Medical Anomaly Detection for Lungs Images

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***Abstract*—It becomes more interesting through with respect to images & multimedia processing in computer vision and medical image analysis where we use Deep Anomaly Detectors (based on AI) to capture anomalies times more accurately. The quick spread of digital content and the visual data complication make it a must to have strong anomaly detection methods in place to affirm data integrity and security. However, classical methods have not achieved parity with this more sophisticated appreciation for the subtleties in visual data. In this work, we fill in this gap by introducing a new method based on an ensemble of deep learning and anomaly detection, employing well-known neural networks architectures pretrained on various datasets. This strategy applied to medical imaging, especially for chest X- rays, can make the highest efficiency (diagnostic performance) in model prediction, achieving overfitting and model is easy to transfer relatively poor, through hierarchically stacked CNN structures. The experimental results show that both of our proposed methods outperform many existing methods for lung tumor and diseases detection, which means our methods are very effective for lung abnormality detection.**

***Index Terms*—CNN, RNN, Image Processing**

I. INTRODUCTION

Medicine is one of the domains where a big scientific leak occurred during recent years, mostly powered by explosive rise of Machine Learning (ML) and its more fancy counterpart - Deep Learning (DL) [1]. As a result of these Technologies, now many of the diseases like TB, and lung diseases are becoming employed in an advanced way of radiographs. It is now achieving great success in conditions including lung cancer or Swelling and inflammation in the main passages or COPD [2]. X-ray (Plain radiograph) and computed tomography (CT) can provide more comprehensive information about lung diseases, although most of available information within this modality remains largely unused.We have reviewed lung CT scans to improve the diagnosis of the disease by applying traditional ML approaches like K-means, SVM, KNN, Random Forest (RF) classifier, and Decision Tree (DT), which are big contribute in this field. ML is a subset of AI and uses the data which trains the model like for pattern recognition and then predict things, in Deep Learning (another subset of ML), uses artificial neural networks to extract or represent intricate patterns that further streamline and vastly improve diagnostic results. Analysis of lung CT scans to detect abnormalities, performed by deep learning techniques such as convolutional neural networks (CNN) [3], is important in some researches. Not only that, but recurrent neural networks (RNNs) [4] like long short-term memory (LSTM) are being used in great numbers for the detection of lung cancer also. Finally, multiple tasks have been addressed on lung CT scans using generative adversarial networks (GAN) from disease detection to image segmentation. The Cancer Toolkit is able to automatically classify nodules as either normal or abnormal, further classifying abnormal nodules as cancerous or pre-cancerous through this same process executed by the deep learning algorithms of CNNs, RNNs, as well as GANs. This next-level diagnostic capability often outperforms human radiologists with the same data.

Machine learning techniques have been successful, in reducing the number of diagnoses in lung diseases and aiding in detection. These methods are continuously advancing to handle amounts of data, which will enable them to manage and interpret the extensive data generated by medical tests like CT scans [5]. The integration of learning (DL). Machine learning (ML) in diagnosing lung conditions transforms early detection, impacting treatment approaches and patient outcomes positively. By analyzing lung tissue this tool enhances patient care quality by facilitating treatment planning. Consequently, in this study, we investigate the use of ML and DL in diagnosing the lung diseases from the X-ray scans and images show in Fig.1.

We need radiation to help make detailed images of the insides of our body, such as when we take CT scans & X-rays. These processes are very important for the diagnosis of lung related diseases, as explained. Nevertheless, each technique gives birth to such images which have their peculiar uses. Still, the X-ray is advantageous in areas with limited resources due to the following viable reasons:

- Use & Goals: Most commonly, X-rays are used as a diagnostic tool for a range of conditions from pneumonia to osteoporosis, to early signs of lung cancer. On the other side, we require CT scans for a detailed kind of study like tissues (bones, diseases, blood vessels etc). They help diagnose a large number of different conditions such as cancer, heart disease and injuries due to traumas.
- Processing time: X-rays are much faster in scanning of the lungs than CT scans, as CT scan machines are needed to rotate the machine around the body parts to capture the different angles of the body part.

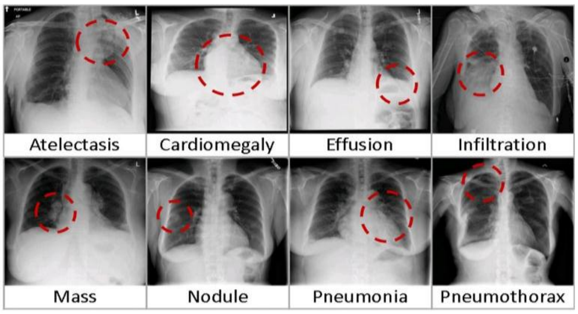

Fig. 1. Different types of Lungs Disease

- Understanding: CT scan is more costly compared with X- ray as a result of it entails advanced expertise and more info than X-ray. An x-ray examination on the detector are sent out of the body (an electric beam) The patient lays on a table which covers the portal (the round part of the CT scanner) while the X-ray unit and scanners all rotate around him to perform the scan.

When lung diseases such as lung nodules are detected early, the X-ray changes are small, which may cause doctors to diagnose the disease due to lack of knowledge or fatigue. On the other hand, the use of deep image segmentation and other image processing techniques in image processing can be reliable and provide effective identification of the disease [6]. For example, patients suspected of having COVID-19 must first be isolated and the isolation period must be 14 days because some diseases are difficult to detect. You will receive an antigen test every day during your quarantine period. If there is a difference or some uncertainty in the antigen source, misdiagnosis will occur due to false positive and negative results. This is a waste of personnel and equipment. While the differences in the nature of the two lung diseases above are highlighted, many other definitions for various lung diseases and conditions also deserve attention. Therefore it is very important to address these issues in real time with appropriate and quick solutions.

As the X-rays are fast and inexpensive, they are frequently used in the diagnosis of many lung diseases shows in fig.1. The brain is not the only organ capable of deep learning- based image visualization. Many medical applications use this technology, including CT scans of brain tumors, X-rays of the legs, retinal images of the eye, images taken with microscopes, and more. Our top choice is due to its popularity, wide range of applications, low cost, mature technology, etc. due to taking into account deep learning. Today, artificial intelligence can solve problems of this nature with its powerful calculations and image processing capabilities. Similar to passive driving, feature extraction once required manual feature extraction, but manual interaction has now become unnecessary. Many things that once required human intervention can be created without human intervention. Medical images and other images comparable to human vision have long been in the throat- in-the-neck to compete in the past 20 to 30 years, while deep learning has turned the medical industry around [7]. It has an integrated specifies of classification and deterministic algorithms which allow for effective and robust diagnosis of a wide range of cases. In addition, there are a lot of medical applications which exploit deep learning models for image processing and image classification, which spans across different medical specialties. This accuracy and the speed of computations are due to the advanced image processing technologies and complex algorithms that are structured within a deep learning framework [8].

II. RELATED WORK

CNNs are one of the best methods of analyzing medical images today; They are very good at sharing photos. A priori models, function models, and sequential models are some of the modern CNN models that we will discuss in the next section.

Liu et al. CNN based model was proposed for the diagnosis of particular three diseases. Extracted features from the CNN architecture and SVMs are trained on those features that are learned in all of three methods. In the second approach, CR creates a kernel from feature space then it is trained in the SVM classifier. Finally, we include the third method as a distinct category that combines the two notions mentioned. Although these training methods decrease the study time, they have limitations, which makes them inappropriate as a diagnostic tool.

Mask RCNN is a machine developed by Amit Kumar Jaiswal, Prayag Tiwari, Sachin Kumar and Deepak Gupta. This deep neural network model is capable of extracting local and global features. Pixel-by-pixel division is performed, and evaluation of radio data shows that this method is more efficient. This approach reveals the affected area and provides a heat map so the product reviewer can better understand it. However, the integration of Mask RCNN models ResNet50 and ResNet101 leads to less deviation than expected and requires more GPU processing resources during training.

That is what Ibrahim and Elshennawy illustrate with four mod els. Two of the four are pre-trained models: ResNet152v2, Mo bileNetV2; CNN, LSTM-CNN are completely from scratch. Confidential/Proprietary They built a deep learning neural network model to automatically detect signs of pneumonia based on the chest X-ray [9]. One of the drawbacks of PyTorch is its massive overhead and huge weights which are in hundreds of millions [10], [11]. This approach comes at a cost in terms of work and operational complexity.

Naik and Edla [12] developed a model for pulmonary nod ule classification and recognition from computed tomography (CT) images using multiple deep learning methods. To prevent late diagnosis, CT scans need to be more accurate in classifying lung nodules for the infectious lungs. The deep learning techniques used for classifying lung nodules leads to good results compared to other methods. After adding the changes, the deep learning method improved the classification accuracy. Using deep learning to identify early stages of malignant disease and new implications for nodule classification [13].

III. METHODOLOGY

Imaging techniques are often used to diagnose lung abnormalities such as pneumonia and cancer, and early diagnosis can increase a patient's survival rate. This study presents two in-depth studies to analyze lung CT scans and chest X-rays. This section provides information about deep learning techniques and decision making. Finally, imaging performance measurements (IPM) support the effectiveness of the above-mentioned methods. This section provides an overview of the dataset used, featuring target prioritization, data processing and multiple algorithms show in Fig.2.

Here are the steps that go into making the thing run.
Step No. 1: Compiling the set of Dataset
Step No. 2: Preparing the obtained input. Step No. 3: Enhancement of Data
Step No. 4: Data Training
Step No. 5: Suggested Customized CNN Architecture
Step No. 6: Create Hybrid Model Using My CNN Architecture and PreTrained Models
Step No. 7: Hybrid Model Insights — The function of the suggested hybrid model

A. Datasets

14 images of different diseases including cardiomegaly, emphysema, effusion, hernia, nodule, pneumothorax, atelectasis, pleural thickening, mass, edema, consolidation, infiltration, fibrosis and Pneumonia are available in the special collection. There are 5606 images in total and out of these, 5000 images are used to train the model, 303 images are taken for testing the model, and rest of the images are used as the validation set.

B. Preprocessing and Data Augmentation

Different resolution photos inside the datasets However, the CNN models require an exact one size for images. This meant that the size of every image in the set was resized to 224x224. Scaling down the input photos will result in faster image processing and thus faster model performance for the given task.

Many people are already familiar with data augmentation, which involves slightly altering an image during each training epoch to generate much more training data. This work uses the following augmentations: rescale, rotation, shear, zoom, and horizontal flip. We need this method to reaches the highest degree of accuracy as in this case we let CNN model to be trained on larger dataset.

C. Deep Learning Algorithms

This paper uses these data to implement the CNN model sequence and function, which combines CNN with data augmentation. Discriminant tree model is used in planning studies. Four different model algorithm techniques were approached in this proposed architecture.

D. Sequential Model

The sequential order is created by stacking the layers in a pattern called a sequential pattern. The order in which layers are stacked determines which layers receive access. Each layer has learned properties, and as you progress through this layer, the model can detect diseased and non-diseased from a chest X-ray [14]. The array model consists of five convolution layers. ReLU removes all slopes when the building is not in use, but Leaky ReLU allows small slopes to pass through [15]. Additionally, maximum pooling is done after each release. Optimizer Adam is used with a learning rate of 0.0001.

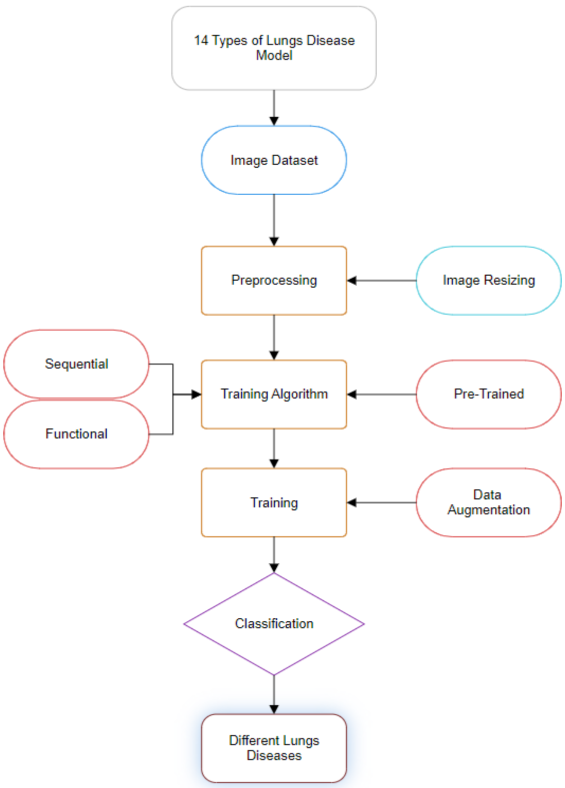

Fig. 2. Workflow of the classification model

E. Functional Model

The other methods lack the flexibility of the functional model. It can connect any two layers that are at odds with one another and advance linearly. This enables us to build increasingly intricate and advanced networks. After passing through the first layer, the input moves along the architecture as planned. This approach, in contrast to the pretrained model, also trains from scratch [16]. The suggested functional model contains two convolution layers: one with a 1x1 window on top of a 3x3 window and another with a 7x7 window. The input is routed independently through the two convolution layers, and the output from each layer is concatenated before being routed through five 3x3 convolution layers. . The Learning rate which was used at the time of training the model was 0.0001.

F. Pretrained Model

The easiest and hence surely the most popular way of them all on how to classify images. Instead of building a model from scratch and training it, in this approach we simply run the images on pretrained model's weights on a huge dataset of lungs disease pictures and classifies the obtained diseases [17], [18]. This particular process, transferring weights learned from previous training to the classification process, is called as transfer learning. Overall this model gives more efficient results and accuracy in less we can say training time. This pretrained model is a CNN Model that is previously trained on the ImageNet dataset, for example, VGG-16, Resnet50, DenseNet121. It is also very famous for its incredible accuracy, having reached up to an accuracy of 99.66%.

IV. ARCHITECTURE

A. Hybrid Model

To achieve greater accuracy, hybrid anomaly detection models for lung images are used in multiple designs. To extract the lung from the features of CT Images before proposed network was trained, a different model, which is a modified layers of Convolutional Neural Network (CNN), was trained. This is the Custom CNN, CustomCNN. This forms the basis. Next, DenseNet121 and LSTM are combined with CustomCNN to take advantage of both the dense and time dependent networks for better inference in the optimization model. Finally ResNet and Bi-LSTM were added to Refined Temporal Spatial Model for better removal of residuals and time dependence. VGG16 is then added with the enhanced model in Accuracy Boosted Model to workout the extraction feature the accuracy of error detection. This combination gradually improves the cleanliness of the surface and trunk of the body, resulting in a powerful composite model that can identify abnormalities in the lung image show in Fig.3.

B. *CustomCNN*

A 'CustomCNN' architecture, developed for the identification of lung imaging abnormalities, is a custom four- layer convolutional neural network (CNN). The architecture consists of an input layer followed by three Convolution layers and a fully connected layer. The features in the input lung disease images are extracted in each convolutional process, to secure useful information for lung disease. Both ReLU and many other optimization techniques augment variance, and in turn, help the model in identifying complex patterns. The layers are what preserve the overall characteristics of the surface used to assemble the parts by shrinking the surface dimensions. The performance of the extraction is largely dependent on the architecture used in 'CustomCNN' to make sure that crucial, abnormality-reflecting features are adequately learned and retained to be used for confident diagnosis in the clinic.

C. *Enhanced Feature Model*

The three networks CustomCNN, DenseNet121 and LSTM are combined together in 'Enhanced Feature Model' to enhance the results for lung detection. The high connectivity of the DenseNet121 improves the model capturing the features of the variable. An LSTM of a recurrent neural network models the time dependence of the lung image series. Models are trained on the accepted models and not the combination of these images. It fuses spatial and temporal information to provide an improved lung abnormality measurement and enhances the abnormality detection process.

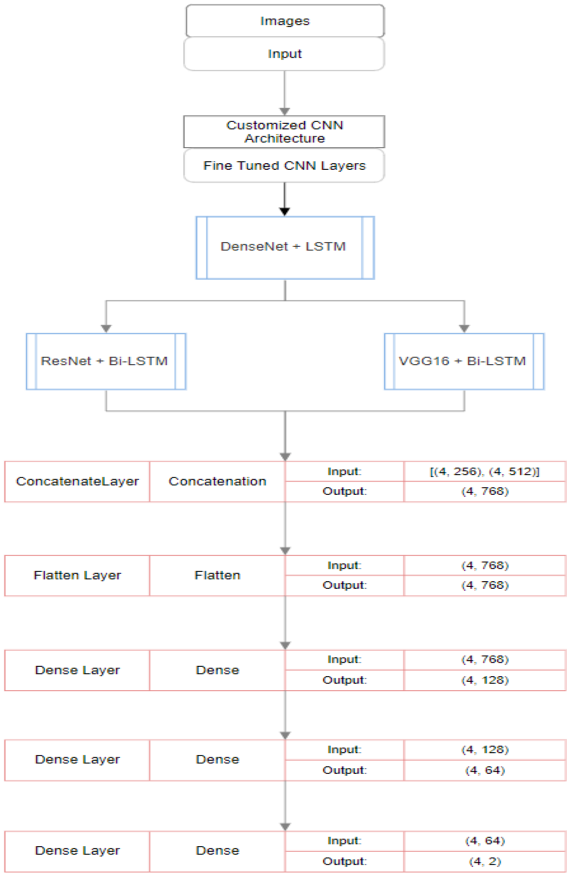

Fig. 3. Proposed Hybrid Model.

D. *Refined Temporal Spatial Model*

They used his pre-trained models and added ResNet and Bi-LSTM to 'Refined Temporal Spatial Model' to enhance anomaly detection in lung images. ResNet: designed to better capture the held-out information being largely lost in the traditional CNNs in a lot of detection and even recognition tasks. Bi-LSTM is bi-directional recurrent neural networks, in which the effects of physiology of the lung sequence are well learned, with both forward and backward sequences. This combination provides a complete view of the body and size of the abnormality, helping the model learn the tiny patterns that are different in lung images that it can correctly identify and describe a difference.

E. *Accuracy Boosted Model*

VGG16 is then stacked along with the improved model of 'Accuracy Boosted Model', allowing for a better representation of the data in lung imaging. VGG16: It is a very deep and effective architecture with the capability to learn complex patterns and is used in many Image classification tasks (High removal). To extract lung features, a hybrid model is built by VGG16 and an improved model. This allows it to better see small patterns that may represent irregularity. By utilizing the VGG16 large-scale representative study, this integration better automates scaffold collection and image refinement for different ultra fine pulmonary levels with VGG16, which will enable to approach to quality level, and the result is the same as when packaged to be a binary file when all tools are set up.

IV.RESULTS AND DISCUSSION

In the Proposed method, different models are trained and their gains & losses are collected; the test accuracy is also taken; after that the comparative analysis is done with the other studies using CNN for the detection of lung diseases [19], [20]. The accuracy, precision, recall, and F1 score are the performance metrics that are being considered for this suggested study.

(i) Accuracy: The most common and easy metric to have in a classification model is accuracy. It works by dividing the number of correct predictions (both True Positives and True Negatives) by the number of predictions made. Recall, however, warps the concept of how often the model correctly predicts, and accuracy in the title, somewhat from a global perspective. Nonetheless, there are scenarios when it is not enough on its own, especially for unbalanced datasets, the precision, recall, and the F1 score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

(ii) A good precision score should be as close to 1 as possible which means very few false positive predictions are made by the classifier. It happens when the true positives (TP) and true positives and false positives (TP+FP) are the same. So there is almost no possibility to have a false positive which leads to a precision of Inversely, precision decreases as the number of false positives increases, which encourages the ratio of true positive cases correctly predicted to all predicted positive instances.

$$Precision = \frac{TP}{TP + FP}$$

While recall gives an overall measure of all the correct positive predictions, precision will specifically highlight how many of the correct predictions among the positive predictions were indeed true, which gives us more of a handle purchasing power of the classifier against false positives.

(iii) Recall is defined as follows and is also referred to as sensitivity or true positive rate:

$$Recall = \frac{TP}{TP + FN}$$

(iv) The F1-score is a measure that considers recall as well as precision, and its definition is as follows:

$$F1score = 2 * \frac{\text{precision} * \text{Recall}}{\text{precision} + \text{Recall}}$$

In the hybrid model it works with CNN architecture and different models and make a hybrid model which gives highest accuracy of each diseases which shown in Table in Fig.4

AUC: AUC (Area Under the Curve) is sort of a canvass of a master storyteller, it paints what a model has in store in a most elegant way. It is quantifies the area under the ROC curve, which is the trade-off between true positive rate and false positive rate. The AUC values lie between 0-1, in which a higher score represent better discrimination ability. In simple words, it is the combination of a measure of any model that is able to correctly classify both True Positives and True Negatives and outcomes of the model which is unable to identify True (True Positives and True Negatives)which are legally separated as the True class from the False (False Positives, False negatives) ones in Fig.5.

S No.	Diseases	Accuracy
1.	Cardiomegaly	98.0693
2.	Emphysema	92.7393
3.	Effusion	98.6798
4.	Hernia	99.6699
5.	Nodule	95.7095
6.	Pneumothorax	96.7789
7.	Atelectasis	89.7689
8.	Pleural_Thickening	95.7095
9.	Mass	95.7098
10.	Edema	97.6897
11.	Consolidation	94.0594
12.	Infiltration	97.3597
13.	Fibrosis	98.0190
14.	Pneumonia	99.0099

Fig. 4. Accuracy of Different Diseases

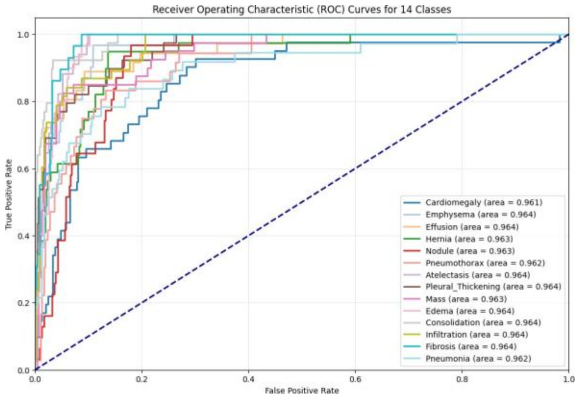

Fig. 5. ROC Curve of All Diseases

V. FUTURE DIRECTIONS

Algorithms leveraging deep learning are reshaping the ability to diagnose lung cancer based on X-ray images. If we wish to make a more substantial impact on the patients, we need to augment the data diversity and quality. Clinical decision support systems that incorporate deep learning into the clinical flow are necessary to enable fast and accurate diagnosis. Imagine implementing such privacy and security constraints by enforcing the use of privacy preserving and secure AI systems which should be compliant with health regulations as well. Clinical standards could benefit from a collaboration between physicians and cognitive scientists. Explain the AI technology and trust will increase, setting the direction towards opening the opacity of deep learning decisions. This will result in the merging of different fields, such as visual examination, x-ray, CT scans, patient history, genetics, to obtain a proper diagnosis of the disease.

VI. CONCLUSION

The CNN architecture model proposed in this paper was tested on different lung disease dataset and presented competitive results as compared to the previous work. We presented an improved sequence model that significantly outperforms the core set of F1 scores, precision, and recall for many organisms. In addition, the working model we have produced takes lower time and shows a higher degree of efficiency and specificity for different diseases. Chest X-ray is the first that comes to mind when we talk about lung diseases, but due to the heavy noise characteristics, technical limitations, current deep correlations are hard to done. We first did this by performing an analysis on chest X-ray data in order to train a hierarchical classification model, and on which we could apply a specially designed convolutional neural network for detecting abnormalities within high-resolution X-ray images. This is how deep learning will contribute to more careful diagnosis, rather than the fact that in the old school of reliance on trial-and-error cycles.

Future adjustments to the optimizers, learning rate, and addition of additional data augmentation may result in even higher classification accuracy for the suggested CNN models. Early stopping methods will probably shed more light on lung illness diagnosis, which can be used to prevent overfitting.

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