CHEST X-RAY PULMONARY TUBERCULOSIS DETECTION USING DEEP LEARNING

P. Viswanatha Reddy [1], Assoc.Prof, Dept. of CSE. Vishwan.happy@gmail.com
Veeram Sai Sudheer Reddy[2], Student UG Scholar, veeramsaisudheerreddy@gmail.com
V. Jaswanth Reddy [3], Student UG Scholar, v.jaswanthreddy2002@gmail.com
S. Jyothi[4], Student UG Scholar, jyothijyo2003111@gmail.com
Y. Sandhya [5], Student UG Scholar, sandhyabtech2003@gmail.com
R. Indra Kumar, student UG Scholar, indrakumarmounika1234@gmail.com

Abstract:

Doctors and radiologists are still using manual and visual manners to diagnose chest radiographs. Thus, there is a need for an intelligent and automatic system that has the capability of diagnosing chest X-rays. This thesis aims to employ a deep neural network namedas region-based Convolutional Neural Network for the classification of chest X-rays into normaland abnormal images. The Region based Convolutional Neural Network is trained and tested on chest X-rays obtained for public databases which contain normal and abnormal radio graphs. A Performance based comparison is carried out between two networks where the first one uses input chest X-rays without processing or enhancement and the other one uses input images thatare processed and enhanced using histogram equalization. Experimentally, it is concluded that the Region based Convolutional Neural Network achieveda good generalization power in diagnosing the unseen chest X-rays into normal or abnormal. Moreover, it is seen that the enhancement of images using histogram equalization helps in improving the learning and performance of network due to the rise in the accuracy achieved when images are enhanced.

Keywords: Deep network, Region based Convolutional Neural Network, Radiographic classification, Generalization, Intelligent

1.INTRODUCTION

Medical X-rays are images are generally used to diagnose some sensitive human body parts such as bones, chest, teeth, skull, etc. Medical experts have used this technique for several decades to explore and visualize fractures or abnormalities in body organs (Eretal.,2010). This is since X-rays are very effective diagnostic tools in revealing the pathological alterations, in addition to its non-invasive characteristics and economic considerations. Chest diseases can be shown in CXR images in the form of cavitations, consolidations, infiltrates, blunted costophrenic angles, and small broadly distributed nodules. The interpretation of a chest X-ray can diagnose many conditions and diseases such as pleurisy, effusion, pneumonia, bronchitis, infiltration, nodule, atelectasis, pericarditis, cardiomegaly, pneumothorax, fractures and many others (Eretal.,2010).Classifying the chest x-ray abnormalities is considered at ought ask for radiologists. Hence, over the past decades, computer aided diagnosis (CAD) systems have been developed to extract useful information from X-rays to help doctors in having a quantitative insight about an X-ray. However, those CAD systems haven’t achieved a significance level to make decisions on the type of conditions of diseases in an X-ray (El-Solhetal.,1999). Thus, the role of them was left as visualization functionality that helps doctors in making decisions. Recently, accurate images classification has been achieved by deep learning based systems. Those deep networks showed super human accuracies in performing such tasks. This success motivated the researchers to apply those networks on medical images for diseases classification tasks and the results showed that deep networks can efficiently extract useful features that distinguish different images classes (Ashizawa etal., 2005). Convolutional neural networks have been applied to various medical images diagnosis and classification due to its power of extracting different level features from images.

Traditional networks have been also used in classifying medical diseases, however, their performance was not as efficient as the deep networks in terms of accuracy, computation time, and minimum square error achieved. In this work, deep learning based networks are employed to classify most common thoracic diseases. Two Region based Convolutional Neural Network are examined in this study to classify the chest X-rays into two common classes: normal and abnormal which may have different types of diseases that may be found in chest X-ray, i.e., Atelectasis, Cardiomegaly,

2. SYSTEM ANALYSIS

2.1 Existing system

- **CAD4TB:**

CAD4TB is a computer-aided detection (CAD) system developed by the Netherlands-based company

- **TB**-Net:

TB-Net is a deep learning model developed by researchers at the Indian Institute of Technology (IIT) Bombay

- **Deep** TB:

Deep TB is a deep learning-based system developed by researchers in China.

- Relies heavily on manual interpretation by radiologists, which can be time-consuming and subjective.
- Traditional computer-aided diagnosis (CAD) systems may lack accuracy and efficiency for large-scale screening due to limitations in feature extraction and classification methods.

2.1.1 Disadvantages of existing system

Efficiency: By employing automated TB detection through deep learning, diagnostic workflows can be streamlined, resulting in reduced time and resource expenditure for screening and diagnosis.

Consistency: Deep learning models yield consistent and reproducible outcomes, mitigating discrepancies in diagnoses that may arise from manual interpretation by different radiologists.

Continuous Refinement: Deep learning models can undergo continuous refinement and updates with additional data, leading to potential advancements in performance over time and bolstering their efficacy in TB detection.

2.2 Proposed system

ALGORITHMS :

- Deep Learning
- Region based Convolutional Neural Network
- Data Training

Automation: Deep learning models automate the process of TB detection, reducing reliance on manual interpretation and potentially speeding up diagnosis.

Scalability: Once trained, deep learning models can be deployed at scale, allowing for efficient screening of large numbers of chest X-ray images, which is especially beneficial in regions with high TB prevalence.

2.2.1 Advantages of proposed system

- **Efficiency**: By employing automated TB detection through deep learning, diagnostic workflows can be streamlined, resulting in reduced time and resource expenditure for screening and diagnosis.
- **Consistency**: Deep learning models yield consistent and reproducible outcomes, mitigating discrepancies in diagnoses that may arise from manual interpretation by different radiologists.
- **Continuous Refinement**: Deep learning models can undergo continuous refinement and updates with additional data, leading to potential advancements in performance over time and bolstering their efficacy in TB detection.

3.SYSTEM DESIGN

3.1Dataflow / block diagram

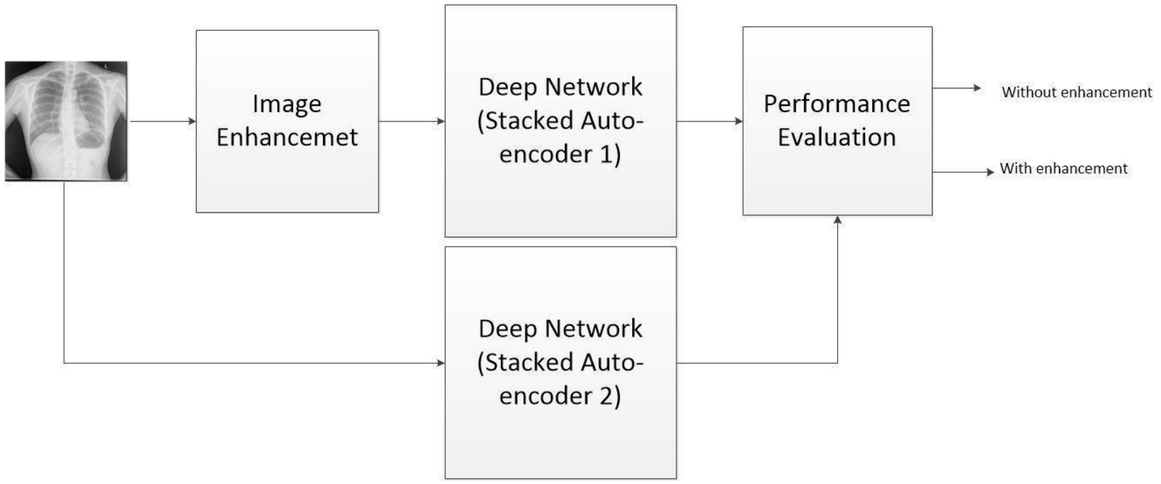

Fig 3.1: System design

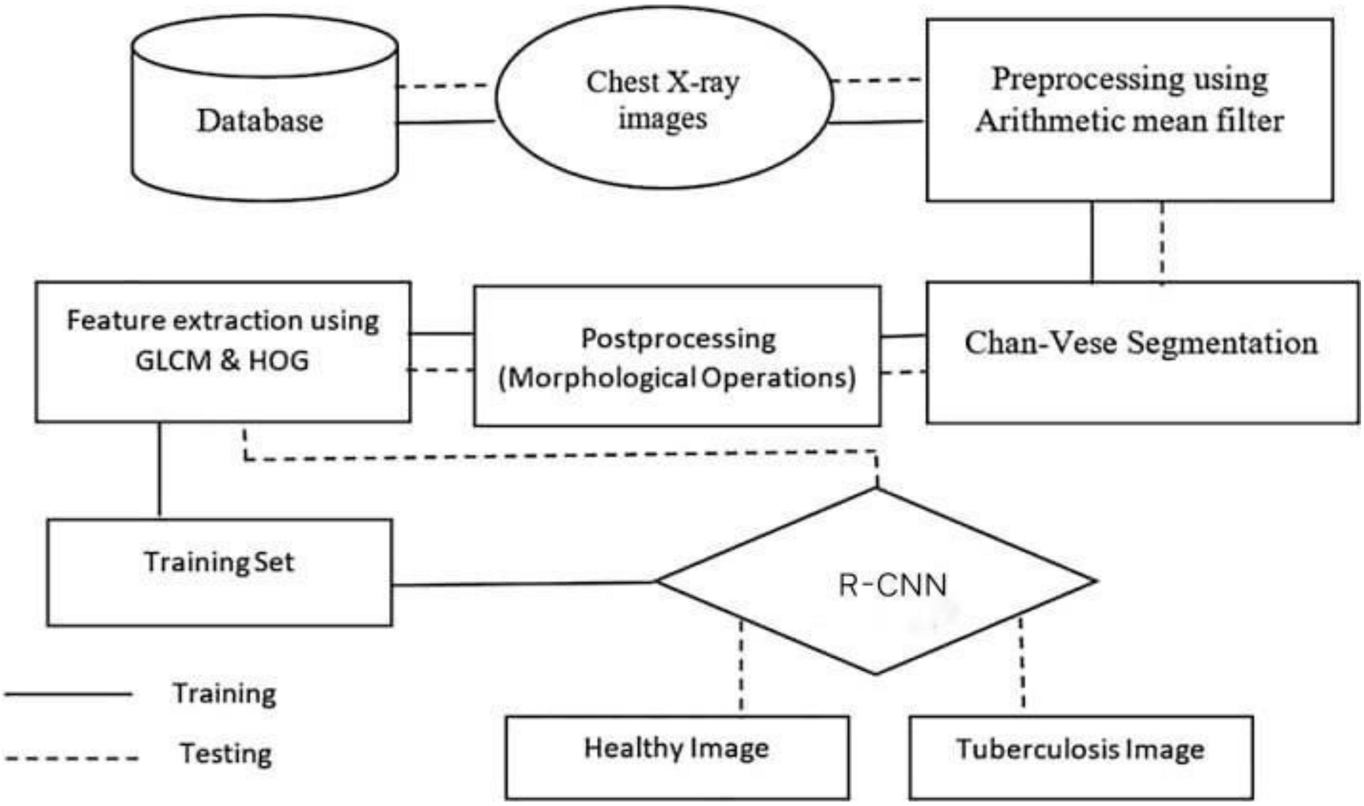

Fig 3. 2: Data Flow Diagram

3.1Description of the flow

This study presents original research for the diagnosis of chest X-rays using deep learning. A deep network named as region-based Convolutional Neural Network (RCNN) is selected to be usedas the brain in this work. This selection came from the few researches that were conducted for the chest X- rays classification using this kind of networks. Thus, there is a need to investigate the effectiveness and performance of region-based Convolutional Neural Network in classifying the chest X-rays and detecting whether a radiograph has a disease or it is normal (healthy). Two auto- encoder networks were used to build the proposed Region-based Convolutional Neural Network thatis then used to be as the intelligent classifier of the chest X-ray images. The auto-encoder was first trained layer by layer using greedy layer-wise training until a network of two hidden layers, one input, and one output network is formed. Therefore, these trained auto-encoders were all stacked together and the proposed Region-based Convolutional Neural Network is formed. The proposed network is trained to classify chest images into normal which have no abnormalities or diseased images regardless of the type of the disease. A sample of the database normal and abnormal chest X-rays is shown in Figure 14. Note that in this work, two deep models are employed. Both models are Region-based Convolutional Neural Networks with the same learning parameters, however, forthe first model, which we call RCNN1, the chest X-rays are fed directly into the network, without processing and enhancement. The second network model, which is called RCNN2, was trained on images that are processed and enhanced before being fed into the network. The aim of the use of two models is to investigate the effects of processing and image enhancement on the auto-encoder training and testing performance.

4.IMPLEMENTATION

Module description with algorithm / Pseudo code

MODULES:

1 .Authentication Module:

- This module handles user authentication, including the login and sign-up functionalities.
- It manages user accounts, passwords, and authentication tokens.

2. Image Upload Module:

- This module allows users to upload chest X-ray images for tuberculosis detection.
- It handles image file uploads, validation, and storage.

3. Tuberculosis Detection Module:

- This module performs tuberculosis detection on uploaded chest X-ray images.
- It uses deep learning models to analyze the images and classify them as either positive or negative for tuberculosis.

3. Result Display Module:

- This module displays the detection results to the user.
- For positive cases, it provides detailed analysis and information about the tuberculosis findings.
- It may include visualizations, textual explanations, and references to medical literature.

4. Logout Module:

- This module handles user logout functionality.
- It clears the user's session and authentication tokens to ensure secure logout.

5. User Interface Module:

- This module implements the user interface (UI) of the website.
- It includes the design, layout, and interactivity of the login, sign-up, image upload, result display, and logout pages.

6. Backend Server Module:

- This module serves as the backend server for the website.
- It handles incoming HTTP requests from the frontend, processes data, and communicates with the database and other external services.
- It may be implemented using a web framework like Django, Flask, or Express.js.

5.CONCLUSION

This thesis presents the employment of deep networks, in particular Region-based Convolutional Neural Network, in a medical field challenging task, which is the classification of chest X-rays into normal and abnormal images. Such a classification medical system is needed as it makes the radiologist's job faster and easier. A Region-based Convolutional Neural Network is employed in this work and it was trained and tested on 470 and 283 images, respectively. The network is first trained on images taken directly from the database, without processing and enhancing. Then same network was tested and performance was evaluated in terms of training time, error, and accuracy. The same network was trained again on the same images but here the images were enhanced using histogram equalization. Also, this network was tested and an evaluation of its performance was carried out. The performance of both networks was discussed and a comparison of the two network performance was shown, in terms of accuracy, error reached, training time, and number of iterations needed. After this comparison it was seen that the network that uses enhanced images outperformed the one that used unprocessed images as it achieved a higher recognition rate during testing. In conclusion, the testing of Region-based Convolutional Neural Network showed that it gained a good capability of diagnosing the new unseen chest X-rays and correctly classifying them into normal or abnormal images. Thus, it can be stated that the RCNN can be a good classifier for the chest X-rays classification with a small margin of errors. Moreover, it is seen that the enhancement of chest X- rays using histogram equalization has a good role in improving the learning of the Region-based Convolutional Neural Network, which results in a better accuracy during the testing of the network.

6.FUTURE ENHANCEMENT

Fine-tuning Models:

- Continuously fine-tuning deep learning models involve updating their parameters based on new data, which helps improve their performance over time.
- Access to larger and more diverse datasets is crucial for fine-tuning models effectively. This may involve collaboration with multiple healthcare institutions to aggregate data.
- Transfer learning techniques, where knowledge from pre-trained models is transferred to new tasks, can be utilized to accelerate model training and improve performance with limited labeled data.

Multi-Modal Fusion:

- Combining information from multiple imaging modalities or clinical data sources can provide a more comprehensive understanding of tuberculosis cases.
- For example, integrating data from X-rays, CT scans, patient demographics, and medical history can improve the accuracy and reliability of tuberculosis detection.
- Fusion techniques such as feature concatenation, attention mechanisms, or multi-task learning can be employed to effectively integrate information from diverse sources.

.

7.REFERENCES

1. Demner-Fushman, D., Kohli, M.D., Rosenman, M.B., Shooshan, S.E., Rodriguez, L., Antani, S., & McDonald, C.J. (2015). Preparing a collection of radiology examinations for distribution and retrieval.Journal of the American Medical Informatics Association, 23(2), 304-310.

2. Demner-Fushman, D., Antani, S., Simpson, M., & Thoma, G.R. (2012). Design and development of a multimodal biomedical information retrieval system. Journal of Computing Science and Engineering, 6(2), 168-177.

3. Jaeger, S., Karargyris, A., Candemir, S., Folio, L., Siegelman, J., Callaghan, F., & Thoma, G. (2014).Automatic tuberculosis screening using chest radiographs. IEEE transactions on medical imaging, 33(2), 233-245.

4. Xue, Z., You, D., Candemir, S., Jaeger, S., Antani, S., Long, L.R., & Thoma, G.R. (2015). Chest x- ray image view classification. In Proceedings of the 28th International Symposium on Computer- Based Medical Systems (CBMS) (pp. 66-71). Brazil: Ribeirão Preto.

5. Candemir, S., Jaeger, S., Palaniappan, K., Musco, J.P., Singh, R.K., Xue, Z., & McDonald, C.J. (2014). Lung segmentation in chest radiographs using anatomical atlases with nonrigid registration. IEEE transactions on medical imaging, 33(2), 577-590.

6. Shiraishi, J., Katsuragawa, S., Ikezoe, J., Matsumoto, T., Kobayashi, T., Komatsu, K.I., & Doi,
K. (2000). Development of a digital image database for chest radiographs with and without a lung
nodule:receiver operating characteristic analysis of radiologists' detection of pulmonary nodules.
American Journal of Roentgenology, 174(1), 71-74.

7. Dong, Y., Pan, Y., Zhang, J., & Xu, W. (2017). Learning to Read Chest X-Ray Images from 16000+Examples Using CNN.

In the Proceedings of the IEEE/ACM International Conference on ConnectedHealth: Applications, Systems and Engineering Technologies (pp. 51-57). USA: Philadelphia.

8. Cernazanu-Glavan, C., & Holban, S. (2013). Segmentation of bone structure in X-ray images using convolutional neural network. Advanced Electrical and Computer Engineering, 13(1), 87- 94.

9. Patil, S.A., & Kuchanur, M.B. (2012). Lung cancer classification using image processing. International Journal of Engineering and Innovative Technology, 2(3).

10. Er, O., Yumusak, N., & Temurtas, F. (2010). Chest diseases diagnosis using artificial neural networks.Expert Systems with Applications, 37(12), 7648-7655.

11. El-Solh, A.A., Hsiao, C.B., Goodnough, S., Serghani, J., & Grant, B.J. (1999). Predicting active pulmonary tuberculosis using an artificial neural network. Chest, 116(4), 968-973.