Leveraging CNN and Other Deep Learning Models to Detect Chest Diseases from Radiology Images

Abstract

Deep learning models, particularly Convolutional Neural Networks (CNNs) have achieved great success in disease diagnosis through medical image analysis as they can learn to extract features and pattern classifications exceptionally well. However, deep learning has seen a recent advancement with Vision Transformers (ViT) that can use the Transformer architecture, which offers superior scalability and attention mechanisms. Throughout this research the use of both CNN and ViT architectures along with other deep learning models are seen as promising for automatic detection as well as classification of chest diseases from chest X Ray images. We fine tuned various deep learning models and pre-trained on the giant dataset of thousands of X-ray images which includes normal and disease affected cases (e.g. pneumonia, tuberculosis, and cardiomegaly). Model robustness was improved with plentiful data augmentation and preprocessing techniques. Following this study it has been proved that deep learning models, notably pre-trained variants, offer better performance for multi-class disease classification in terms of better accuracy and stronger feature encoding. This research highlights how deep learning models such as ViT, ResNet and Densenet can change medical image analysis with more precise and scalable solutions for clinical diagnostics.

I. Introduction

Chest diseases like pneumonia, tuberculosis and cardiomegaly are considered as a global health challenge which leads to the death of millions of people a year. Early and accurate diagnosis of these diseases requires early intervention, and manual analysis of radiology images is usually prone to error and time delays. Correspondingly, the demand for automated, reliable diagnostic tools that can help clinicians by rapidly and accurately classifying disease patterns from images is increasing.

Radiology image analysis, especially chest disease detection has always been dominated by various Deep Learning models, especially Convolutional Neural Networks (CNNs). Learning spatial hierarchies in images plays an important role in DL models such as DenseNet and MobileNet, which have made impressive recognition of complex patterns in X-rays. Nevertheless, CNNs are not without their drawbacks, and in particular are known to struggle with handling long range dependencies and global image context that can be crucial for some medical diagnoses.

In recent studies, Vision Transformers (ViT) inspired by Transformer architectures for natural language processing (NLP) uses self attention over images. ViT seeks for the global context and interactions, rather than rely on local patterns as it takes images into multiple smaller patches to be processed in parallel, where models can easily capture global patterns and learn about the interactions. The ability to model the relationships across an image, has shown promise of outperforming CNNs in some vision tasks.

This research recognizes the strengths of each architecture and attempts to explore the viability of merging Deep Learning models with ViT models to build a hybrid system that achieves more accurate detection and classification of chest diseases from radiology images. Combining the feature extraction abilities of CNNs with ViTs' global context modeling, It is believed that a combined model will outperform individual models for diseases like pneumonia, tuberculosis and cardiomegaly.

A) Research Problem

Chest diseases are considered nationwide most common causes of morbidity and mortality and one of the leading causes of death worldwide. In 2019, chronic obstructive pulmonary disease (COPD) was third leading cause of death, at 3.23 million deaths, and pneumonia and other causes of lower respiratory infections were fourth leading cause of death at around 2.6 million deaths. Tuberculosis(TB) also kills millions a year over 1.4 million, making them a large killer still [16]. These numbers highlight the severity of chest diseases that are indicative of how severe they are in terms of mortality globally and the demand for improved diagnostic and treatment methods to reduce these preventable deaths. Yet the current diagnostic methods, relying on radiologist's manual interpretation of chest X-rays, may be error prone and time consuming, which delays the treatment and sometimes even misdiagnoses. In order to tackle these challenges, the growing application of deep learning models has been relied on to help automate chest disease detection with the help of speed and accuracy improvements. But, while successful these models have limitations. For example, Convolutional Neural Networks (CNNs) are unable to understand global constraints in images, but Vision Transformers (ViTs) are powerful but need lots of data and are computationally expensive. This demonstrates more robust solutions which overcome the shortcomings of current models are needed.

Detection of these diseases is critical to improving patient outcomes, especially in resource constrained settings and behavior with respect to class imbalances in real world data[5], and the need for accurate and timely detection is of utmost importance. One of the most commonly used diagnostic tools for disease discovery via CXR images is manual interpretation, which is error-prone and time consuming. To overcome these challenges, deep learning techniques, namely Convolutional Neural Networks (CNNs), have been extensively used to solve chest disease detection. Recent work has demonstrated that CNN architecture misclassifications in disease detection especially come to light in the confusion matrix results of both Support Vector Machine (SVM) and Convolutional Neural Network (CNN) models[6]. The wrong misclassifications could make the system unreliable in the real world medical diagnostics.

Traditional methods of detecting various chest diseases from Radiology images depend heavily on expert radiologists and medical professionals. However, even experienced medical professionals can face difficulties while interpreting chest X-rays as their appearance may present similar characteristics, making accurate interpretations challenging[17]. This challenge results in an inaccurate interpretation of diseases which may cost the patient's life. Furthermore, in some cases radiologists require longer analysis times which is not ideal in emergency situations where rapid decision making is crucial. Deep learning techniques offer a promising solution to these problems by aiding the radiology department in achieving faster and more accurate interpretation, ultimately improving both efficiency and patient care.

Additionally, It can be difficult for radiology experts to continuously gain knowledge about new diseases and their detection patterns. The chest X-rays can be ambiguous and subject to interpretation by radiologists, image quality, case complexity and radiologist expertise, resulting in a slow diagnosis of pneumonia and subsequent treatment delay[15]. Unlike radiologists, deep learning models can be simultaneously updated and trained with new data, allowing them to adapt in clinical knowledge and progressive disease patterns. Moreover, as these models are trained with a large scale of dataset, they have the ability to uncover many correlated patterns between diseases which cannot be observed immediately with human eyes. This ability is valuable for researchers to improve their work and provide better patient care.

The development of these Deep Learning models has been proved to be promising in the medical image analysis. However, To fully leverage these technologies in detecting chest diseases there are still a huge number of obstacles which need to be overcome such as the Inability of the model to interpret rare or less common diseases, lack of extended, balanced and labeled dataset, computational cost etc[14]. In recent years, the medical sector has seen the implementation of deep learning models at a large scale in critical image analysis and disease detection. Numerous Deep Learning models such as CNN, ResNet, DenseNet, VGG etc have been able to achieve great accuracy in evaluation metrics such as F1, Recall, Precision, AUC-ROC etc. Despite all these achievements in detecting various diseases, all these models have drawbacks which disrupt the utilization of these models to their full capacity. Imbalance and unlabeled dataset is one of the many flaws of deep learning techniques as the models require a large amount of labeled and balanced features to achieve high accuracy. If the models are trained on a large scale of well-annotated data, they will be well optimized and be able to utilize to their fullest extent in clinical disease detection[13].

Having this in mind, one needs to ask if deep learning models, especially Convolutional Neural Networks (CNNs), can be leveraged to its fullest extent to accurately detect and classify chest diseases from chest X-ray images. CNNs have been used in numerous studies on medical images with many CNNs such as DenseNet, MobileNet, ResNet which have shown the favorability of CNNs in diagnosing diseases. Despite excellent performance, such models struggle to model global image context and have high demands for data. To fill these gaps, some research has been done on the integration of Vision Transformers (ViT), Nevertheless, this hybrid approach remains underexplored and it has great potential in compensation for the two shortcomings of CNNs and ViTs to significantly enhance diagnostic accuracy.

As such, this research seeks to answer the question:

How to leverage CNN and other deep learning models to their fullest in accurately detecting and classifying chest diseases from chest X-ray images?

This research will answer the above question by exploring a hybrid combination of CNN and Vision Transformers (ViT) instead of using standalone CNN models, aiming to leverage the strengths of both architectures for more accurate chest disease detection from X-ray images.

B) Research Objectives

The aim of this research is to create an automatic chest disease detection system leveraging various deep learning models while improving accuracy in medical image analysis. Common chest diseases such as pneumonia, tuberculosis and cardiomegaly are detected from radiology images. The objective of this research are:

1. To deeply understand various Deep Learning Models and their applications.

2. To deeply understand strengths of CNN and other DL Models in feature extraction and ViTs in global context modeling.

3. To leverage CNN and other DL Models for chest disease detection.

4. To evaluate the performance of these models in terms of different evaluation metrics such accuracy, F1, recall, AUC-ROC, sensitivity etc.

5. To offer recommendations for improving and optimizing the performance of these models in real-world medical applications.

II. Literature Review

Chest diseases are one of the leading reasons of death worldwide. According to WHO in the year 2019 alone, 3.23 million people died due to various chest diseases [1]. It is projected that the amount of COPD globally is expected to reach 600 million [2]. Detecting these diseases at an earlier stage can help us to reduce the number of fatalities.

Although X-ray and CT scans are widely available, detecting these diseases at an early stage remains a challenge due to human error, overlapping symptoms, and time limitations. We can leverage CNNs in these circumstances as these models have demonstrated exceptional analytic performance in this sector.

II.1. Related Works

In this section, we aim to analyze previous studies and research completed, related to using DL to detect respiratory diseases. We go through the techniques used, extract the results achieved, and challenges associated with this field.

The researchers in [7] have used DL techniques like VGG-16, VGG-19, Densenet, Autoencoder, Resnet, and CNN to identify 4 different types of respiratory disease with an accuracy greater than 95%. They have also deployed SDG or Adam functions for cross-entropy and optimization to prevent overfitting. However, they have used a relatively small size of dataset composed of 5600 images and while detecting COVID-19 their model seems to give out a considerable percentage chance of cancer detection.

In [8] the researchers focused on finding different types of pneumonia to detect COVID-19 more precisely. Although CT is more reliable than X-ray they have used X-ray images as it is more widely available and easy to access. They divided 305 COVID-19 X-ray images and for other diseases, they used a total of 109,948 images which were split into i sets. Set-A consisting of 2 classes was used to train a CNN from the ground and later connected with a pre-trained CNN corresponding to SET-B consisting of 4 classes. By using CNNs Alex-Net, VGGNet, ResNet, and optimization techniques Adam and SDG were able to achieve accuracy of 82.98%±0.02, 90.13%±0.14, and 85.98%± 0.07, respectively. The research's accuracy may further be improved by using more COVID-19-related data currently available.

According to the [9] EfficientNet-B0 and EfficientDet-D0 can be utilized to determine the diseased areas of eight various chest diseases. The NIH dataset of 112,120 images from 30,805 patients was used to train their model called CXray-Effdet. Their model was able to achieve an AUC score of 0.908 and a mAP score of 0.926. The model had recall scores of 90.91, 89.62, 89.33, 93.82, 90.81, 93.60, 94.85, and 95.94 for the diseases Atelectasis, Cardiomegaly, Effusion, Infiltration, mass, Nodule, Pneumonia, and pneumothorax respectively. Compared to AlexNet, GoogLeNet, VGG-16, and ResNet-50 the model can have a performance gain up to 22%. However, the model's performance can be further improved by considering more instances for detecting more diseases, taking measurements to improve the accuracy of the distorted images, and balancing the data using augmentation and an advanced class-balancing strategy.

The paper [10] mainly examines a deep learning method for tracking chest diseases by using chest x-ray sample pictures. These X-ray images have been classified by CNN and filtered by 15 different categories. It is also categorized by a feature named 'No Finding' which means a healthy heart. The CNN architecture played a vital role to remove the traditional struggle to detect low and high-level data. The CNN architecture comes with some effective layers such as ReLu, convolutional layer, pooling layer, and fully connected layer(explained earlier) that help to reduce the runtime and have more potential efficient outcomes. In this paper, the architecture has trained on a total of 14 datasets of chest X-rays and a total of 112k amount of labeled X-ray images. It also handles the overfitting(explained) issue by using dropout and max pooling techniques. Adam optimizer has been used to optimize its total performance and as a result, the model generates 89.77% of accuracy. In terms of accuracy and reliability, this CNN model outperforms the majority of the existing models.

The research [12] is also focused on using CNN architecture to detect pneumonia through chest X-rays which is also a deep-learning method. As pneumonia causes several inflammation and especially to childrens it has major health risks. The traditional pneumonia detection method is heavily dependent on skillful radiologists only and they manually do the x-ray test which is really time-consuming. This research helps to break out from the same old traditional manual x-ray detection to hot cake in the nowadays research sector which is CNN CNN-based medical engineering method. They developed two different CNN models- one is dropout layer supported and another isn't which classifies chest x-ray images into non pneumonia and pneumonia categories. As this research is based on comparatively limited datasets, the CNN model accurately handles the overfitting issue. Compared to the previous report this paper has worked on over 5 thousand x-ray images(Kaggle dataset) which was augmented data(focused on rescaling and flipping). A total of 4 types of transformation of the CNN model have run with various combinations which were based mainly on data augmentation and dropout with an accuracy of 75-91%(the highest). The paper also states that, to improve pneumonia detection this deep-learning CNN model will surpass the traditional manual radiology test very soon.

The researchers in [11] inquired about the implementation of two CNN architectures(VGG16 and XCEPTION) based pneumonia detection throughout chest x-ray images. To train their dataset, transfer learning has been used along with recently mentioned CNN models. As the initial dataset was not much sufficient, data augmentation was also applied by flipping and rotating images to expand the set with a total of 5800 chest X-ray images which can handle both pneumonia-affected and non-affected cases. Since the dataset has expanded with more detailed information the model is evaluated by accuracy, recall, specificity, precision and f1 score. In terms of overall accuracy and specificity, the VGG16 model performs well with 87% and 91% which is a better outcome for non-affected pneumonia cases. On the other hand, Xception model performs well in higher recall sensitivity with 85% which is extremely successful for detecting pneumonia-affected cases. So, according to this report we can determine that, the VGG16 works better for general classification while the Xception model works better for sensitive pneumonia-affected detection.

According to the [3] the aim is to present a hybrid model which incorporates DenseNet and MobileNet architectures to predict lung diseases (pneumonia, COVID-19) using the chest X-ray (CXR) images. The objective of the authors was to improve diagnostic accuracy through use of convolutional neural networks (CNNs). They used DenseNet to address the vanishing gradient problem because it was good at this and MobileNet was good for mobile applications. Depthwise Separable Convolution is also used in architecture to reduce computational costs without compromising on performance as well. Over 40,000 X-ray images for the dataset and evaluated them using various performance metrics, such as precision, recall, and ROC AUC. In classifying lung diseases the model was able to predict with 96% accuracy. The results from this study showed that the hybrid model is superior to CNNs for clinical diagnostics.

The research work [4] proposes systematic review of deep learning methods to detect diseases of the chest, notably pneumonia, tuberculosis, and COVID-19 using chest X-rays (CXR) is presented. It provides a taxonomy of deep learning models used for disease classification such as CNN. And also discusses some of the key datasets such as ChestX-ray14 and CheXpert.

This paper points out the issues encountered by traditional models including datasets imbalance and computational expenses and offers possible paths for the future development including optimally classifying multiple classes and information integration between AI models and clinical practice. Real world application is limited however deep learning has the potential to automate the detection of chest diseases up to a certain degree.

The research work [5] proposes an AI driven system from detection to classification of chest diseases from chest x-rays specifically focusing on COVID 19, Tuberculosis and Pneumonia. To this end, the system is based on Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) both trained on a dataset of 10,000 X-ray images. For performance improvement, preprocessing, feature extraction and data augmentation is important. The CNN model outperformed the SVM model in terms of 96-97% of the accuracy and better confusion matrix. Additionally, the paper states that the system is user friendly, when healthcare professionals can quickly upload X rays and get the diagnostic results, it is a practical system meant for clinical use. However, the paper didn't discuss how well the model performs on other datasets, or how it behaves with respect to class imbalances in real world data.

The paper [6] mainly examines work on automating these five chest diseases (COVID-19, Pneumonia, Pneumothorax, Tuberculosis and Normal) based on eight pre-trained CNNs: AlexNet, DarkNet-19, DarkNet-53, DenseNet-201, GoogLeNet, InceptionResNetV2, MobileNetV2, and ResNet-18. The dataset had 3500 Xray images and DenseNet-201 turned out to be the best feature by scoring 97.49% accuracy. To improve model performance, such as preventing overfitting, the author implemented Data Augmentation techniques on the images performed such as random rotations, reflections, and shears. The classification process involves two phases: CNNs are trained in the training phase on a part of an augmented dataset, and then used in classification phase to classify a new image. All are trained with an Adam optimizer over 30 epochs using 5 fold cross validation. To evaluate the models, performance metrics such as accuracy, sensitivity, specificity, precision, recall and F1-score were used. The paper emphasizes the prospect of deep learning in enabling fast and correct lung disease diagnosis suitable for real time clinical applications.

The research [13] proposes the application of Deep Convolutional Neural Networks (CNN) to improve the detection accuracy of various chest diseases. Mann et al. proposed three different CNN models : DenseNet121, ResNet50, EfficientNetB1 to detect chest diseases based on 14 different thoracic pathologies using radiographic images.Their collected dataset consists of 112120 X-ray images of about 30805 different patients and has been labeled into 14 different classes including a "No Finding" label. The dataset was split into three different parts - Training, Validation and Testing set to minimize the inaccuracy in the test results. All the models developed in this paper were pre-trained on various different datasets and performed training on X-ray datasets using a fine-tuning technique called transfer learning. Standardization and rescaling of the dataset was done to maintain consistency with the pre-trained models. The authors also used the loss function "Weighted Binary Cross-Entropy" to minimize the imbalance in the dataset. Evaluation metric AUROC was used to evaluate the test results and performance of the models. The results have proved that DenseNet121 outperformed ResNet50 and EfficientNetB1 CNN models in detecting various chest diseases. For instance, DenseNet121 scored a AUROC score of 0.9120 for Cardiomegaly detection whereas ResNet50 scored 0.7410 and EfficientNetB1 scored 0.8840 proving that DenseNet121 outperformed the other two CNN models. The aim of the authors is to expand the work area and evaluate the models with more data to diagnose a wide range of diseases.

Khurana et al. conducted a research [14] using the deep learning models along with RT-PCR testings to aid in detecting and diagnosing COVID-19 using CT and Chest X-Ray images. The authors conducted a research using two publicly available datasets consisting of 4000 X-ray and 4000 CT images. The datasets were split into 75:25 ratio for training and testing purposes. The datasets belonged to binary classification with them containing Covid-19 positive and negative images. Four convolutional neural network models: ResNet-50, EfficientNetB0, VGG-16, and a custom CNN were compared for detecting COVID-19 using X-ray and CT images. While pre-processing the dataset, images were rescaled to 224x224 to maintain uniformity. The models were then trained on the dataset and were evaluated through recall, test accuracy, precision, specificity and F1 score. Among the models, ResNet-50 outscored the other three models in detecting COVID-19 with an accuracy of 98.9% on CT scan and 98.7% on X-ray images and lowest false-positive rate. Although the authors were able to achieve a higher accuracy in detection of COVID-19, an increment in the dataset could potentially end up with a lower accuracy. Therefore, authors should have used a higher number of images to produce more accurate results in detecting COVID-19. The authors concluded that while the deep learning models are promising, they should be used along with RT-PCR rather than replacing them in detection of COVID-19.

Murali et al. conducted a study [15] and compared three different deep learning models for multi class diagnosis of chest diseases using X-Ray images. The authors used two publicly available datasets for the training and evaluation of the deep learning models. The following models were used to diagnose the chest diseases based on X-Ray images: CNN, ResNet, ViT-v1, ViT-v2, ViT-ResNet. AUC-ROC and accuracy evaluation metric was used to evaluate the performance of each model. The results showed that while the ResNet model performed the best among all the other models, ViT models also showed significant potential in the detection of chest diseases. ResNet was able to achieve an accuracy of 93% and a ResNet model with ViT encoder outperformed ResNet model with an accuracy of 93.9% proving the potential of ViT models in predicting chest diseases based on X-Ray images. The authors concluded that while the ViT models showed a promising result, a large number of well annotated dataset should be used to evaluate the models. They also included that the models will have a better performance if fine tuned for disease specific diagnosis.

III. Work Plan

The chest disease detection process in this research consists of three main stages:

1. **Data Preprocessing**: In this stage, the preparation is to be done with the chest X ray images so that the images are formed for the model. First, they go for shrinking images, normalizing pixel values, and applying augmentation techniques using data like rotation, flipping, cropping and increase the data diversity and avoid overfitting.

2. **Feature Extraction and Model Building**: Finally, hybrid model combining CNN and Vision Transformers (ViT) used to preprocess images as follows. Local textures and edges are extracted in the CNN part, global context and relationships between the whole image are captured by the ViT part. Both architectures are then fed into a comprehensive model which extracts features from them and then is split into training and testing sets which can then model the input.

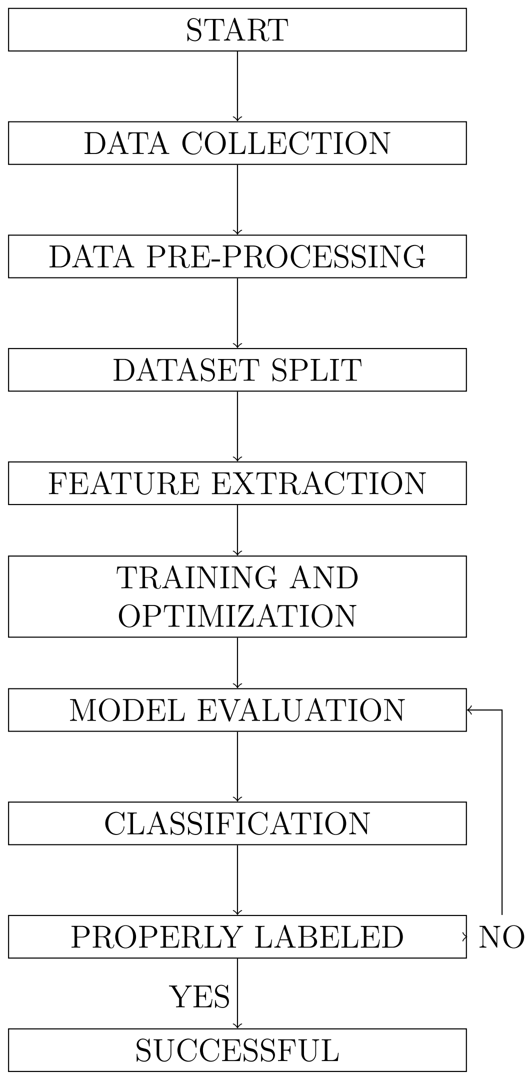

Figure 1: Chest disease detection process

3. **Prediction and Evaluation**: The model is trained and the model is then used to predict chest X-ray images. Images are classified into disease category variables (pneumonia, tuberculosis) using the features. Performance is evaluated using precision, recall and AUC-ROC F1 scorers to learn the better difference between normal and disease affected X-rays.

IV. Conclusion

Despite the great progress in deep learning models for recognizing chest diseases from medical images, a lot of work still remains to be done. Despite the success of Convolutional Neural Networks (CNNs) in recognizing complex patterns in chest X-rays, they struggle to capture global image context and struggle with long range dependencies crucial for accurate medical diagnoses. In contrast, Vision Transformers (ViTs) fill this gap with its power to encode global relations in an image while consuming enormous amounts of labeled data and being computationally expensive. Only recently, we have been observing a narrow research on either CNNs or ViTs, but we lack information for a hybrid approach that combines both architectures. This research aims to explore a hybrid combination of CNN and Vision Transformers (ViT) instead of using standalone CNN models, aiming to leverage the strengths of both architectures for more accurate chest disease detection from X-ray images.

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