Disease Detection from Lung X-ray Images based on Hybrid Deep Learning

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Abstract. Lung Disease can be considered as the second most common type of disease for men and women. Many people die of lung disease such as lung cancer, Asthma, CPD (Chronic pulmonary disease) etc. in every year. Early detection of lung cancer can lessen the probability of deaths. In this paper, a chest X ray image dataset has been used in order to diagnosis properly and analysis the lung disease. For binary classification, some important is selected. The criteria include precision, recall, F beta score and accuracy. The fusion of AI and cancer diagnosis are acquiring huge interest as a cancer diagnostic tool. In recent days, deep learning based AI for example Convolutional neural network (CNN) can be successfully applied for disease classification and prediction. This paper mainly focuses the performance of Vanilla neural network, CNN, fusion of CNN and Visual Geometry group based neural network (VGG), fusion of CNN, VGG, STN and finally Capsule network. Normally basic CNN has poor performance for rotated, tilted or other abnormal image orientation. As a result, hybrid systems have been exhibited in order to enhance the accuracy with the maintenance of less training time. All models have been implemented in two groups of data sets: full dataset and sample dataset. Therefore, a comparative analysis has been developed in this paper. Some visualization of the attributes of the dataset has also been showed in this paper.

Keywords: CNN, Vanilla NN, VGG, STN, Capsule Network.

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1. Introduction

The world is developing day by day but the diseases on health is rapidly increasing for the purpose of the environment, the bad climate changes, the life style of human, and so on. It is increased the risk along with diseases for human. Most significant issues that this paper will emphasis on lung diseases according to deep learning. Approximately 3.4 million people acceded in 2016 to chronic obstructive pulmonary disease (COPD), affected generally by pollution and smoking, whereas 400,000 people pass away from asthma [1-3].

With numerous lung diseases people can grow, here is just any specimen of diseases people can protect if they discover it out prior. With the expertise computer and machine power, the prior credentials of diseases, mainly lung disease, this paper can be assisted to detect prior besides more correctly, which can protect numerous people in addition to decrease the diseases on the method. The health scheme has not established in time through the growth of people [3, 4].

Many researcher has done forward in their investigation to propose to humanity, relating machine learning scheme to predict X-ray image and solution the problem [5-7].

With the control of computers along with the huge volume of records being unrestricted to the widespread, this is a high time to put up resolving this complication. Wishing to put up additional to the society, serving those who are not capable to suffer for medical expenditures, in this solution can put up decreasing medical costs with the enlargement of computer science for health and medical science projects. For implementation, the big lung X-ray data is culled from Kaggle [8, 9].
1.1 Related work

The authors of [11] proposed the deep CNN with power to recognize clinical lymph node diagnosis task and achieved several consequences even the appearance of low difference adjacent architecture achieved from CT. In another research, the paper of [12] developed thoraco-abdominal problems for lymph detection as well as classification of lung disease conducting deep CNN. They addressed various CNN architectures besides acquired 85% sensitivity at 3 false positives each patient. The authors of [13] addressed a CNN scheme with the procedure of data expansion. They offered that even image data sample trained and achieved from light microscopy with the advanced model was capable to obtain high accuracy. The paper of [14] used CNN model to evaluate the data achieved from MRI. They advanced an efficient of CNN structure to produce MRIs radiological grading. This studies have implemented well manners radiological data excluding that data size was restricted with 100 patients sample. So, a complete study is requisite to conduct deep learning with power over thousand patients’ samples to obtain the reliable and accurate predictions. In [15] offered the significance of AI with a state of art in the classification of chest X-ray and analysis. Furthermore, the work [10] described this issue besides organized a novel 108,948 front outlook database ChestX-ray8 where the 32,717 X-ray images was unique patients. They conducted deep CNNs to validate results on this lung data as well as achieved promising results. In [15] also addressed that database of chestX-ray8 can be prolonged by containing various classes disease and would be valuable for another research study. The paper [16] suggested a network for deep convolutional 121-layer with the dataset of chestX-ray14. Publicly available in this dataset has X-ray images for fourteen diseases. They also addressed that their algorithm has been provided very high efficiency. The paper [17] described that a dataset for big labeled is the point of achievement for classification tasks and prediction. They offered a big dataset that contains of 224,316 radiographic chest images from 65,240 patients. CheXpert is the name of the dataset. Formerly, they conducted CNNs to indicate labels to this dataset constructed on the prospect indicated by model. This model has been used lateral and frontal radiographs with observing the output. Moreover, the author of [17] released a benchmark dataset. Further this big dataset availability is extremely anticipated that image with all object should be recognized lightly and segmentation. It should be worked accurately. Therefore, a various method is obligated to perform both object detection and instance segmentation. Such as powerful approaches are FCN and F-RCNN. This extended F-RCNN network is known as Mask R-CNN as well as it is superior than F-RCNN according to accuracy and efficiency. The authors of [20] addressed Mask R-CNN method for segmentation and object detection. The paper [20] compared their algorithm according to results and provided the best algorithm from COCO 2016 [21,22]. In [23] prolonged their method by presenting a segmentation for instance level by predicting features of convolutional.

1.2 Description of dataset

1.2.1 Sample of dataset [8]

This file contents the random sample (5%) of the full dataset:

- It carries 5,606 images where the images size is 1024x1024
- To create patient data and class labels for the complete dataset such as a csv file.

Description of class: There are 15 classes (one is "No findings" and another 14 diseases) in the complete dataset, but subsequently this is severely compact version of the complete dataset, various of the classes are scarce with the considered as "No findings": Atelectasis-508 images, Pneumonia-62, Hernia-13 images, images, Edema-118 images, Emphysema-127 images, Cardiomegaly-141 images, Fibrosis-84 images, Pneumothorax-271 images, Consolidation-226 images, Pleural
Thickening-176 images, Mass 284 images, Effusion - 644 images, Infiltration 967 images, Nodule-
313 images, No Finding - 3044 images.

1.2.2 Full/ Complete dataset [9]
The contents of the dataset can be summarized as follows:

- It has 12 files accompanied by 112,120 total images and its size 1024x1024
- To create patient data and class labels for the complete dataset such as a csv file.

Description of class: There are 15 classes (one is "No findings" and another 14 diseases). Images can
be categorized as one or more disease classes or "No findings": Pneumothorax, Consolidation,
Infiltration, Emphysema, Atelectasis, Effusion, Fibrosis, Pneumonia, Pleural_thickening, Hernia,
Cardiomegaly, Nodule Mass, and Edema.

From the expertise and current conditions of technology, we believe that this paper can put up some
segment to the people in building and analyzing a model basis of this valuable data set.

The data set covers valuable records for the model. In this paper will construct as: age, patient data,
gender, snapshot data and X-ray images. As of this foremost information, this paper will use it to the
model.

In analysis from X-ray records, the doctor can diagnose a factor of the patient's health and medical
condition, as a result data for X-ray chest image, the intelligent machine can help the physician in the
proper diagnosis or analysis of the lung disease, some records on gender and age will similarly be
deliberated to improve the accuracy of this scheme.

1.3 Problem Statement
In recent times, a big dataset of X-ray data was open on Kaggle in according to considered lung
disease dataset. In this paper implement this dataset using novel deep learning method such as CNN
+ VGG + data + STN.

In this paper will exploit an analysis of this lung data set, at that time use a novel Deep Learning
scheme to predict in which the patients have various lung disease. In this paper conduct a binary
classification using input is the various patient's dataset (such as age, X-ray images, gender, View
Position) as well as output is detect diseases otherwise not.

The complexity is a novel dataset, in our analysis is in which this is a big dataset however has never
been trained full, dataset has numerous noise, as well as X-ray image of the lung for various
diseases are not expected to make available in sufficient information to evaluate whether a affected
patient may be sick.

In this research will conduct Machine Learning like as Deep Learning to categorize data with creating
models on behalf of diagnosing patients. The key point of this paper: assembling the treating of patient
records with data as of X-rays, conducting CNN through the recognized pre-trained model. It is the
first time conducting the CapsNet for lung dataset using this method.

1.4 Metrics
The estimation metrics conducted here will be recall, precision as well as F-beta scores (where \( \beta \) is
0.5) designed for binary classification. It has been detected diseases otherwise not. In that situation F
score is superior to accuracy for the reason that using binary classification detect or found diseases
otherwise not, the programs are imbalanced. Such as, say you have a minor classifier in which just
predicts the class of majority, it will achieve 80% accuracy while there is a 90/30 split as well as 50% accuracy when there is a 50/50 split.

These directories will be estimated on a discrete testing data from the main dataset.

These displays will be estimated for various diseases – detect/found disease otherwise not.

If the circumstance is positive as well as not negative, now the indicators:

True Positive (TP) - The amount of patient affected diseases is estimated to be affected.

False Positive (FP) - The amount of patient who are ill is predicted to be ill.

False Negative (FN) - The amount of patient deprived of the disease is forecast to be wrong.

\[
Recall = \frac{TP}{TP + FN} \quad (1)
\]

\[
Precision = \frac{TP}{TP + FP} \quad (2)
\]

Recall and Precision can work on the amount of affected patient. So it overcomes the skewness property of the data besides the significance of evaluating a patient illness.

Precision denotes the proportion of patient who properly forecast the disease in the entire number of patients who were expected to be ill. Recall denotes the proportion of patient who properly predicts sickness on the entire number of patient truly infected. These parameters can play a significant role in predicting this lung disease. An index can be introduced that is the fusion of precision and recall.

An amalgamation of recall and precision F score can be deduced in the following form:

\[
F_\beta = \left(1 + \beta^2\right) \frac{Recall \times Precision}{\beta^2 \cdot Precision + Recall} \quad (3)
\]

Various \(\beta\) will display the significance between various precision and various recall. There are two fundamental ideas for selecting the significance of recall and precision:

- We need assurance of the implemented model that a people is anticipating a lung disease, which states that both expectation is appreciatively confident because while a person is detected with a lung disease, it is really heartbroken. It is highly significant, since it can be considered a system to support doctors using further diagnostic processes. As a result, low recall and high precision correlated with small \(\beta\) is needed. \(\beta = 0.5\) has been assumed for F-\(\beta\) score.

- The proposed models should keep away from mispronouncing sick people in order to avoid illness. Models should avoid missing patients at risk. This situation will prefer high recall and low precision value correlated with large \(\beta\). \(\beta = 2\) has been assumed for F-\(\beta\) score.

The proposed work will help doctors for detecting diseases quickly because in order to determine the disease a patient needs many test. The affected patient will be worried before realize additional results, therefore this paper suggests F-0.5-score where \(\beta\) is 0.5.

2. Analysis of the chest X-Ray image dataset

2.1 Data Exploration

Chest X-ray tests are very common and cost-effective (X-ray) medical imaging techniques available. On the other hand, lung or chest X-ray clinical diagnosis can be demanding. But sometimes it may be more problematic than lung diagnosis through CT (Computed tomography) imaging for chest.
There is a scarcity of resourceful public datasets. Therefore, it is very challenging and difficult but it is not impossible in order to realize clinically relevant diagnosis and computer aided detection in various medical sites using chest or lung X-rays. One crucial obstacle in generating big chest X-ray datasets is the absence of properties for labeling numerous images. Before the emancipation of this data, Openi was the biggest in public available in Kaggle where the 4,143 chest or lung X-ray images are available.

This Chest X-ray images dataset is consisted of 112,120 chest or lung X-ray images using disease labels of 30,805 single patients. For generating these labels, some authors conducted NLP to text-mine classifications of disease from the related radiological information. This labels are estimated to be greater than 90% accurate as well as appropriate use for weakly-supervised learning. Wang et al. [10] localized some common thorax diseases using a small percentage of the dataset.

In this data 5,606 chest images are included with its size of 1024x1024.

![Figure 1](image.png)

**Fig.1.** Sample of dataset where its size 1024x1024

Patient data and Class labels of the total dataset can be illustrated as follows:

- Patient ID
- Finding Labels such as disease type
- Image Index
- View Position: X-ray orientation
- Patient Gender
- Patient Age
- OriginalImageHeight
- OriginalImageWidth
• OriginalImagePixelSpacing_x
• Follow-up
• OriginalImagePixelSpacing_y

The data encloses valuable records for the set of data constructed as: gender, age, snapshot data, view position as well as lung X-ray images. We will use this key information in order to train the CNN model.

### 2.2 Exploratory Visualization

At first, a sample data is analyzed in this study. Finally, full data is analyzed.

Now, there are some plots in which will display us further about the lung disease data.

![Visualization of the amount of patients using sex and disease where sample dataset uses](image)

**Fig. 2.** Visualization of the amount of patients using sex and disease where sample dataset uses
Figure 2 and 3 display few diseases with actual some cases for example, Fibrosis, Pneumonia, Hernia, and few many frequent lung diseases for example, Atelectasis, Effusion, Infiltration. Distribution of disease is actually uneven.

In this dataset, the entire number of males is higher than entire number of females and the quantity of confirmed circumstances is greater than the amount of males diagnosed through lung disease.

**Fig. 3.** Visualization of the amount of patients using sex and disease where full dataset uses
2.2.1 View Position

Posterior-anterior (PA) Position: It is a standard position used for finding a regular mature chest radiograph. Patient attitudes standing with the anterior position of chest employed alongside the anterior of the film. The containers are replaced forward adequate to bit the film, confirming in which the scapulae do not unclear a part of the lung areas. The Posterior-anterior film if observed as if the lung diseases patient is fixed in a position.

Anterior-posterior (AP) Position: It is conducted while the patient is immobilized, debilitated, or incapable to collaborate with the Posterior-anterior process. The heart is at a bigger space from the film. Therefore, it seems more expanded than in a Posterior-anterior. The scapulae are generally detectable in the lung fields for the reason that they are not replaced out of the vision in a Posterior-anterior.

This types can be realized in which these two categories of position will display the records in the chest X-ray inversely along with the topics specified. As a result, this is moreover an influential feature for the construction of the model.
An example from an image having two types of position of the same patient is showed in figure 6. The difference can be clearly observed.

Fig. 6. (a) Posterior-anterior (b) Anterior-posterior position

Fig. 7. Age distribution of sample dataset
Fig. 8 visualizes age distribution that can be realized in which middle-aged patients are more possibly to improve lung disease as well as that patients are more possibly to aim for medical tests. Young patients are similarly concentrating on primary diagnosis.

In order to distinguish whether a person is affected by lung disease or not, some important attributes has been chosen the data needed to build the model. The attributes will be: X-ray, X-ray view position, Age, Gender.

2.3 Proposed Algorithms

Some basic algorithms such as CNN has been proposed firstly and then hybrid model with the addition of CNN has been proposed in order to enhance the training time and detect the disease effectively with less number of tests.

2.3.1 Convolutional Neural Networks

This proposed algorithm is an influential algorithm for image processing with image data as like as our evaluation. Specified the big data in the full lung image dataset, this is actually the suitable process to apply, several parameters are deliberated as follows:

- Architecture Neural network where we select the suitable architecture
- Preprocessing parameters
- Sufficient tuning
- Special transformer
- Training parameters
- Enhance more data in the system not only lung X-ray images
2.3.2 Capsules Network
Using the influence to discriminate several objects from various perspectives, the capsule network can be suitable for the reason that our lung X-ray image data has two categories of View Position. As like CNN, this paper has particular things to prepare as follows:

- Architect Capsules Networks where the suitable architecture has been selected
- Preprocessing parameter
- Training parameters

2.4 Benchmark
According to this problem, the benchmark model will be a model of vanilla CNN. In this proposed work “vanilla CNN for Sample dataset” and “vanilla CNN for Full dataset” has been used.

In past days, no researcher constructed a complete deep learning based NN model for this lung X-ray image dataset. But we have proposed a basic CNN and then optimized hybrid CNN model with the addition of VGG, STN etc. in order to compare to which model is optimal and which gives good output.

Architecture or structure for the model of vanilla CNN is described using the block diagram showed in figure 9.

![Fig.9. Structural design for the model of vanilla CNN](image)

A model of basic CNN with four Convolutional layers resulting all Convolution layer is the Max Pooling. The Convolution layers are growing in depth. The following two categorizes to classify are Dense and Flatten.

CNN is the typical for handling as like visual problems. According to this simple model, in this paper will effort to accept the pattern of diseases by confirming that CNN will effort with lung X-ray images.

3. Methodology
3.1 Data Preprocessing
In this preprocessing of data for mutually full dataset as well as sample dataset in “Data preprocessing” contains of next steps:

- For images:
  1. At first rescale all images for the purpose of reducing size with the feature in which creates training faster.
(ii) The all images are transformed to rgb and gray. Mutually are conducted for various models.

(iii) In this next step the numpy array uses for read the images at that time normalize by separating the images matrix using 255.

- For additional data:
  
  (i) Discrete specific features into specific features.
  
  (ii) Normalize the age field to the numeric system then along with the year, at that time normalization field.
  
  (iii) Eliminate the outliers theme owing to data around age very large.
  
  (iv) There are two essential attributes, this paper will conduct as 'View Position' and 'Patient Gender' in indiscriminate both dataset

All image data when processing is put away for future use.

This preprocessing process has the resulting modifiable parameters: Resize images form

3.2 Implementation

We will go into the analysis of the two major options that will apply as follows:

3.2.1 Optimized CNN

This is the key scheme of this paper and can be realized on Jupiter Notebook: “optimized CNN for sample dataset” and “optimized CNN for full dataset”.

It is the architecture or structure for this method

![Fig.10. Architecture of VGG16 for feature extraction](image1.png)

![Fig. 11. Full architecture of Optimized CNN](image2.png)
The structure contains of three key layers in the ensuing order:

- **Spatial transformer layers**
  
  (i) It has initially three layers.
  (ii) The initial part is $\lambda$ to transfer the default routing [-0.5: 0.5], which refers to that the features of the lung X-ray image have a normal value of 0.
  (iii) The second part is Batch Normalization.
  (iv) The third layer in this part is Spatial Transformer, which is conducted to remove the maximum significant features for lung diseases classification.

- **Extraction of features layers**
  
  (i) VGG16 model has been pre-trained.
  (ii) A group of 13 layers as presented in the Fig. 10 where VGG is the feature extraction, there are various pre trained classifier on the other hand at this time this paper is trying previously with VGG16 since this is a model of simple designed for learning time as well as training faster.

- **Classification layers**
  
  (i) In this case, first layer is defined as the Flattened layer as of the output of the VGG16 layers with additional 5 features such as 'Gender Female', 'Gender Male', 'Age', 'View position PA', 'View position AP'. These additional 5 features will similarly attack the sorting, such as this simulation has seen upon, therefore they are assembled to this following layer. According to this layer is called dropout layer.
  (ii) The last two layers are dense when both Dropout layer, with a continuing reduction in depth.

The sequence of steps in this process is described as follows:

- Load of dataset has been treated into ram and processing this data as previously where the Images stored in RGB lung X-ray image format.

- Implement the network structural designed by the way of an architect.

- Implement the metric function as well as Precision score, Binary accuracy through threshold, F beta score using beta with threshold.

- Implement data model generator, checkpoint, and loss of model function.

- Train model using training parameters, validation loss with training/logging training/validation with accuracy.

- Test this dataset.

3.2.2 Capsule Network

In this Capsule Network, this paper had a minor modify from the main Hinton architecture with the purpose of it could perfectly effort with this lung image data set. At this time is the structure taken from the research paper by Hinton. This paper will simplify the modifications right below:
Main portions of this model summarized as:

- Convolution layer with filters = 256, strides = 2, kernel_size = 9, activation = 'relu', padding = 'same'. This layer was improved as of the original classifier from strides = 1 to strides = 2, the image was 28x28, the reason creature that with the MNIST data Hinton tested Capsule Network, as well as the data was 64x64, the output of this classifier will be considerably compacted, with strides=2, as well as we will agree so that we will acquire less features than strides = 1, subsequently we have improved the strings consequently we consider the output of lung images have been considerably concentrated. Therefore, we vary from padding equal 'valid' to padding equal 'same'.
- Primary Capsule with dim_capsule=8, strides=2, kernel_size=9, n_channels=32, padding='same', simply variations with Hinton's structure in which the padding equal 'valid' is exchanged with 'same'.
- Digit Capsule (we change the similar name in which Hinton situate) with n_class=num_capsule, dim_capsule=16, stable of the set routings equal 3.

As like CNN, the application steps are applied in this next step:

- Load of dataset has been treated into ram and processing this data as previously where the Images stored in RGB lung X-ray image format.
- Implement the network structural designed by the way of an architect considered beyond with the parameters illustrated.
- Implement of the metric function containing Precision score with threshold, Binary accuracy, F beta score with beta and threshold, Recall score with threshold. There is a minor modify from CNN to the output form (None, 2) in place of CNN with the output form (None, 1).
- Implement data model generator, checkpoint, and model loss function.
- Training model using training parameters, validation loss besides training/logging training/validation accuracy.
- Apart from best model besides model for test on testing dataset.

3.3 Refinement
The beyond part states through specific of my tweaks. Let us be frequent and improve:

CNN and deep learning are employed by Keras through the tensorflow-gpu is used for backend.
3.3.1 Optimized CNN

Experimenting and changing with numerous image sizes, it is found that the 64x64 image size was good enough and slight enough for the classifier to the shape of the image capture.

The spatial transformer is used and front layer is supported as a layer. A “locnet” model is used in this STN layer. “locnet” means localization network. It helps for separating key features from the images.

Non-complementary dataset has been tested in various spaces on the structural design. The 1st layer can be considered most suitable and pertinent. Adjustment as well as improvement of the thresholds of recall, precision, and F-beta score is necessary. The index of the dropout layer need to be refined.

3.3.2 Capsule Network

The parameters selected for Capsule network are: Convolution layer with filters = 256, strides = 2, kernel_size = 9, activation = 'relu', padding = 'same'. This layer was improved as of the original classifier from strides = 1 to strides = 2, the image was 28x28, the reason creature that with the MNIST data Hinton tested Capsule Network, as well as the data was 64x64, the output of this classifier will be considerably compacted, with strides=2, as well as we will agree so that we will acquire less features than strides = 1, subsequently we have improved the strings consequently we consider the output of lung images have been considerably concentrated. Therefore, we vary from padding equal 'valid' to padding equal 'same'.

The metric function containing Precision score with threshold, Binary accuracy, F beta score with beta and threshold, Recall score with threshold is implemented. There is a minor modification from CNN to the output form (None, 2) in place of CNN with the output form (None, 1).

Parameters for training are similarly offered to ensemble the machine configuration for example, learning rate, batch size=32.

4. Results

Some abbreviations are used for the models that have been tested:

- Vanilla RGB: Vanilla CNN model for RGB images
- Vanilla gray: Vanilla CNN model for gray images
- CNN + VGG: Optimized model with VGG16 pre trained model
- CNN + VGG + data: Optimized model with VGG16 pre trained model and extra data
- CNN + VGG + data + STN: Optimized model with VGG16 pre trained model and extra data and Spatial Transformer
- CapsNet basic: Capsule Network with Hinton’s architecture
- CapsNet changed: Capsule Network with my changed architecture

4.1 Model Validation and Evaluation

During improvement, a validation set was conducted to estimate the model.

The resulting is a transformation graphic representation of loss in training systems conforming to full dataset and sample dataset.
Fig.13. CNN + VGG + data + STN for sample dataset

Fig.14. Vanilla CNN for sample dataset

Fig.15. Capsule Network for sample dataset
After the beyond three graphic representations, it is simply to realize that the vanilla CNN is working the poorest, it overfilled too early and clogged because of our early stopping checkpoint model. Capsule Network looks to be working however convergence is very slow. CNN + VGG + data + STN looks to effort well however is converging very slowly, possibly owing to very little data on the amount of features after the images are very big, as a result we want additional data in full dataset.

**Fig.16.** CNN + VGG + data + STN analysis for full dataset

**Fig.17.** Vanilla CNN analysis for full dataset

**Fig.18.** Capsule network analysis for full dataset

All three of these models The evaluation of all model is implemented in this paper which is greater than the sample lung dataset. We found that the vanilla CNN was stopped and overfilled by the model of Early stopping, VGG + CNN + STN + data, with very sophisticated systems as established. The
convergence is fast as well as is still too useful convergence, will also have provided higher results if this paper train this model using more epoch. Performance of the Capsule Network is too better, however slower convergence in addition almost difficult to modify the losses value.

From the beyond diagrams, it can be established that CNN + STN + VGG + data is the greatest with some specific parameters as declared above.

4.2 Justification

An evaluation of the accuracy of the approaches on two groups of data sets: full dataset and sample dataset, the following comparisons have been performed on the data use for testing differed from validation and training:

**Table 1.** Calculation of recall, precision, F-beta score and training time or epoch according to different architecture for the purpose of full dataset and sample dataset

| Dataset    | Structural design | Recall   | Precision | F beta (0.5) score | Accuracy | No. parameters | training time or epoch |
|------------|-------------------|----------|-----------|-------------------|----------|----------------|------------------------|
| Sample Dataset | Vanilla gray      | 0.50     | 0.58      | 0.56              | 0.52     | 321225         | 2 s                    |
|            | Vanilla rgb       | 0.59     | 0.62      | 0.62              | 0.51     | 322793         | 2 s                    |
|            | CNN+VGG           | 0.56     | 0.65      | 0.63              | 0.67     | 15252133       | 16 s                   |
|            | CNN+VGG+data+STN  | 0.62     | 0.62      | 0.64              | 0.68     | 15488051       | 19 s                   |
|            | CNN+VGG+data      | 0.59     | 0.65      | 0.64              | 0.68     | 15240769       | 16 s                   |
|            | CapsNet changed   | 0.18     | 0.71      | 0.27              | 0.58     | 12167424       | 37 s                   |
|            | CapsNet basic     | 0.60     | 0.62      | 0.62              | 0.59     | 14788864       | 75 s                   |
| Full Dataset | Vanilla gray      | 0.58     | 0.68      | 0.65              | 0.67     | 321225         | 51 s                   |
|            | Vanilla rgb       | 0.61     | 0.68      | 0.66              | 0.68     | 322793         | 53 s                   |
|            | CNN+VGG+data+STN  | 0.63     | 0.69      | 0.68              | 0.71     | 15488051       | 431 s                  |
|            | CNN+VGG           | 0.62     | 0.68      | 0.67              | 0.69     | 15252133       | 384 s                  |
|            | CapsNet changed   | 0.48     | 0.61      | 0.59              | 0.63     | 12167424       | 856 s                  |
|            | CapsNet basic     | 0.51     | 0.64      | 0.61              | 0.62     | 14788864       | 1815 s                 |

Our best model is CNN + VGG + data + STN, which is better than the benchmark Vanilla CNN. It can be seen that the important indicator that they have defined is the F 0.5 score of the best model is 0.67. Training time is bigger than Vanilla CNN, but my best model is still focused and can be improved by continuing training with more epochs as the above analysis.

The Capsule Network model does not seem to work well; the number of parameters is only equivalent to my best model but the training time is much longer.

As a result of my best model-CNN+VGG+data+STN is F 0.5 score=68% with accuracy of 71%, it still does not meet the requirement to use in hospitals, need more time and computer power to further analyze the data, improve the algorithm can meet the requirements. However, this is also a good first step, and this result is very good when the normalized data set is public and there are many mistakes in labeling.

4.3 Free-Form Visualization

This paper is tested with twenty random instances, the surgeon, either a patient or a physician, just completed in records about age, X-rays, view position, and gender. We have been evaluated and detected the illness of a patients before moving forward with the investigation on more significant trials. For the purpose of the prediction of diseases, we have calculated the F beta score where beta
is 0.5. It means that we are determining and sure to the condition of a patient such as the condition of sadness and shock before formal diagnosis.

![Example of analytical lung image dataset with finding](image1)

**True: Fibrosis, Predict: Finding, confident: 0.58584183**

![Example of analytical lung image dataset with prediction](image2)

**True: No Finding, Predict: No Finding, confident: 0.074103214**

**Fig.19.** Example of analytical lung image dataset with finding

Most of the above results are precisely very similar, however there are the evaluation of some cases are incorrect as follows

![Example of analytical lung image dataset with prediction](image3)

**True: Pneumothorax, Predict: No Finding, confident: 0.48332688**

**Fig.20.** Example of analytical lung image dataset with prediction
It has some demerits of the prediction that the ill person is not ill, ignore shocking patients as well as require more tests formerly the doctor provides the ultimate diagnosis. The beta of the F score is 0.48 for the confidential cases which is proximate to the threshold. So, we have selected as 0.5 beta score. It means that the chance of the illness is approximately half.

4.4 Reflection
We offered the diagnosis and detect the lung disease using the patient's lung X-ray data plus around extra records. The ideal solution of this paper is to have a hybrid CNN with the describe the data process as follows:

- Research for support data, domain information, resolved issues, approaches, and solution data for similar paper. Some potential methods are investigated and listed.
- Data set of a sample data is downloaded with metric selection, preprocessing, analyzed.
- We have tested multiple structures, improving and testing on a sample lung dataset.
- Finally, we have used best architects for the purpose of test the full lung dataset, continue improving and statistics.

This paper is based on a novel dataset and not several researchers find out or published article. This is a critical problem and if do it well, it will create a massive contribution to the public. This paper has been tested many novel and interesting approaches for example, Capsule Network and Spatial Transformer has presented that this paper has verified significant results.

4.5 Improvement
This paper may be done well to increase our results as follows:

- The model needs testing in order to differentiate each type of disease. As a result, the data problem can be explained for each disease which is very skew.
- The proposed model should be trained with huge number of epoch with the change of a few parameters for getting fast convergence.
- The probability of getting significant features will be increased if the size of training shots can be increased. But it can create output of long training time.
- Several Pre-trained models can be experimented in order to implement CNN with the fusion of VGG.
- Very complex “locnet” module has been used in order to implement hybrid CNN with the addition of spatial transformer.
- In order to extract more features, CapsNet has been proposed after adding some more layers. But it will provide very long training time.

5. Conclusion
The selected CNN model has not actually rapid convergence and small loss, as a result still require more enhancement can be fixed to detect lung disease in the hospital. We still expect to long time, power of computer to run to progress this deep learning based model as much better. This paper is implemented a very novel dataset in which is collected from NIH. This data is very complicated so we are implemented with solution this problem of dataset. It will be contributed to the community. This data has tested many novel and remarkable systems for example, Capsule Network, Spatial Transformer and it has also presented that we have recorded many significant results. X-ray images
are hardly to see clear and the dataset is not standardized. It is very difficult to implement a very novel scheme of capsnet. Therefore, there is not considerably record to improve it. Full dataset has huge number of data, so it provides a big challenge for us being restricted to the power of computer. As a result, this paper has acquired our desired output, but to be capable to use in hospitals, additional progresses are required to enhance the precision of the deep learning based model. Generally, basic CNN has poor performance for rotated, tilted or other abnormal image orientation. Therefore, hybrid systems have been exhibited in order to improve the accuracy with the maintenance of less training time.

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