composite image fusion process that blends the one image with another in case both images come under the same dimension. The formula to obtain the image composite process is given below.

$$f(x) = h[g(x)] \tag{2}$$

Where for every occurrence of x pixels the replacing the gradient color function of g(x) is applied. The outcome of the image looks like the composite of two images.

E. Morphology Segmentation

The non-linear image processing technique handles the shape of the region or the features that determine the unique identification of the region that is segmented. The semantic object segmented after the binary conversion and fusion technique, further processed with few morphology steps includes, image dilation, opening the smaller area and closing the smaller holes etc. Once certain steps are applied, the sharpened image object is highlighted in the binary masked form.

F. Ensemble Model

1) Feature based approach: The proposed DECNN architecture is tuned to handle the given input images of different parameters. The lung images and Liver images are tested separately. The proposed Deep Net consists of 1x1000 samples of feature points to the input layer arranged with DECNN model 1. The ReLu layer and Classification layer follows. The fully connected layer extracts 384 samples. The database images are trained in the same way, extracting the features and forming 1x1000xN training vectors.

Fig. 2 shows the feature based approach on small object detection in which the preprocessed images induced to feature extraction process, where the unique pixel intensity points systematically extracted by the KAZE feature detector. It acts as a extractor for Gaussian scale space with particular instance of linear diffusions of pixel intensity.

2) Image based approach: Another approach where the test image of dimension 100x100 is fetched to the input layer arranged with DECNN model 2. Certainly, the database images of both Lung and Liver are trained in the same way by applying morphology operation and cropped image of 100x100 is considered.

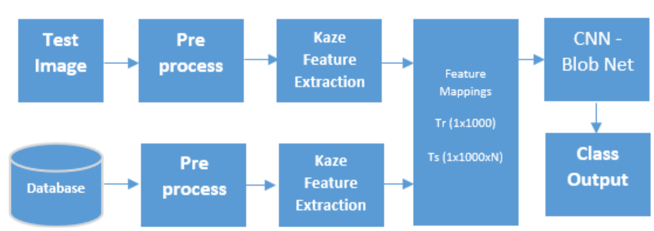

Fig. 2. Feature based Approach with DECNN – Blob Net.

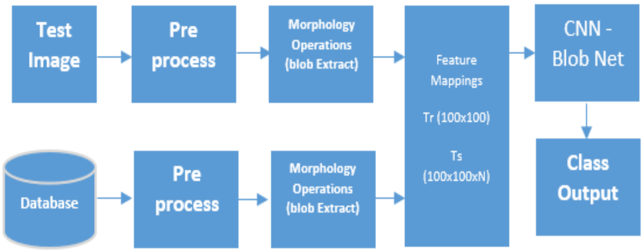

Fig. 3. Morphology based Approach with DECNN – Blob Net.

Fig. 3 shows the Morphology segmentation based image object extraction through Blob extraction process. The region oriented related boundary pixels are tuned to extract from the background image by selecting the initial similar pixels. Morphology segmentation is helpful in analysis of structural understanding of the semantic object. By tuning the structure the prediction quality will get improved.

3) Decision model: Based on the feature based result that runs up to 1000 epochs, to train and test the given input data, the decision is made using the quantitative measures such as accuracy and error tolerance. The system also focuses on reducing the false negative values. Hence in order to get the result with reduced false rate, the ROC curves are formed. The final decision classifies whether the given test image belongs to Class A = Tumor, Class B= Nodule or Class C= Normal. In few cases tested, Normal and nodule belong to the same class and regarding the similarity coincidences further the system is improved with tuned DECNN models.

ALGORITHM

Novel Deep BlobNet
Read x=Input Image
Y=preprocess(x);
[fea_1, ya]=kazeFea_1(Y);
[fea_2, ya]=MorpFea_2(Y);
Perform Fea Map;[fea_1,fea_2]
Store Fea Map -> fea.mat;
Train: DeepBlobNet (Train_images);
Pred_Y_1= DeepBlobNet (Train_Images, Test_images);
Pred_Y_2= DeepBlobNet (Train_fea, Test_fea);
Decision_model(Pred_Y_1, Pred_Y_2);
Plot Confusion (Pred_Y_1);
Plot Confusion(Pred_Y_2);
Perfrom Q_measure (Tp, Tn, Fp, Fn);
End

VI. Results and Discussions

A. Preprocessing

Fig. 4 shows the complete pre-processing steps involved in the proposed system. The input image of the lung CT is read from the database. The image is preprocessed in which the RGB image is converted into grayscale image. The grayscale image is converted into a binary image and colour space masking is done. After the masking process has completed morphological segmentation that enlarges the open pores and highlights the open area. The binary converter image is cropped and a binary mask with inverted images is applied.

B. Feature Extraction

Fig. 5 show the simulation result of case feature extraction of the one test image. The feature extracted area after the masking part is used to highlight the unique pixel points that vary with the intensity being verified. This feature information is mapped as a vector as training vector and testing vector before the DECNN classification is being applied.

C. Classification

Fig. 6 show the classification accuracy of proposed deep blog net which consists of pretrained images and the feature data as a vector map dinner randomly distributed scale. The training vector is framed and runs for 20 iterations. The higher the number of iterations is robust that the accuracy obtained will be noted. If maximum accuracy is obtained at the initial stage itself then the If maximum accuracy is obtained at the initial stage itself then the hydration would be stopped. Iterations would be stopped.

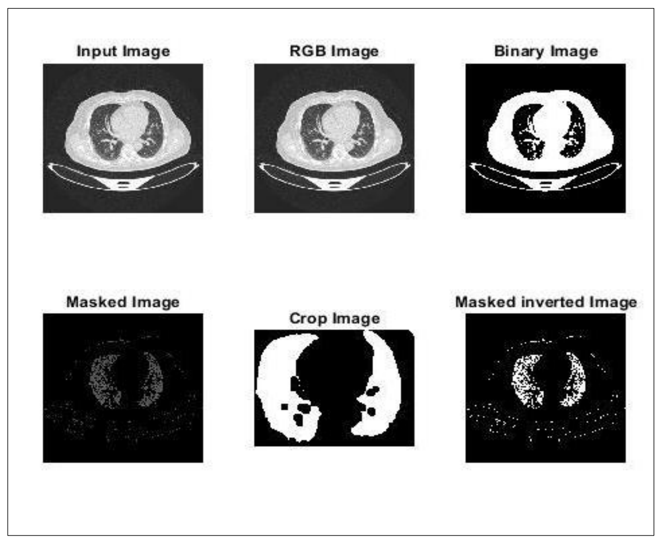

Fig. 4. Simulation Result showing Preprocessing Output, Masked and Morphology Extracted Outputs.

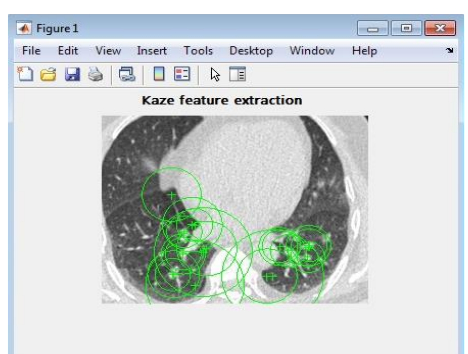

Fig. 5. Simulation Result showing Feature Extraction Output.

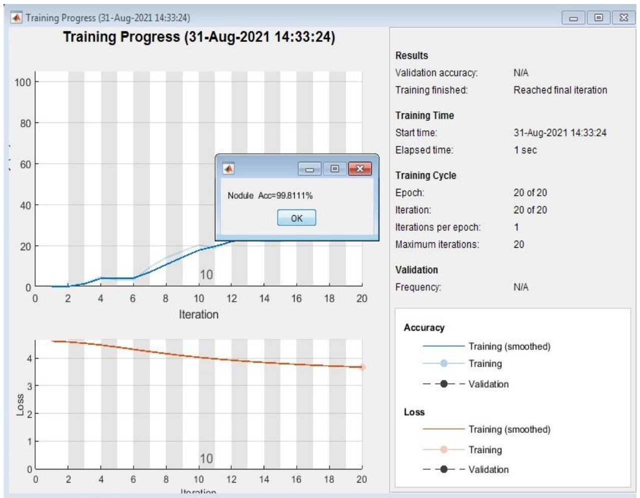

Fig. 6. Classification Notification and Internal Loss Function.

TABLE I. COMPARATIVE ANALYSIS OF ACCURACY WITH RESPECT TO EXISTING SYSTEM

Reference	Algorithm	Input Type	Accuracy
[10] M. Menikdiwela et al., (2017)	VGG16-RCNN	Spider Image dataset	84%
[11] Z. Yang et al., (2019)	YOLO V3-SlimNet	Traffic Image dataset	85%
Proposed System	Deep Blob-Net (pre-trained)	Medical images	99.8%

Table I shows the comparative study of existing lung tumor detection systems using VGG 16 architecture with recurrent convolutional neural network [10] and YoLo V3 model that detects the smaller objects in the given scene image. Comparatively the proposed architecture created using deep Blob-net utilizes the medical images for testing purposes and achieved the accuracy of 99.8% for the static data trained with the network.

D. Comparative Graphs on Accuracy

Fig. 7 shows the comparative performance of existing system and proposed system and its references. The proposed system uses the static data for developing the Novel structure. Further the system need to be improved with respect to real time data and dynamic analysis.

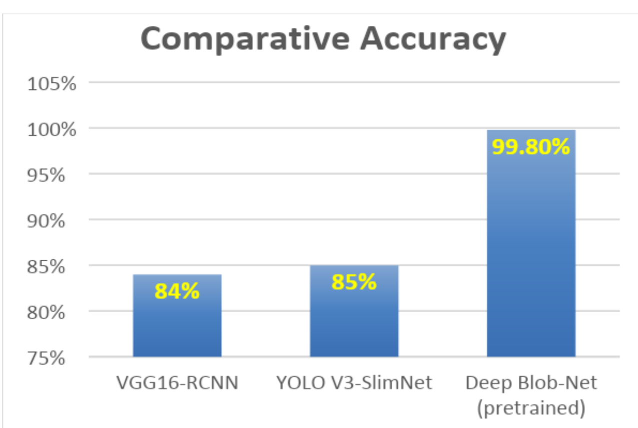

Fig. 7. Comparative Accuracy of Existing System and Proposed System.

VII. CHALLENGES

The development of blob-Net creates difficulty in tuning the layers since the parameters of the lung and liver vary. According to the static dataset the DECNN layers are tuned, whereas in case of application of dynamic dataset the accuracy and statistical performance is affected. Improving the number of images for training, obviously improve the performance of the convolution process.

VIII. CONCLUSION

Small objects' location in medical images turns into a fascinating field of research that assists the medical specialists to analyze diseases more accurately [2]. Due to intensity variations and motion artifacts, the images are in frequent sequence of motion; hence determining the tiny objects in the image is difficult. A Novel ensemble Deep learning network is developed using the convolution neural network. The system architecture is structured to ensemble two DECNN models with two variant input vectors. The first one utilizes feature based approach, and another method uses Image Morphology based approach. Based on the performance of both the results, a final decision model is developed to fetch the output class. Our proposed approach achieved 99.8% accuracy for static data and 75% accuracy approximately for dynamic data. Further the system is expanded to produce more dynamic results by training the real time input data. The performance is measured through loss function that lags during the increased epochs.

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