Industrial Engineering Journal
ISSN: 0970-2555
Volume : 49, Issue 7, No. 1, July : 2020

IDENTIFICATION AND EXPOSURE OF TUBERCULOSIS IN CHEST X-RAY IMAGES APPLYING DEEP LEARNING TECHNIQUES

Mallishetty. Praveen Kumar, K.Venkata Nagendra, Modem. Jeevan Kumar,
Dept of Computer Science and Engineering, Sree Venkateswara College Of Engineering, Nellore (Dt), Andhra Pradesh, India.
P.Rajesh, Dept of Electronics and Communication Engineering, Sree Venkateswara College Of Engineering, Nellore (Dt), Andhra Pradesh, India.

Abstract
Deep learning is one of the 10 mainly innovative data analysis methods. Multiple-level abstraction data representations can be learned using deep learning. The greatest advantages for visual object recognition come from deep learning by means of the aid of deep learning, tuberculosis (TB) may be recognised in X-ray pictures. Radiologists, who are in short supply, may be better able to diagnose and treat TB with the help of these new tools. The software systems CAD4TB, qXR, and Lunit INSIGHT (CXRs) have all been used to search for anomalies in chest X-rays. The learning-based programme from CAD4deep TB uses a heat map graphic to highlight the abnormal location. From abnormal chest X-rays, the qXR algorithm may be able to identify 15 anomalies. There are 10 anomalies that may be seen on the chest radiographs using the Lunit INSIGHT CxR programmed.
Deep learning-based computer-aided detection (CAD) systems need a human observation to verify its usage. The receiver operating characteristic (ROC) curve is used to evaluate the precision of CAD software. Ethical and scientific standards must be adhered to while using deep learning in medicine.

1. INTRODUCTION

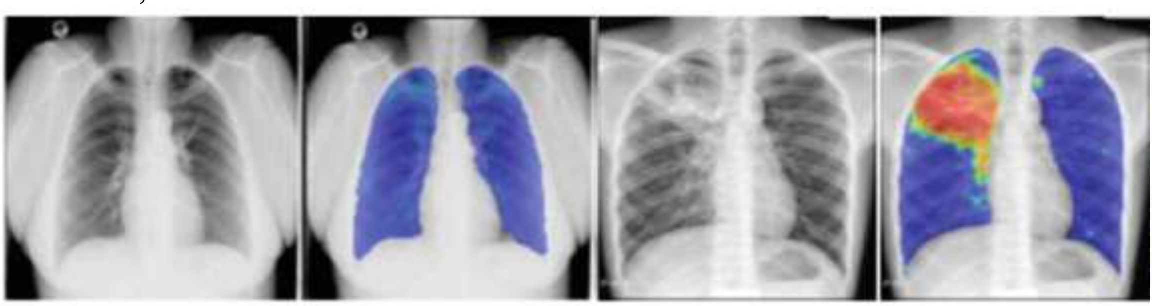
Early disease detection is essential for effective tuberculosis (TB) prevention and control. Numerous factors, such as poverty, slum overpopulation, poor nutrition, mental health issues, drug use, and HIV infection, contribute to the high TB prevalence [1]. Due to poor healthcare and a shortage of CXR readers, the TB detection gap may be increasing worse in a number of countries. Acid-fast bacillus (AFB) tests, sputum cultures, questionnaires, chest X-rays, and tuberculin skin tests (TST) are a few of the screening methods used to detect TB. The WHO recommends a chest X-ray as the first step by diagnosis of tuberculosis (TB). For the diagnosis of illnesses of the chest, chest radiographs are required. The significance of X-ray images in identifying tuberculosis was constrained by the need for an X-ray machine, trained employees to operate the system, and a lack of specificity on the part of observers. The advent of digital radiography revolutionised computer-aided TB detection (CADT) [3]. It depends on the radiologist's training if they can correctly identify TB from a CXR.

1.1 Deep Learning

Research and diagnosis for medical imaging have never been easier to automate thanks to deep learning (DL). It might reduce the strain placed on radiologists in clinical situations [4]. Deep learning in radiology is used for a variety of tasks in this field, image registration, segmentation, neurological disease diagnosis, X-ray, CT, mammography, and MRI image computer-aided detection systems, as well as natural language processing (NLP) for report text analysis [5]. For conventional machine learning algorithms to successfully extract features from raw data, a strong understanding of the topic is required. During training, the classifier uses these characteristics as feature vectors. Patterns in the input can be categorised [6]. The extensive training data gathering and computer capacity have increased

interest in deep learning and neural networks [7]. The automatic extraction of features from a raw dataset is possible with DL approaches.
A raw dataset's features can be automatically extracted using DL algorithms. Convolutional neural networks based on deep learning are also used in CAD systems to classify and identify images of images of various medical images to identify illnesses [8, 9]. CNNs' convolutional structure makes them a dependable tool for computer visualization issues. Medical image analysis companies are now using CNNs and other deep learning techniques [10] for medical image analysis. The classifier and feature extraction are both elements of CNN. In a CNN, feature extraction is done by employing convolutional layers. Fully linked layers [11] can be used as a classifier.

1.2 CAD4TB
The Radboud University Medical Centre in Nijmegen, the Netherlands, created the CAD4TB programme as a screening tool. The CE-certified CAD4TB was made available by Delft Imaging Systems [12]. In order to distinguish between normal and pathological X-ray pictures, the CAD4TB software is taught by means of machine learning techniques and tagged images. An X-ray picture of the chest might be accepted as input by the CAD4TB software. CAD4TB generates a heat map showing the locations of the abnormalities in the picture together with an abnormality score that runs from 0 to 100. This threshold value is used to categories CXR pictures as usual or unusual.
Here threshold number is often in excess of 50%. The result of CAD4TBV6 is shown in Figure 1. [13] Compares clinical officers with digital CXR screening using CAD4TBv1.08 for accuracy in TB detection. The CAD4TB integrates many detection methods, such as textural anomaly recognition (TAR), shape abnormality detection (SAD), lung field detection, and clavicle identification, to provide a more complete diagnosis (CD). To lessen false-positive results, a CD system and a TAD system working at the pixel level are coupled. This leads to a visual choice. The SAD method calculates an anomaly score depending on the morphology of the lungs. The SAD system score and TAD system score were compared, and the findings were added to create the final abnormality score. The abnormality score of a fresh CXR picture was determined using a k-NN classifier trained on texture and shape abnormality scores [14]. According to CAD4TBv1's anomaly detecting mechanism, Figure 2 demonstrates. If you have a fresh CXR image of CAD4TBV 1.08, the procedure is as follows: The unobscured lung area is automatically segmented for the fresh CXR picture using SAD and TAD detection methods;



(a) (b) (c) (d)

Fig. 1 Using CAD4TBv6, here are two examples of CXRs and the associated production heat maps. **a)** CXR picture by means of no TB and a score of 17 abnormalities. **b)** Heat map of the corresponding anomaly. **c)** CXR picture showing TB positivity and a score of 82 abnormalities. **d)** Heat map of the corresponding anomaly

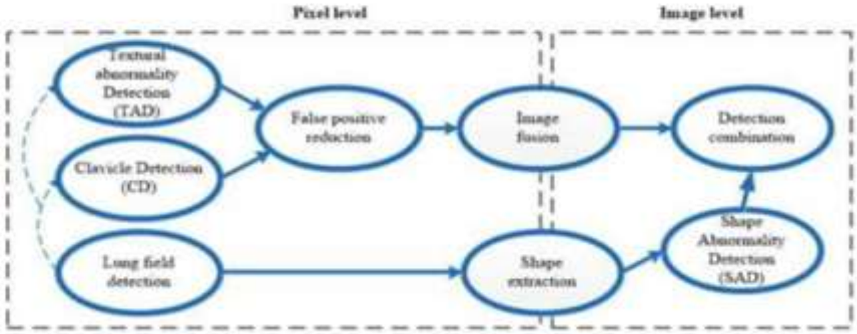


Fig. 2 combining different detection methods

When given a new CXR image, the SAD system forecasts the abnormality score based on the training information for textural or shape abnormalities scores. The unusual score is dependent on lung shapes.
Researchers Muyoyeta et al. assessed the CAD4TBv1.02 programme for tuberculosis detection in a real-world setting without success. The researchers had demonstrated that CAD4TBv1.02 has a poor specificity and a high sensitivity. The chest X-ray screening performance of CAD4TB v3.07 was compared to that of radiologists by Steiner et al. [17]. Melendez et al. [19] and Philipsen and Melendez [18] both looked at the use of automated digital chest radiography (ACR) before the Xpert MTB test. During a chest X-ray (CXR) screening, Melendez et al. evaluated the automated software CAD4TB version 5 [20]. In CAD4TBv5, support vector machines were utilized as a catogorizer to surpass prior iterations. CAD4TB versions 3.0, 4.0, 5.0, and 6.0 be evaluate to the Xpert test, following Murphy et al. [21]. The specificity and sensitivity of CAD4TB v6 were both above 90%.
Even while the earlier CAD4TB v5 and v6 versions were more specific, they had gradually lost some of it over time. This idea is the foundation of the 2018 release of the deep learning-based programme CAD4TBv6. In contrast to earlier versions of CAD4TBv6, which had a lower age restriction of 16 years [22], CAD4TBv6 now supports processing images of individuals as young as four years old. It was important for the CAD4TB programme to support a DICOM image format, process images from CR or DX sources, and work with photographs of people who were at least four years old.

Fig. 3 qXr programme produces a picture that is abnormal.

1.3 qXR

In order to quickly and accurately identify diseases, The artificial intellectual ability-based start-up company Qure.ai, founded in India, integrates deep learning and machine learning techniques. Utilizing qXR, it is possible to identify pleural tuberculosis, consolidation, cardiomegaly, pulmonary, cavity, and hilar expansion., as well as other conditions on a chest X-ray [23]. An Indian CAD programme called qXR (Qure.ai, Mumbai, India) was used to assess the diagnostic precision of a reference standard for tuberculosis (TB) that has been confirmed microbiologically. The QXR program's output to the DICOM chest X-ray picture is shown in Figure 3. All varieties of X-ray machines are supported by the qXR

software, which can handle a huge variety of X-ray images of various quality and exposure. In 2018 [25], the commercial CAD software qXR obtained CE certification.
Using qXR software, TB is identified in India's public health screening programme. With an AUC of 0.81 for the receiver operating characteristic (ROC) curve, qXR discovered microbiologically confirmed PTB. The AUC for the other anomalies varied from 0.75 to 0.94. by means of a radiologist as a indication, the qXR software produced an AUC of 0.87. The most current CAD4TB version has an AUC that be higher by qXR.

1.4 Lunit INSIGHT CXR
Consolidation, nodule, calcium calcification, fibrous tissue, pneumothorax, pneumoperitoneum, atelectasis and cardiomegaly are among 10 abnormalities that may be detected by Lunit INSIGHT CXR 3 by screening on the chest X-ray picture. The CE mark appears on Lunit INSIGHT [26]. Figure 4 displays the final JPG pictures (various abnormality scores

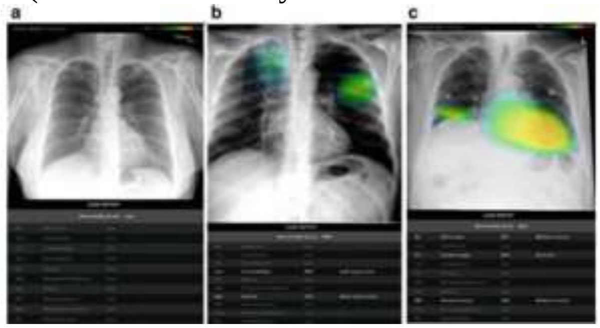
a b c


Fig. 4 Output of the Lunit INSIGHT CXR 3 software Chest X-ray pictures in JPG format for DICOM.
Three images were created from the DICOM Chest X-ray images using the Lunit INSIGHTCXR3 programme: a normal image, a nodule through an irregularity score of 66%, and a nodule with an irregularity score of 82%. To find TB-related abnormality in chest X-ray pictures, the researchers in Qin et al. [27] looked at three deep learning algorithms, including CAD4TB, qXR, and Lunit INSIGHT. The three DL systems were examined and contrasted by the authors.
Lunit (South Korea) used version 4.7.2 of the Lunit INSIGHT programme to produce the chest X-ray picture. Lunit and CAD4TB can read CXR pictures that are in the DICOM format. The CAD4TB result falls into the anomaly score range of 0 to 100 when detecting tuberculitis. The qXR and Lunit lung abnormalities of cavitation, nodule, pneumothorax, and other types were seen on the CXR picture. In identifying patients with and without tuberculosis, deep learning-based softwares CAD4TB, qXR, and Lunit beat skilled human readers.

1.5 TimBre
Docturnal is a telemedicine-related non-invasive point-of-care technique for diagnosing and screening TB and diabetic retinopathy. TB screening programme TimBre was created by Docturnal, a privately held business. This software simplifies the TB detection process [28]. A microphone array was used to capture a patient's cough, and clinical information including demographics, TB status, current medical problems, family history of TB, sleep and cough habits, and HIV had to be entered into the TimBre app. After that, a real-time machine learning analysis was performed on the movie to look for any indications of tuberculosis (TB). If the screening results are good, doctors typically suggest a chest X-ray to diagnose the condition. TimBre's app had an accuracy rate of 85% when compared to conventional TB testing technology. TimBre is now being tested as an investigational development at a few chest hospitals in Hyderabad and Narayana Hrudayala in Bangalore.

1.6 Conversation

In low-income countries, pre-screening techniques utilize deep learning-based algorithms that can accurately diagnose TB from CXR pictures. For TB detection, there's multiple software tools, databases, as well as performance indicators. Performance indicators for the detection of TB used by various authors in their publications include sensitivity (SN), particularity, and AUC, commonly referred to as "The Area over a Receiver Operating Characteristic (ROC) Curve," (SP).

Conclusion

Deep learning-based CAD systems and automated TB screening might offer a more complete diagnosis. Deep learning-based CAD structure is categorized a large number of normal CXRs with excellent sensitivity for TB screening in areas with dense populations [34]. The price of radiographic TB testing might be decreased using these CAD techniques. Future advancements in deep learning-based screening technologies may raise the specificity and accuracy of CAD methods for TB detection.

References

1. K. Paquette, M.P. Cheng, M.J. Kadatz, V.J. Cook, W. Chen, J.C. Johnston, Chest radiography for active tuberculosis case finding in the homeless: a systematic review and meta-analysis. Int. J. Tuberc. Lung Dis. **18**(10), 1231–1236 (2014). https://doi.org/10.5588/ijtld.14.0105
2. J.Y. Wu et al., The role of chest radiography in the suspicion for and diagnosis of pulmonary tuberculosis in intensive care units. Int. J. Tuberc. Lung Dis. **13**(11), 1380–1386 (2009)
3. C. Schaefer-Prokop, U. Neitzel, H.W. Venema, M. Uffmann, M. Prokop, Digital chest radiography: an update on modern technology, dose containment and control of image quality. Eur. Radiol. **18**(9), 1818–1830 (2008). https://doi.org/10.1007/s00330-008-0948-3
4. M. Bigelow et al., Integrating AI into radiology workflow: levels of research, production, and feedback maturity **7**(1) (2020). https://doi.org/10.1117/1.JMI.7.1.016502
5. M.A. Khan et al., Lungs cancer classification from CT images: an integrated design of contrast based classical features fusion and selection. Pattern Recogn. Lett. **129**, 77–85 (2020). https://doi.org/10.1016/j.patrec.2019.11.014
6. S. Wang, R.M. Summers, Machine learning and radiology. Med. Image Anal. **16**(5), 933– 951 (2012). https://doi.org/10.1016/j.media.2012.02.005
7. GauthamA,BhatejaV,Tiwari A, Satapathy SC(2018)Animprovedmammogram classification approach using back propagation neural network. Data Eng. Intell. Comput. **542**, 283–291 (2018). https://doi.org/10.1007/978-981-10-3223-3
8. V. Bhateja, M. Misra, S. Urooj,Non-linear polynomial filters for edge enhancement ofmammogram lesions. Comput. Methods Programs Biomed. **129**, 125–134 (2016). https://doi.org/10. 1016/j.cmpb.2016.01.007
9. V.P. Vianna, Study and development of a computer-aided diagnosis system for classification of chest X-ray images using convolutional neural networks pre-trained for ImageNet and data augmentation 1–7 (2018)
10. H. Greenspan, B. Van Ginneken, R.M. Summers, Guest editorial deep learning in medical imaging: overviewand future promise of an exciting newtechnique. IEEE Trans. Med. Imaging **35**(5), 1153–1159 (2016). https://doi.org/10.1109/TMI.2016.2553401
11. L. Pigou, S. Dieleman, P.J.Kindermans, B. Schrauwen, Sign language recognition using convolutional neural networks, in Lecture Notes in Computer Science. Lecture notes in artificial intelligence. Lecture notes in bioinformatics, vol. 8925 (2015), pp. 572–578. https://doi.org/10.1007/978-3-319-16178-5_40

12. WHO/UNITAID, *Tuberculosis Diagnostics Technology and Market Landscape* (UNITAID Secr. World Health Organization, 2014)
13. P. Maduskar, M. Muyoyeta, H. Ayles, L. Hogeweg, L. Peters-Bax, B. Van Ginneken, Detection of tuberculosis using digital chest radiography: automated reading vs. interpretation by clinical officers. Int. J. Tuberc. Lung Dis. **17**(12), 1613–1620 (2013). https://doi.org/10.5588/ijtld.13.0325
14. L. Hogeweg, C. Mol, P.A. De Jong, R. Dawson, H. Ayles, B. Van Ginneken, Fusion of local and global detection systems to detect tuberculosis in chest radiographs, in Lecture Notes in Computer Science. Lecture notes in artificial intelligence. Lecture notes in bioinformatics, vol. 6363, LNCS, No. Part 3 (2010), pp. 650–657. https://doi.org/10.1007/978-3-642-15711-0_81
15. M. Muyoyeta et al., The sensitivity and specificity of using a computer aided diagnosis program for automatically scoring chest X-rays of presumptive TB patients compared with Xpert MTB/RIF in Lusaka Zambia. PLoS ONE **9**(4), 16–18 (2014). https://doi.org/10.1371/journal.pone.0093757
16. M. Muyoyeta et al., Digital CXR with computer aided diagnosis versus symptom screen to define presumptive tuberculosis among household contacts and impact on tuberculosis diagnosis. BMC Infect. Dis. **17**(1), 1–8 (2017). https://doi.org/10.1186/s12879-017-2388-7
17. Steiner et al., Screening for pulmonary tuberculosis in a Tanzanian prison and computeraided interpretation of chest X-rays. Public Health Action **5**(4), 249–254 (2015). https://doi.org/10.5588/pha.15.0037 Deep Learning-Based Software Tools for Tuberculosis Detection… 223
18. R.H.H.M. Philipsen et al., Automated chest-radiography as a triage for Xpert testing in resourceconstrained settings: a prospective study of diagnostic accuracy and costs. Sci. Rep. **5**(March), 1–8 (2015). https://doi.org/10.1038/srep12215
19. J. Melendez et al., An automated tuberculosis screening strategy combining X-ray-based computer-aided detection and clinical information. Sci. Rep. **6**(October 2015), 1–8 (2016). https://doi.org/10.1038/srep25265
20. J. Melendez, R.H.H.M. Philipsen, V. Sunkutu, N. Kapata, Automatic versus human reading of chest X-rays in the Zambia National Tuberculosis Prevalence Survey **21**(April), 880–886 (2017)
21. K. Murphy et al., Computer aided detection of tuberculosis on chest radiographs: an evaluation of the CAD4TB v6 system (2019), pp. 1–11 [Online]. Available: https://arxiv.org/abs/1903.03349
22. Our Improved CAD4TB Software is Now Reliable for Children | Delft Imaging. https://www.delft.care/cad4tb6/Qure.ai Chest X Ray Study. https://qure.ai/qxr/
23. M. Nash et al., Deep learning, computer-aided radiography reading for tuberculosis: a diagnostic accuracy study from a tertiary hospital in India. Sci. Rep. **10**(1), 1–10 (2020). https://doi.org/10.1038/s41598-019-56589-3
24. Qure.ai | qXR Becomes First AI-Based Chest X-ray Interpretation Tool to Receive CE Certification. https://qure.ai/news/2018/05/31/qXR-CE.html Lunit INSIGHT for Chest Radiography. https://insight.lunit.io/cxr/
25. Z.Z. Qin et al., Using artificial intelligence to read chest radiographs for tuberculosis detection: amulti-site evaluation of the diagnostic accuracy of three deep learning systems. Sci. Rep. 1–10 (2019).