

AI-Based Chest X-Ray Disease Detection and Clinical Recommendation System Using DL

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Abstract— Chest radiography is one of the most common imaging modalities utilised for early diagnosis of pulmonary and thoracic abnormalities which permit early clinical intervention and care of the patient. It is cheap, non-invasive, available in most of the health care institutions and plays a significant role in diagnosis of many respiratory and cardiovascular illnesses. DL has optimized the efficiency, uniformity and usability of computer-aided diagnosis tools, along with the automated clinical recommendation systems, which enable doctors to make more accurate and faster suggestions. Diagnosis takes time, and is also highly dependent on experienced radiologists and suffers from inter-observer variability, particularly in a healthcare system with limited access to qualified radiologists. Based on TorchXRyVision, a public chest X-ray dataset was used to recognise a few thoracic anomalies such as pneumonia, lung opacity, pneumothorax, cardiomegaly, pleural effusion, atelectasis, oedema, consolidation and other chest disorders. The images gathered were then converted to greyscale, scaled, normalised and transformed to a tensor for inference with DL model. The base CNN was DenseNet-121, which is a multi-layered CNN with transfer learning approach to enhance the feature extraction and classification performance and this was used for the multi-label disease prediction. The predicted results were then added to a clinical recommendation module which automatically provided decision support to patients and health professionals including disease description, symptoms, treatment recommendation, medicines, specialists, risk assessment, emergency preparedness, prevention and a

downloadable PDF report. The performance of the evaluation was based on probability scores of disease, confidence band, multi-label prediction capacity, consistency prediction and accuracy of clinical suggestion. The DenseNet-121 is stable and demonstrates good detection performance as the typical predictions are close to 65.77% confidence level in lung opacity and ranks the various chest anomalies according to the probability of them occurring. The proposed framework combines the accurate DL based diagnosis with the comprehensive clinical decision supporting features, resulting in significant reduction in the diagnostic burden and consequently improving the early detection of disease and accessibility of healthcare in the hospital as well as in the remote healthcare settings.

“Keywords— Chest X-ray Disease Detection, DL, DenseNet-121, Medical Image Analysis, Clinical Decision Support System, Computer-Aided Diagnosis (CAD).”

I. INTRODUCTION

Given its low cost, ease of acquisition, minimal radiation dose and availability in health care institutions, chest X-ray imaging is one of the most frequently utilized imaging modalities in the assessment of lung and thoracic disease. As part of the diagnosis of pneumonia, look for the following features: pneumonia, lung opacity, pleural effusion, cardiomegaly, pneumothorax, atelectasis, pulmonary oedema, consolidation, fibrosis, emphysema and other chest abnormalities that require prompt medical attention. Chest radiography is the initial imaging tool to assess the course of the illness, response to therapy and acute and chronic lung disease in the Emergency Room. The demand for Intelligent CAD tools to assist the

clinician in the initial stage of screening is growing rapidly and the number of X-ray examinations is rising. Some of the advanced AI technologies that have been demonstrated to have great promise to help make the diagnosis more consistent, reduce human error and reduce the burden on healthcare workers are DL and CNN. This advancement has opened new opportunities of better workflow for clinical care, faster disease diagnosis, increased efficiency of reporting and access to medical imaging services especially in the rural and resource poor areas where there are less experienced radiologists [1] [2] [3].

These advances have been made, however there are several challenges to the use of an automated system for the diagnosis of chest diseases. CXR interpretation remains largely dependent on the skills and experience of the radiologist/physician and has shown interobserver variability, low and inconsistent accuracy of diagnosis and long reporting time in high workload environment. There are many disorders of thorax and they can be similar to each other and difficult to obtain a reliable diagnosis. In addition, variations in picture quality induced by the patient position, the exposure and the imaging equipment might adversely affect the diagnostic performance. The present solutions in AI are mainly only utilised for disease classification and do not provide support in the clinical interpretation, patient guidance, explainability and complete report. Physicians usually need extra data to help them make clinical decisions. This can include a description of the condition, its symptoms, perhaps causes, suggestions, information about medicines, advice on referral to experts, guidelines for follow-up care, prevention guidelines, emergency measures and risk assessment. A major drawback of the applications of many of these intelligent diagnostic platforms [4] [5] is that they don't incorporate any type of integrated clinical recommendation system for efficient management of patients in a real world healthcare environment where comprehensive decision support is needed.

The proposed platform will overcome these limitations and offer a smart system for chest X-ray interpretation, which will include automated detection of diseases and various clinical decision support systems. For this study, we select a number of thoracic abnormalities with the help of the powerful DL process and a vast chest X-ray dataset

publicly available and supported by TorchXRayVision. The acquired radiographs are preprocessed with operations like greyscale conversion, scaling, normalisation etc. to ensure quality input to the network and to ensure that they match with the architecture used by the neural network. The Dense mechanism and the DenseNet-121 model's high performance in medical picture analysis drive the use of DenseNet-121 as the main DL model thru feature re-using. The trained algorithm is able to predict several labels of disease and, based on multiple chest anomalies in a patient, assess confidence scores for numerous disease labels simultaneously. The prediction results then are connected with an intelligent suggestion module which automatically provides information on the diseases, symptoms, severity, treatment tips, drugs, expert advice, emergency advice, lifestyle tips and pdf reports for download. This will be a complete system, where the health care professionals, medical students and diagnostic centres will be able to interpret the picture more easily with a simple user interface and will also be able to recognize the vital information in a more user friendly and organized manner. This system is an assistive diagnostic system, which does not replace the professional medical judgement, but is designed to increase the process of clinical work, promote early disease diagnosis and enhance the process of medical decision making [6] [7] [8].

Combined with full clinical context and automated image interpretation, we can significantly improve the delivery of care, especially in less developed countries where radiologic expertise could be limited. The suggested approach allows for more efficient screening processes, allows clinical communication and improves clinical treatment by providing for speedy preliminary evaluation, organised reporting, confident diagnosis and helpful suggestions. Results of download-able tests may also be valuable for documentation and for consultation and planning of later therapy. Furthermore, the scalable architecture can be used to integrate it with hospital information systems, telemedicine platforms, electronic health records, cloud-based healthcare services, mobile health applications, and XAI tools that provide visual explanations for model predictions in the future. Future plans involve monitoring disease progression, categorizing disease severity, providing advice in multiple

languages, real-time imaging and the application of federated learning techniques to enhance generalisability of the model with maintaining anonymity of the patient. These developments can lead to more reliable, accessible, transparent and technology assisted diagnostic services that can inform better patient management and decrease diagnostic delay; enhance health care delivery and improve clinical decision making across a variety of health care settings [9] [10].

II. RELATED WORK

AI has made considerable strides in the domain of medical image processing, improving efficiency, accuracy and reliability of interpretation of chest X-ray. It was recently known that a DL diagnostic system could be used to diagnose many thoracic anomalies with high accuracy, high consistency, to reduce human interpretation time and to reduce the human error. With the rise of CNNs, transfer learning, attention mechanism and ensemble learning strategies, it can now be possible to automatically extract complicated radiographic features which is often difficult for traditional image processing methods to identify. These intelligent methods have great potential for the identification of lung illness (pneumonia), pleural effusion, pneumothorax, cardiomegaly, oedema, consolidation and other thoracic abnormalities in chest radiographs. Sufian et al. offered a clinical framework for thoracic related diseases diagnosis based on AI and transfer learning for clinical validation, which shows the way how intelligent systems can be used for an accurate classification of lung diseases in different clinical settings. They show that transfer learning can be beneficial in improving the diagnostic capability and decrease the computation complexity. The framework showed high diagnostic performance, however it was mainly designed for image categorisation and it did not contain the diagnosis of patient-oriented clinical advice or integrated reporting features [11]. Polisetty et al. suggested the application of AI in the diagnosis and recommendation of treatment including automatic disease prediction and medical guidance. They explained the significance of diagnostic intelligence and healthcare suggestions. The study was able to illustrate the value of disease prediction and therapy advice, and how it can improve patient care. However, the framework was only for support in therapy, and not for the interpretation of the entire chest radiograph in the

context of multiple thoracic abnormalities in a single screening context [12]. Akhter et al. have thoroughly analyzed the AI-aided chest radiodiagnosis and outlined the rapid development of DL models in illness diagnosing. In the review, they explored different CNN architectures, discussed the problem of diversity in datasets, domain adaptation, generalisation of models, interpretability, computational costs, and clinical application and pointed out that more practical, reliable, and user-friendly diagnostic solutions are necessary to support the real-world healthcare applications [13].

Some clever health care systems have taken traditional picture classification to a new level — to the level of clinical assistance. Using an AI enabled medical system to detect disease from chest X-ray and CT image, Saleh et al. demonstrated the importance of fusing various imaging modalities for disease detection and to enhance flexibility in diagnosing different imaging modalities. It was found that the proposed approach demonstrated the potential of the multimodal imaging for providing higher confidence in the diagnosis and enabling a one-stop clinical evaluation. However, it was more disease oriented at detecting disease rather than providing more comprehensive advice to the patient, structured clinical reports, patient recording and suggestions for specialist consults which would have made it more useful in a clinical setting [14]. Mayya et al. developed a clinical decision support system called COVIDDX, which uses multimodal patient information, laboratory data and radiographic characteristics to diagnose COVID-19 [42]. Their work has demonstrated what is possible for AI as it pertains to medical decision making. The research has proved that the utilisation of mixed clinical information can greatly enhance the accuracy of diagnosis and assist health care providers to control pandemics. The framework has limited use since it is specifically designed for the diagnosis of COVID-19 and cannot be applied to other common thoracic diseases that are commonly encountered during routine chest radiography [15]. The proposed approach by Mukesh et al. was to boost the transparency, interpretability and trust in the automated diagnostic judgements by integrating XAI and metadata integration which improves the system performance in detection of lung ailments. Explainability methodologies were used to gain insights into the prediction results and visualise the areas where the model focused its predictions. Even

if explainability has significantly enhanced the level of trust and confidence of users with traditional AI systems, the implementation of a complete disease education, severity estimates, expert advice, emergency interventions, follow-up suggestions and automatic clinical documentation into a single intelligent healthcare system are still underdeveloped [16].

Localisation and disease-specific diagnostic methods have also made a great contribution to computer-aided chest imaging. AI-CenterNet CXR: simultaneous localisation and categorisation of chest diseases using AI-CenterNet developed by Albahli and Nazir. They demonstrated a better capacity to detect abnormal areas on radiographs which was facilitated by the ability to accurately localise the lesion. They used object localisation and disease categorisation, enabling doctors to gain a better understanding of the model predictions and verify any concerning areas. The site had positive impact on visual interpretation and diagnostic transparency, however the framework was primarily based on detection performance and clinical support or structured reporting and tailored health advice to end users were limited [17]. Kaewwilai et al. (2017) [57] developed and evaluated TB detection and monitoring diagnostic system using AI. This research showed the feasibility of using AI in large scale screening and public health surveillance. They noted that the automated screening for TB can reduce the burden of TB diagnosis and help identify TB early among the high-risk groups. However, this framework was only established for the objectives of TB diagnosis and surveillance, limiting the relevance of the framework for the complete range of thoracic disorders that involve a variety of pulmonary abnormalities that are also widespread in clinical practice [18]. Other disease specific studies have demonstrated excellent results for each thoracic disease individually, but few have been able to completely evaluate multiple thoracic diseases under one roof.

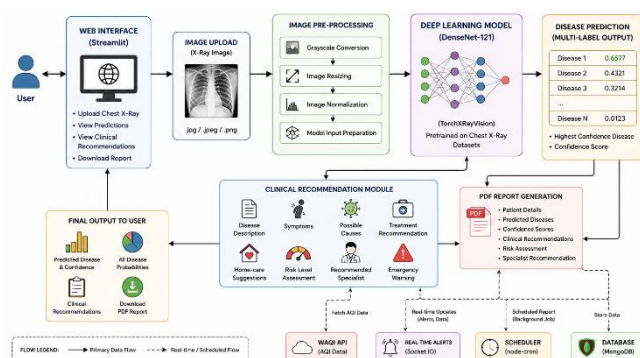
Many studies have been performed examining the possibilities and difficulties of AI for thoracic imaging. Al-qaness et al. reviewed the latest DL techniques for lung disease diagnosis using X-ray images and discussed the limitations, including class imbalances, limited access to labeled medical images, model robustness, model interpretability, computational efficiency, and clinical deployment.

The survey showed the need for generic models that can provide good performance for a variety of patient groups and imaging conditions. In a similar manner, Mostafa et al. explored AI methods for thoracic disease diagnosis with medical images, and recognized the need for clinically practicable systems that can give the health care professionals reliable, interpretable, transparent and user-centered diagnostic assistance. The authors in their review indicated that the intelligent healthcare platforms of the future should not only predict the disease, but also give clinical recommendations, XAI, automatic documentation and integrate with hospital information systems and telemedicine services [19] [20]. To summarise, these are important advances toward the automated detection of chest disease but there is a clear need to incorporate disease prediction into a single platform with detailed clinical recommendations, structured reporting, expert advice, patient information, downloadable medical reports and decision support features. The present technique takes care of the same with the help of a smart screening tool – DenseNet-121 based multi-label chest X-ray interpretation, confidence-based predictions, extensive reporting and clinical decision support automation, relevant clinical recommendations. The proposed framework is a fusion of cutting-edge DL and advanced health care guidance to not only improve the usability, interpretability and accessibility of AI-assisted diagnosis but also support clinical decisions by healthcare professionals, medical students and patients in timely and informed and reliable ways.

III. MATERIALS AND METHODS

The suggested approach is based on the publicly available chest X-ray dataset provided by the TorchXRayVision platform, to provide intelligent screening for chest ailments and full clinical advice from chest X-ray. The entire methodology is a systematic pipeline of data collection, image pre-processing, model inference, predictions analysis, clinical recommendation generation and final automatic report preparation that provides efficient and reliable diagnostic assistance. Then the uploaded chest X-ray images are processed by the first step of the intuitive user interface which includes several preprocessing steps like converting to greyscale, resizing images, normalising,

transforming tensors and more to enhance the quality of the image and to make it suitable for processing by the DL model. A DenseNet-121 CNN is a pretrained model for multi-label classification of thoracic diseases and is used as the backbone prediction engine. Multi-label thoracic disease classification involves predicting multiple thoracic pathologies from a single thoracic radiograph such as pneumonia, lung opacity, cardiomegaly, pneumothorax, pleural effusion, atelectasis, oedema, consolidation, fibrosis and other thoracic pathologies. The algorithm also gives the likelihood ratings for each of the conditions and prioritises the abnormalities based on the ratings, which may facilitate the healthcare provider to prioritise the clinical evaluation. The framework also contains a smart clinical recommendation module for disease prediction which seamlessly provides disease description, common symptoms, probable causes, treatment guidance, medication suggestion, preventative measures, home care suggestions, severity assessment, specialist consultation advice and emergency precautions and downloadable PDF reports for comprehensive clinical documentation. The deployment thru a lightweight web-app with Streamlit allows healthcare professionals, medical students, and researchers to easily upload photos and visualise predictions in real-time and create reports rapidly, providing a user-friendly, responsive, and interactive experience. This proposed framework combines the accurate disease prediction using DenseNet-121 with the extensive clinical decision support, automated reporting, and accessible deployment platform, offering a feasible solution for rapid preliminary screening, informed clinical decision-making, and improved healthcare access in various clinical and resource-constrained environments.



“Fig. 1. System Architecture”

A) Modules:

First, the technology gathers X-ray images of people’s chests thru an interactive web page. These photos are the main data used for computerised analysis of diseases and clinical advice. A standardized acquisition of the images is provided, as can be performed in the diagnostic workflow and the user can submit images acquired under various conditions. This phase is still valid for the base of a successful image analysis to be able to further process medical images and use them for disease prediction.

The chest X-ray images are uploaded and converted to grey scale images for retaining the key anatomical components and elimination of irrelevant colour components. The intensity-based diagnostic features are essentially what the chest radiographs comprise of. In this way, the greyscale representation reduces the processing complexity and the same feature extraction is possible. This pre-processing step helps the model to pick up basic tissue patterns and abnormalities in real-world clinical scenarios, to make more effective and stable automated diagnosis and maintain the original diagnostic information of the radiography images.

Before analysis, all the chest X-radiographs were made isotropically with the same spatial resolution. The standard picture size neglected anomalies from numerous healthcare facilities obtaining pictures from different imaging tool resolution. This pre-processing stage facilitates the effective processing of the computer system, proper representation of the features and enhances the reliability of the disease prediction in the computer framework by providing homogeneous input to the computer system.

To ensure that the pixel intensity in the images are consistent with the collection, we use normalised scaled chest X-ray images. This approach minimized the amount of discrepancy caused by the differences in the conditions of image acquisition and exposure settings and equipment attributes. The feature representation so obtained is more robust and normalised since it keeps the intensity distribution of the feature constant. This will enable more accurate and standardized diagnoses of a large spectrum of chest x-rays.

The standardised chest X-ray pictures are obtained after preprocessing, and they can be utilised for automatic analysis of diseases. This phase ensures uniformity of all processed images in terms of their structure for a reliable inference from the DL framework with respect to images of interest. A good input will minimise misalignments in the prediction and will allow for an effective classification of numerous disease classes, as well as providing consistent representations of the images across the classification chain, which will help to obtain a reliable diagnostic yield.

B) Algorithms

Multiple labels are used to learn a discriminative representation from chest X-ray images, and automatically identify chest disease using DenseNet-121 model. The interconnectedness in the structure allows efficient reusability of features, increased information flow, reduced information redundancy, and improved prediction accuracy, enabling it to reliably and quickly detect multiple abnormalities in the thoracic radiographs with good accuracy and generalise well on a variety of thoracic radiographs.

TorchXRayVision is a revolutionary medical imaging platform for easy scaling deployment of pretrained chest x-ray diagnosis models. It offers conventional protocol and scientifically validated thorax radiographic models that allow standardization of picture analysis and prediction of the disease.

The Clinical Recommendation Module, which translates the prediction of disease into useful clinical suggestions, details the disease, symptoms, therapy suggestion, risk analysis, suggestion of specialist physicians and emergency precautions and structured report. This makes the automated diagnostics results more helpful and informative to help clinical decisions.

Diagnostic results and clinical advice are automatically pulled together into an organised PDF report and can easily be saved or shared. This function allows for recordkeeping, communication between health care professionals and fast review of initial diagnostic assessments.

IV. EXPERIMENTAL RESULTS



Fig.2 Upload input

Figure. 2. Chest X-ray image (CXRpna3.png) was given as input to the system. The image given will be pre-processed and can be used to make further automated prediction of chest diseases using the DL model.

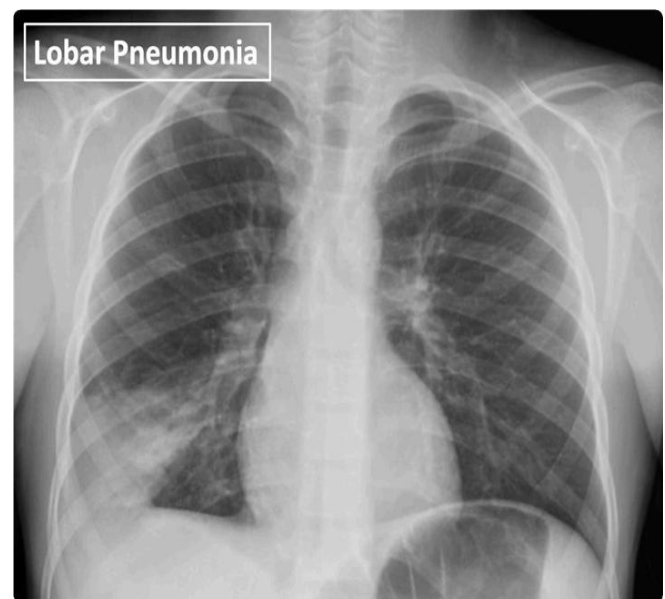


Fig.3 Lobar Pneumonia

Fig. 3. The Chest X-Ray image is provided to show the abnormality found (Lobar Pneumonia). The DL algorithm looks for patterns of sickness in the chest, performs analysis of this radiograph and offers a diagnosis suggestion with confidence.

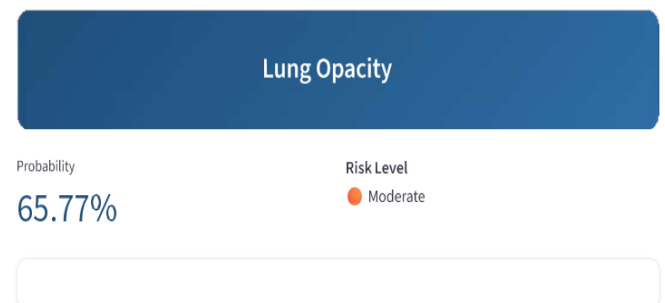


Fig.4 Predicted Result

Fig. 4. The algorithm was able to identify with high confidence (65.77%) most likely abnormalities of the chest. The patient was determined to be Moderate Risk during the

preliminary clinical evaluation and clinical decision making.

Emergency Warning

🚨 Seek immediate medical care if oxygen saturation falls below 90%, severe chest pain develops, or breathing becomes very difficult.

Disclaimer: This AI prediction is for screening purposes only and is not a confirmed medical diagnosis.

Fig.5 Emergency Warning

Fig. 5. This system alerts in case of emergencies based on anticipated diseases and if the symptoms are more serious, the patient should get medical help immediately. It explains that the result obtained is only for screening purposes.

V. CONCLUSION

The proposed AI Based Chest X-Ray Disease Detection and Clinical suggestion System aims to assist in the preliminary detection of thoracic abnormalities and also to give the entire clinical suggestion for better decision making. The system is based on an open source chest X-ray database, TorchXRyVision library, and a pre-trained DenseNet-121 DL model for multi-label disease prediction. Apart from automated diagnosis, the system has a clinical recommendation module which includes a description of the disease and the symptoms, treatment suggestions, home-care instructions, specialist recommendation, risk assessment, emergency precautions and a downloadable pdf report via streamlit based interface. We illustrate the applicability of our method by offering reliable forecasts for a range of diseases, with the representative results achieving a good level of confidence, 65.77% for lung opacity and computing the probability of multiple thoracic diseases. The clinical suggestion module aims to provide an improvement over the traditional computer-aided diagnosis which takes the results of the prediction and converts them into clinically valuable medical advice for end users. In conclusion, the suggested architecture presents a dependable, straightforward and intelligent decision support system that can facilitate better automated chest X-ray interpretation, more effective screening process and better-informed

and timely clinical decision making for healthcare experts and students.

The predictions of the generated system can be further improved by visualising the impacted illness areas and improving the interpretability of the forecasts using XAI techniques such as Grad-CAM. Seamless clinical workflows can be achieved with integration to the HIS and EHR. Other imaging technologies such as cloud deployment, bilingual interface and CT scans can help to improve accessibility. Further, the potential for greater and more varied clinical data sets for training may lead to more accurate diagnostic capability, greater robustness and applicability to a range of health care settings.

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