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A Traumatic Pneumothorax Detection Using Deep Learning

T.Sasi Vardhan[1], Nikhitha Patel[2], Nandini[3], Parsa Sai Prathyusha [4]

[1]Assistant Professor, Department of CSE, Malla Reddy Engineering College for Women, Hyderabad, Telangana, India.
[2,3,4]UG-Students, Department of CSE, Malla Reddy Engineering College for Women, Hyderabad, Telangana, India.

ABSTRACT

In this computer era we are totally going with the automation of everything, in the same way the medical industry is also automated with the help of image processing and data analytics .The best way to control the death cause by cancer is early detection. The medical image or a CTscan image is pre-processed .The contrast of the image is increased with the CLAHE Equalization technique .Then it is segmented with the help of random walk segmentation method. In segmentation the three process will happen the ROI of image is segmented and then the border correction is done. As third part the continuous pixel change is segmented. The classification is the major portion where the cancerous and non-cancerous is identifiedwiththepre trained model. All the methods used above deals with the traditional way of image processing and data analytics. In Future this accuracy will be boosted with the modern XGboost algorithm where less data is used to get high accuracy.

INTRODUCTION

1. PROJECT OVERVIEW

A traumatic pneumothorax growth has turned out to be a standout amongst the most widely recognized reasons for disease in the two people. Countless bite the dust each year because of lung malignancy. The illness has diverse stages whereby it begins from the little tissue and spreads all through the distinctive territories of the lungs by a procedure called metastasis. It is the uncontrolled development of undesirable cells in the lungs. It is assessed that around 12,203 people had lung disease in 2016, 7130 g 5073 females; passing from lung malignant growth in 2016 were 8839. . Biomedical image handling is the most recent rising apparatus in medicinal research utilized for the early recognition of malignancies. Biomedical image handling strategies can be utilized in the restorative field to analysis maladies at the beginning time. It utilizes biomedical images, for example, X-beams, Computed innovation and MRIs. The principle commitment of image handling in the restorative field is to analysis the malignant growth at the beginning time, expanding survival rates. The time factor is basic for tumors of the mind, the lungs, and bosoms. image handling can identify these malignant growths in the early periods of the maladies encouraging an early treatment process.

2.PURPOSE

We proposed a deep learning method for the detection and quantification of pneumothorax in heterogeneous routine clinical data that may facilitate the automated triage of urgent examinations and enable treatment decision support.

LITERATURE SURVEY

EXISTING PROBLEM:

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In the existing system the tests were done based on text and calculations so, the prediction was not accurate. The tests were also done by giving images as an input using algorithms like ANN and Dense neural network, the accuracy was not efficient and low. So to overcome this problem, the prediction was done through image orientation with using convolutional neural network, this algorithm will help in finding with the highest accuracy and fast prediction.

In existing paper, a picture handling procedures has been utilized to recognize beginning time lung malignant growth in CT examine pictures. The CT filter picture is pre-prepared pursued by division of the ROI of the lung. Discrete waveform Transform is connected for picture pressure and highlights are extricated utilizing a GLCM. The outcomes are encouraged into a SVM classifier to decide whether the lung picture is carcinogenic or not. The SVM classifier is assessed dependent on a LIDC dataset.

Disadvantages:

1. The CT filter picture is pre-prepared pursued by division of the ROI of the lung.
2. Discrete waveform Transform is connected for picture pressure and highlights are extricated utilizing a GLCM.

PROPOSED SOLUTION:

The proposed method is based on depth-wise separable convolution network and spectral pooling using wavelet transforms. The network is formulated by combining multi-resolution analysis with deep learning. The traditional CNN layers suffer from over fitting and high computational cost due to large number of parameters generated at each layer. Powerful properties of the Discrete Wavelet Transform (DWT), spectral domain, spectral pooling, and spectral parameterization of convolutional layers are utilized as a means to improve CNNs by improving training convergence, allowing flexible pooling dimensions, and retaining or improving competitive classification accuracies.

The proposed model applies a range of algorithms to the different stages of image processing. In this proposed model, first the CT scan image is pre-processed and the ROI (region of interest) is separated in preparation for segmentation.[17] At the segmentation stage, Discrete Wavelet Transform (DWT) is applied and the feature is extracted by using a GLCM (Gray level co-occurrence matrix) such as correlation, entropy, variance, contrast, dissimilarity and energy. After the feature extraction stage,

classification is carried out by an SVM (support vector machine) for classification of cancerous and

non-concerous nodules

Advantages:

1. The classification is the major portion where the cancerous and non-cancerous is identified with the pre trained mode

2.3 SYSTEM REQUIREMENTS:

HARDWARE REQUIREMENTS:

- System: I3 2.4GHz
- Hard Disk: 500GB
- Ram : 4GB

Software Requirements:

- Operating system : Windows 0
- Coding Language : Python 3.7

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LITERATURE SURVEY:

YEAR	TITLE	METHODOLOGY	RESEARCH PROPOSAL	ALGORITHM
2022	Pneumothorax Recognition Neural Network Based on Feature Fusion of Frontal and Lateral Chest X-Ray Image	Comparative experiments showed that the accuracy of this method was higher than that of the traditional single task pneumothorax recognition network. The main value of our work is that only using image-level datasets can achieve high pneumothorax recognition accuracy.	The proposed method may assist radiologists with the prompt and accurate diagnosis of pneumothorax and precise treatment planning.	Convolutional Neural Network(CNN)
2020	Deep Learning for Diagnosis and Segmentation of Pneumothorax: The Results on The Kaggle Competition and Validation Against Radiologists	The methodology of all top-performing teams from the competition leader board was analyzed to find the consistent methodological patterns of accurate pneumothorax detection and segmentation.	The proposed method supported lung tumor segmentation and lung tumor area recognition and then extraction of affected portion from CT image. Using CAD system, improve the detection and diagnosis of the affected tumor region	Deep learning, Convolutional Neural Network(CNN)
2019	Detection of Lung Cancer in CT Images using Image Processing	The methodology is carried out in five main steps: Data Collection, Image Pre-Processing, Image Segmentation, Feature extraction, Classification	The implementation of proposed system was done using MATLAB software. Database for this study was obtained from the Cancer imaging Archive (TCIA) .	Support Vector Machine(SVM)
2018	Automated detection of moderate and large pneumothorax on frontal chest X-rays using deep convolutional neural networks: A retrospective study	The methodology of detection includes the procedures as follows Image extraction, anonymization, and annotation, Resolution downsampling , Annotation, Frontal image selection, Dataset assembly, Model implementation and models tested	The proposed data augmentation technique has been used to make our models more generalized and robust to overfitting. It can generate more data with different training patterns to help models in the learning process.	Convolutional Neural Network(CNN) & Recurrent Neural Networks(RNN)
2017	Lung tumor Area Recognition and Classification using EK-Mean Clustering and SVM	EK Mean Clustering Algorithm and SVM algorithm methodology is used to diagnose lung tumor in human has been very active in recent period. Here there are four stages used in collection of CT images followed by image preprocessing with median and wiener filter.	The proposed method supported lung tumor segmentation and lung tumor area recognition and then extraction of affected portion from CT image. Using CAD system, improve the detection and diagnosis of the affected tumor region.	Support Vector Machine(SVM)

FEASABILITY REPORT:

1. FEASIBILITY STUDY

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

- ECONOMICAL FEASIBILITY
- TECHNICAL FEASIBILITY
- SOCIAL FEASIBILITY

1.ECONOMICAL FEASIBILITY

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

2. TECHNICAL FEASIBILITY

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

3. SOCIAL FEASIBILITY

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

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METHODOLOGY:

Convolutional Neural Networks (CNNs) are the most commonly employed network architectures for image classification. They have been successfully used in a broad range of applications from computer vision to medical image processing [5,10] and can be optimized in an end-to-end fashion.

Initial work in the medical domain focused predominantly on the re-use of deep learning networks from the computer vision domain (transfer learning). This is achieved either in terms of pre-trained networks, which are used as feature extractors, or by means of fine-tuning techniques, i.e. the adaptation of an existing network to a new application or domain. Promising results for X-ray image analysis have been obtained already by means of features derived from pre-trained networks .

In the following method, a specific network architecture - a residual network - is employed. We use a variant of the ResNet-50 architecture [5] with a single input channel and an enlarged input size of 448 × 448, which allows to leverage the higher spatial resolution of X-ray data, e.g. for the detection of small structures [1]. Therefore, an additional pooling layer was introduced after the first bottleneck block (cf. Fig. 1). The network was trained on the NIH ChestX-ray14 dataset [10] to predict 14 pathologies. For the task of pneumothorax detection, the dense layer for the prediction of pathologies was replaced by a new layer for binary classification.

Multiple-Instance Learning (MIL) [2] provides a joint classification and localization, while only requiring the image-level labels for training. This approach may be advantageous in medical applications [11] where pixel-level labels are difficult to obtain and often require experts to perform the annotation.

To produce local predictions in the image, the full resolution chest X-ray images are partitioned into N overlapping image patches, forming a bag. The goal is to produce a binary classification for each patch where a patch is defined as positive (pi = 1) if it contains pneumothorax and negative (pi = 0) if it does not contain pneumothorax.

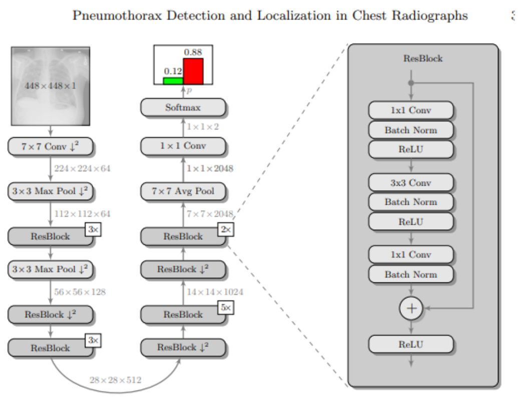

Fig. 1: ResNet-50 architecture of Baltruschat et al. [1] adapted for end-to-end binary pneumothorax classification. ↓ 2 denotes a downsampling operation using a stride of 2. Repeating ResBlocks have been collapsed for readability.

Using the bag labels, it is known that all the patches in a non-pneumothorax image will necessarily be negative. On the other hand, at least one of the patches in a pneumothorax image must contain the pathology and therefore be a positive patch. MIL attempts to learn the fundamental characteristics of the local pathology by automatically differentiating between normal and abnormal characteristics of the chest X-ray. Using these assumptions, MIL provides a mechanism to relate patch-level predictions, p1..N , to bag labels by taking the maximum patch score ˆp as the image-level classification. Fig. 2 shows a schematic of the proposed

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architecture. In this architecture, we use the previously discussed ResNet-50 network as patch classifier.

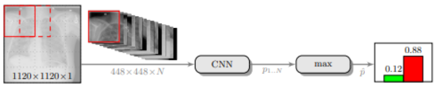

Fig. 2: The proposed Multiple-Instance Learning architecture, using the CNN as patch classifier, for joint pneumothorax classification and localization.

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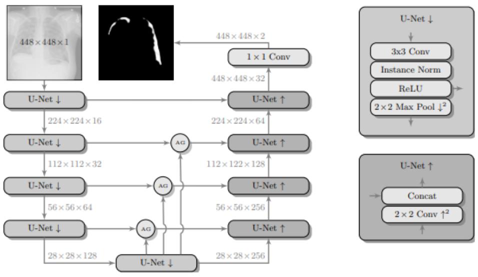

Fig. 3: The proposed FCN architecture using a four-layer U-Net [9] with Attention Gates (AG) in the skip connection [8].

Fully Convolutional Networks (FCNs) are more advanced network architectures, that have been developed for semantic segmentation, i.e. pixel-level classification. The most commonly employed network in this context is the U-Net [9], which consists of a contracting path resembling a CNN, for the integration of context information, and a corresponding expanding path. This allows to obtain probability maps of the same size as the input image, facilitating the image localization. For this experiment, we employ a U-Net with four layers per path and Attention Gates [8]. Attention gates have been proposed as an alternative to a detection component and they are employed in order to facilitate the segmentation of an object of interests. Furthermore, the proposed architecture uses instance normalization instead of commonly used batch normalization in order to harmonize the input data (cf. Fig. 3). In contrast to CNNs, the FCN approach requires pixel-level annotations during the training and predicts probability values for each pixel during the application phase. Therefore, it does not directly generate the image-level label, but requires an additional post-processing step. In the scope of this study, we define the area of the detected pneumothorax as a classification measure. Although such measure is biased towards the detection of large pneumothorax regions, it is conceptually simple and favors the detection of reliable candidates.

3 Experiments The data used in the following experiments consists of DICOM X-ray images, obtained from the University of Washington Medical Center and affiliated institutions, centered in Seattle by scanning radiology reports from the last three Table 1: Experimental set-up for the training of the three networks. The four last rows indicate whether the network uses image-level or pixel-level labels for training and whether it provides classification or localization, respectively.

	CNN	MIL	FCN
number of parameters	24M	24M	2.1M
input size	448×448	448×448	448×448
batch size	16	16	16
learning rate	10^{-4}	10^{-5}	10^{-4}
epochs	40	30	400
image-level labels	+	+	-
pixel-level labels	-	-	+
classification	+	+	◦
localization	-	◦	+

years. Inclusion criteria were: (i) Digital Radiography (DR) images, (ii) Chest radiographs, (iii) Posterior-anterior or anterior-posterior view position, (iv) Adult patients. Any personal health information was removed. Image-level labels were derived from natural-language processing based analysis of the reports. Cases were partially reviewed by a radiologist to confirm appropriate finding in the report's impression section and this represented a critical finding. The resulting dataset contained 1003 images: 437 with pneumothorax, 566 with a different or no abnormality detected. We generated pixel-level annotations of the pneumothorax region for 305 of the positive cases. For training and evaluation, we divided the dataset into

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five cross-validation splits of similar size, such that images of the same patient resided in the same split. To increase the variability of the available data, we augmented the dataset by translating, scaling, rotating, horizontal flipping, windowing, and adding Poisson noise. Input images for CNN and FCN have been created by cropping a centered patch of 448 × 448 from the original images resized to 480 × 480. For MIL we cropped overlapping patches out of the image resized to 1120 ×1120 (cf. Fig. 2). In training, we used the Adam optimizer with default parameters $\beta1 = 0.9$ and $\beta2 = 0.999$, a batch size of 16, and exponentially decreasing learning rate (LR). Refer to Table 1 for an overview of the parameters and to Fig. 4 for the receiver operating characteristic (ROC) analysis we performed to assess the model performance. CNN: The pre-trained ResNet-50 was fine-tuned with an initial LR of $10{-}4$ for 40 epochs. For testing, an average five crop response of the model, i.e. center and all four corners, was used for the classification purpose. Very high and stable results can be reported, with area under curve (AUC) values of 0.96±0.03. MIL: The pre-trained ResNet-50 was also employed as the patch-level classifier within the MIL approach. We chose the binary cross-entropy between the max-

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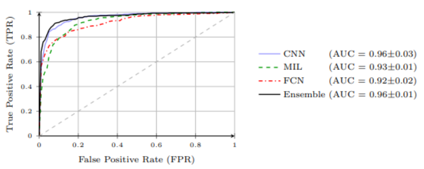

Fig. 4: Averaged ROC curves over five splits for all methods and an ensemble.

imum patch score and the image-level label as the loss function. The batch size was selected as the number of N = 16 patches per image. We trained with an initial LR of $10{-}5$ for 30 epochs and achieved an average AUC of 0.93±0.01 using this method. High patch scores (indicated by thicker red frames, cf. Fig. 5c) give a hint on the location of the pneumothorax. FCN: As pixel-level ground truth annotations were available only for a subset of the images, 871 images in total were used for training the FCN for 400 epochs. As a loss function, a weighted cross entropy (25.0 for pneumothorax pixels and 0.5 for non-pneumothorax pixels in order to account for the smaller size of pneumothorax regions) was employed at pixel-level with an initial LR of $10{-}4$. With an average AUC of 0.92±0.02, the overall performance of this method is worse than the CNN and MIL. On the other hand, the FCN generates pixel-level probabilities (cf. Fig. 5d), which indicate the location of the pneumothorax. The average Dice coefficient for positively classified cases is 54.2%. Ensemble Learning: As can be seen from the previous sections, the different methods, that have been investigated, have their own advantages and disadvantages. However, looking at the performance, the errors made by different architectures do not necessarily coincide. Therefore, we investigated ensemble techniques, using linear combinations of the individual methods. The best parameter combination was identified using exhaustive search. The best ensemble of CNN, FCN, and MIL achieves the highest overall AUC of 0.965 (cf. Fig. 4), but does not significantly (at $p < 0.05$) outperform the CNN. CNN and FCN achieve best results amongst combining two techniques with an AUC of 0.962.

4 Result:

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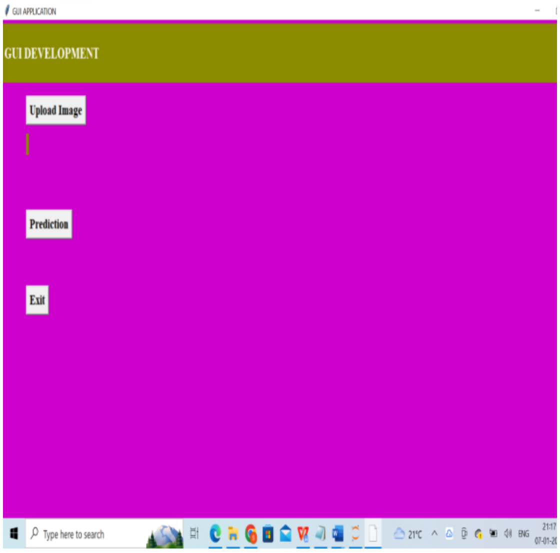

FIG:GUI Application page

This webpage indicates the starting index page of the project.

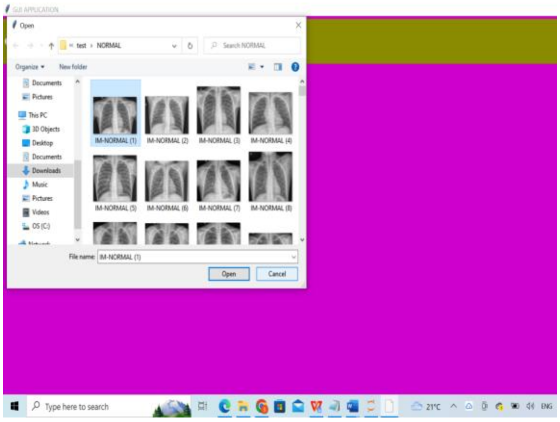

FIG: Insert Image

Fig:Click On Prediction

OUTPUT RECEIVED

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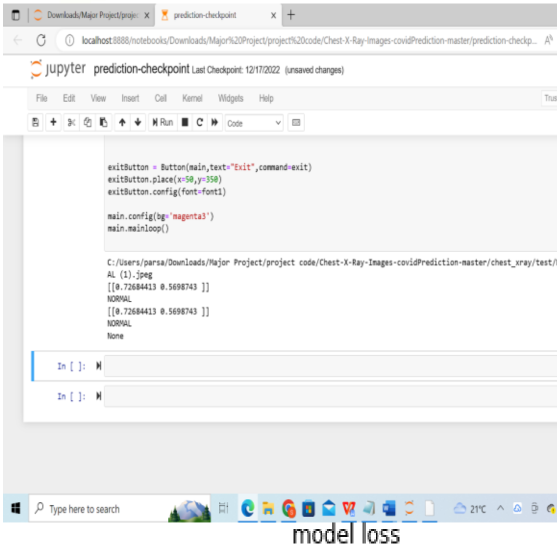

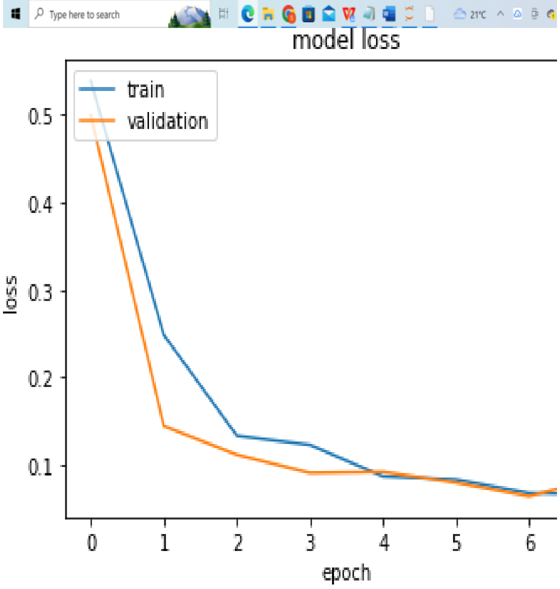

CONCLUSION:

In the principal period of the venture the Region of Interest in a picture is distinguished. The Identif ied district is situated in an item. The highlights in the picture are distinguished by utilizing some picture handling system. In second period of the task the component removed information is then used to arrange the picture is destructive or not utilizing a portion of the SVM – bolster vector machine grouping. At that point some boosting calculation is utilized to expand the exactness of the instrument.

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Transform is connected for picture pressure and highlights are extricated utilizing a GLCM. The outcomes are encouraged into a SVM classifier to decide whether the lung picture is carcinogenic or not. The SVM classifier is assessed dependent on a LIDC dataset. In future the advanced level of algorithm is used to increase the level of prediction while we are in process to include the Extreme gradient boosting Algorithm to use the data set more effectively.

FUTURESCOPE:

In addition, in the current work, we define a picture handling procedures has been utilized to recognize beginning time lung malignant growth in CT examine pictures. The CT filter picture is pre-prepared pursued by division of the ROI of the lung. Discrete waveform Transform is connected for picture pressure and highlights are extricated utilizing a GLCM. The outcomes are encouraged into a SVM classifier to decide whether the lung picture is carcinogenic or not. The SVM classifier is assessed dependent on a LIDC dataset. In future the advanced level of algorithm is used to increase the level of prediction while we are in process to include the Extreme gradient boosting Algorithm to use the data set more effectively.

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