Classification of Liver & Lung Disease Using Deep Learning

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Abstract

Lung illness is one of the most prevalent causes of death in the world. The majority of lung problems are found after they are well advanced. As a result, in the current world, the development of techniques and systems that allow for faster and earlier detection will be critical. Computer-aided diagnosis (CADx) systems perform and are currently expanding on such a role. This study looks at the use of pretrained deep learning architectures to offer rich and robust features. The Gray-level Co-occurrence Matrix, which is commonly used, was compared to these features (GLCM). In contrast to the accuracy of 93.52% attained by GLCM features, deep features generated the highest accuracy of 100%.The Support Vector Machine (SVM) gave the best results when comparing the classification of deep features using five different classifiers in this experiment. To replicate this high accuracy, Linear Discriminant Analysis (LDA) and Regression classifiers were also utilized. Principal Component Analysis (PCA) was also used to evaluate the usage of fewer features and their influence on classification performance. Deep features yielded a classification accuracy of 100% and 4096 features. Even though just 79 characteristics were used when PCA was originally introduced, the accuracy gained was the same. It is therefore promising to employ deep features in combination with PCA to minimize the number of characteristics in the categorization of ill lungs.

Keywords — Lung Liver dataset, Disease classification, Deep Learning, Image processing, CNN, Mobile Net.

INTRODUCTION

Aside from ischemic heart disease and stroke, lung illnesses are now the third greatest cause of mortality. The majority of lung disorders in Malaysia, in particular, are detected at stage (IV) or later. This demonstrates Malaysia's late diagnosis of lung illnesses. Late detection contributes to a greater death rate. However, earlier discovery allows for a better prognosis and treatment, increasing the rate of survival and quality of life. This demonstrates the importance of current research efforts in identifying viable approaches to diagnose illnesses faster for improved treatment planning and execution. This is the driving force for investigations into and proposals for Computer Aided Diagnosis (CADx) systems. Breast cancer diagnosis has also improved because to CADx systems. There is an increasing need for CAD systems, yet the systems that have been installed are still incomplete. The majority of study has been on textural aspects. Textural characteristics have proven to be efficient in categorization. Deep features, on the other hand, have showed a more promising path ahead in recent publications. This is due to the fact that it demonstrates a new sort of robust and extensive depth of characteristics that were previously inaccessible. The main disadvantage of such approaches is the long training period and computational strain of employing big feature sets.The primary goal of this research is to present a classification method for normal and sick lungs that uses deep features from several deep learning architectures. This paper also presents the usage of PCA with deep features and compares the results with various other classifiers to demonstrate the efficacy of deep features.

I. Literature Review

Lung Disease Classification Using Different Deep Learning Architectures and Principal Component Analysis:-

Joel Than Chia Ming, Norliza Mohd Noor, Omar Mohd Rijal, Rosminah M. Kassim, Ashari Yunus:-

Committed to using deep features alongside PCA to reduce the number of features Classification of diseased lungs.overview:We have explored many latest articles related to Deep`s APP Learning disease classification, detailed explanation of proposal structure, trainingDNN method and final score used to process disease detectionperformance, comparing deep learning with other existing popular methods,We found that deep learning methods achieve better results than other methods Explained learning methods and discussed challenges and future in detailProspects for Deep Learning in the Food Sector.A survey of deep learning apps in the medical field.Reviews are about encouraging researchers and collaborators in the field to do better workAccurate Presentation by Disease Detection Experiments Using Deep Learning Techniques Find and implement solutions to classification or regression problems Benefits of lung and liver disease detection and safety testing for human health.

Liver Disease Classification using Deep Learning Algorithm :-

L.Anand, V. Neelanarayanan:-

The proposed technique is evaluated against reliable execution metrics.Experimental results show that the proposed strategy demonstrates a competent arrangementShow compared to early prediction of liver diseasewith other existing technologies.Liver characterization exhibition in the future The base disease is further enhanced using the progression system, Diagnosis of various types of liver disease.

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications:-

Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko:-

MobileNets are primarily based totally on a streamlined structure that makes use of depth-wise version for his or her utility primarily based totally on the limitations of the problem.which characterization of liver sickness assumes a great activity and may be applied in perception structures for early expectation of Liver trouble depending on ANN set of rules and these selected highlights are moreover applied for association of liver illnesses which might be completed via way of means of utilising the characterization process of the trial outcomes reveal that proposed method shows talented association in destiny the exhibition of characterization of liver primarily based totally illnesses will moreover progressed via way of means of utilising development structures .

Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer :-

Devvi Sarwindaa, Radifa Hilya Paradisaa, Alhadi Bustamama, Pinkie Anggiab:-

In this paper, we investigate deep learning methods for image classification.Colorectal cancer detection with ResNet architecture.Deep Learning Classification Facilitates Scientists` Implementation in MedicineIn this study, he trained ResNet-18 and ResNet-50 on colon gland images.A model trained to distinguish between benign and malignant colorectal cancer.The experimental results show that the application of ResNet-50Provides the most reliable performance in precision, sensitivity and specificity valuesIt outperforms ResNet-18 on three types of test data.Evaluate the best performance values on the 20% and 25% test sets,Over 80% curacy, over 87% sensitivity, over specificity Reproducible results for biomedical image analysis. On the other hand, the large intestine consists of the ascending colon, ascending colon,It has also been confirmed by intestinal biopsies.Detect cancer and analyze the morphology of biopsy images.(ResNet) Methods for identifying colorectal cancer, the authors have created severalThere are two ResNet architectural models, specifically ResNet-18 andResNet-50 with three dataset distribution models to test accuracy,Sensitivity and specificity values.According to our analysis, colorectal cancer can be detected with ResNet variants.Accuracy ranges from 73% to 88% and sensitivity values range from 64% to 96%.The classification model created can identify colorectal cancer.

II. Methodology

Existing System:

In the existing there are no methods implemented to check or detect the diseases in lung or liver. The only method is to execute the procedure manually in labs and study by experts, which takes a lot of time and more human work in emergency situations where experts' availability and time constraints are limited. This model emphasizes an existing approach that is created utilizing certain machine learning methods. The procedure is carried out here utilizing the ANN (Artificial Neural Network), which is a machine learning approach, although it does not achieve great accuracy.

Disadvantages:

- Time consuming
- More human effort
- Less feature compatibility
- Low accuracy

Problem Statement:

It is a useful system since it helps in reducing the limitations obtained in existing system by providing the support through classification analysis of lung and liver diseases are affected or healthy using mobile net of Deep learning along with the transfer learning methods. Hence proper classification with their varients using the corresponding datasets. To obtain more accuracy and best prediction in patients health the model is more helpful for the doctors to diagnose Lung and Liver diseases for a patient.

Proposed Method:

In the proposed method, we execute the classification of if the image is lung or liver Disease identification utilizing deep learning methods such as Convolution Neural Network CNN Mobile-Net Resnet50. As image analysis-based techniques for detecting lung and liver disease. As a result, appropriate categorization is critical for lung and liver illness, which will be attainable with our suggested technique.

Advantages:

- Accurate classification
- Less complexity
- High performance
- Easy Identification

Modules:-

1. System:

1.1 Create Dataset:

The dataset containing images of theLung diseases and liver cancer images with the Classification i.e., normal are to be classified is split into training and testing dataset with the test size of 30-20%.

1.2 Pre-processing:

Resizing and reshaping the images into appropriate format to train our model.

1.3 Training:

Use the pre-processed training dataset is used to train our model using Resnet 50 and Mobile-Net Deep learning algorithm along with some of the transfer learning methods.

1.4 Classification:

The results of our model are display of Lung and liver diseases images are either with diseases or normal name.

2. User:

2.1 Upload Image

The user has to upload an image which needs to be classified.

2.2View Results

The classified image results are viewed by user.

Input Design:

In an information system, input is the raw data that is processed to produce output. During the input design, the developers must consider the input devices such as PC, MICR, OMR, etc.

Therefore, the quality of system input determines the quality of system output. Well-designed input forms and screens have following properties −

It should serve specific purpose effectively such as storing, recording, and retrieving the information.

It ensures proper completion with accuracy.

It should be easy to fill and straightforward.

It should focus on user's attention, consistency, and simplicity.

All these objectives are obtained using the knowledge of basic design principles regarding –

- What are the inputs needed for the system?
- How end users respond to different elements of forms and screens.

Objectives for Input Design:

The objectives of input design are:

To design data entry and input procedures

To reduce input volume

To design source documents for data capture or devise other data capture methods.

To design input data records, data entry screens, user interface screens, etc.

To use validation checks and develop effective input controls.

Output Design:

The design of output is the most important task of any system. During output design, developers identify the type of outputs needed, and consider the necessary output controls and prototype report layouts.

Objectives of Output Design:

The objectives of input design are:

To develop output design that serves the intended purpose and eliminates the production of unwanted output.

To develop the output design that meets the end user's requirements.

To deliver the appropriate quantity of output.

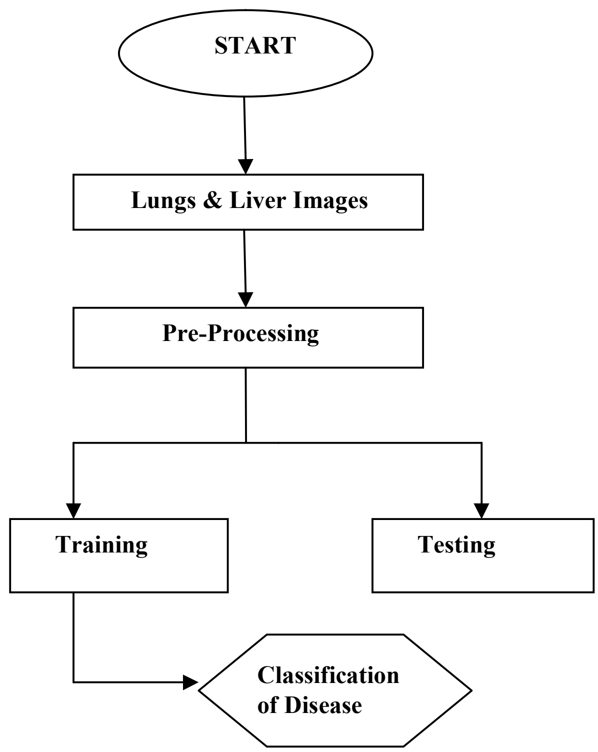
To form the output in appropriate format and direct it to the right person.

To make the output available on time for making good decisions.

Implementation Work:

First we have taken the Lung and Liver Diseases images.
Load the dataset into and Preprocessing .
Here split the data in to train data and test data.After splitting apply the Mobile Net and Resnet algorithm Respectively and fit the train data and test data.We got the best accuracy score for Mobile Net.Later, the entire work is done with Django framework user can view the home, about ,upload page and Results.

Architecture:



Algorithms :

Mobile network:

The Mobile Net model, as its name suggests, was Tensor Flow's first wearable computer vision model, designed for use in mobile applications. Depth-based separable convolutions are used in Mobile Net. The number of parameters is significantly reduced compared to networks with conventional folding of the same depth in the net. The result is a lightweight deep neural network. Depth splittable folds are created from two operations.

1. deep fold.
2. Pointwise convolution**.**

MobileNet, a class of CNNs, can be used to train incredibly small and incredibly fast classifiers.

This convolution arose from the idea that the depth and spatial dimensions of the filter could be separated. hence the name separable. Let's look at an example of the Sobel filter used in image processing to detect edges.Filter, Sobel. Gx for horizontal edge detection and Gy for vertical edge detection.You can separate the height and width dimensions of the filter. The matrix product of [1 2 1] transposed by [-1 0 1] can be thought of as a Gx filter. Notice the camouflage of the filter**.** It shows 9 parameters, but there are only 6. This is made possible by separating the height and width dimensions. Performing depthwise convolution using the same concept to separate the depth dimension from the horizontal dimension (width * height) yields the depthwise separable convolution. Then the depth dimension is covered with a 1*1 filter. The amount of parameter reduction required to obtain the same number of channels in this convolution is **a** matter of consideration.A depthwise separable convolution is a depthwise convolution followed by a pointwise convolution as follows:

1. Channel-wise spatial DK-DK convolution is depth-wise convolution. If we have 5 channels in the above figure, we get 5 DK-DK spatial convolutions.
2. Convolutions used to adjust one dimension are called pointwise convolutions.
3. Deep fold.

Conclusion: Mobile nets are lightweight, low-latency, low-power models with parameters tuned to the resource constraints of various use cases. They can be built for classification, detection, embedding, and segmentation.

Resnet network:

AlexNet won the Grand Prix at the 2012 LSVRC2012 Classification Competition. ResNet has since become one of the most exciting developments in the field of computer vision and deep learning.

The framework provided his ResNets, which enabled training very deep neural networks. This means networks can have hundreds or thousands of layers and still achieve amazing performance.

ResNets were originally used for image recognition problems, but as the study states, the framework can also be applied to tasks not related to computer vision to achieve higher accuracy.

Problem:Deep convolutional neural networks are very good at extracting low-, medium-, and high-level features from images, and adding more layers generally improves accuracy, which raises the question:

Can I improve model performance by simply adding more layers? Another problem arises when the deep neural network starts to converge, the accuracy saturates and then drops off rapidly. This issue was not caused by overfitting as might be assumed, and adding more layers to a good deep model simply increased the training error.This issue was further resolved by creating a deep model from the shallow model's layer and adding an identity layer to it. As a result, newer layers only identify layers, so deeper models should not produce more training errors than their corresponding models.

The authors introduced a deep residual learning framework to solve this problem and consequently added a join that only performs identity mapping.

III. Result

Home Page: Classifying the presence of lung and liver Disease Image Classification, with the help of deep learning and Transfer learning.

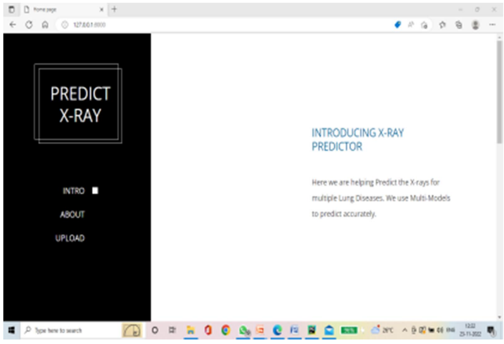


Fig (i)

Upload Image with model selection : Here the images can be uploaded those which are to be classified.

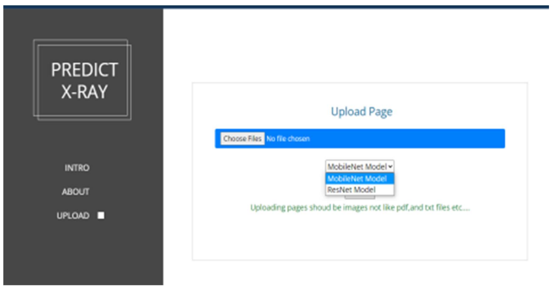


Fig (ii)

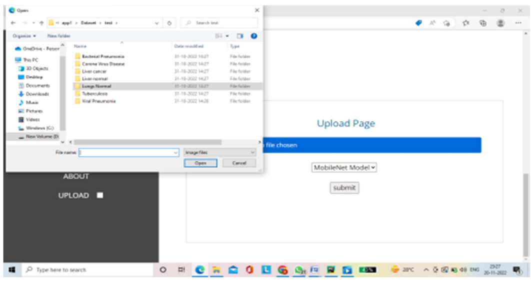


Fig (iii)

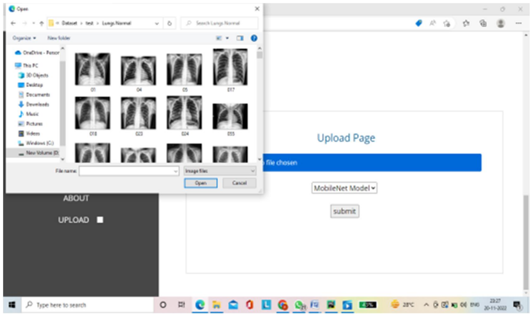


Fig (iv)

Output : The uploaded images are classified.

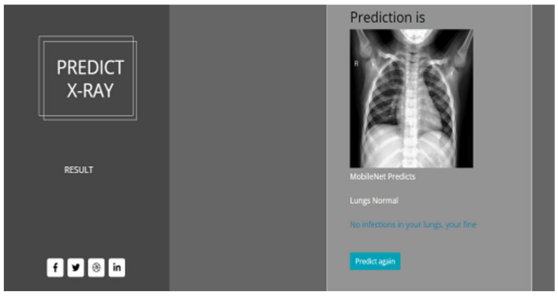


Fig (v)

Graph:

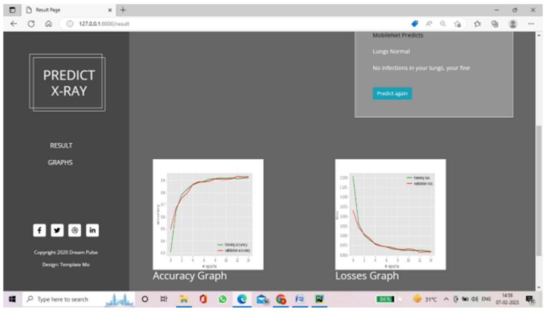


Fig (vi)

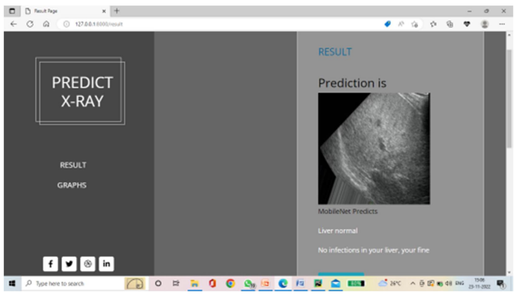


Fig (vii)

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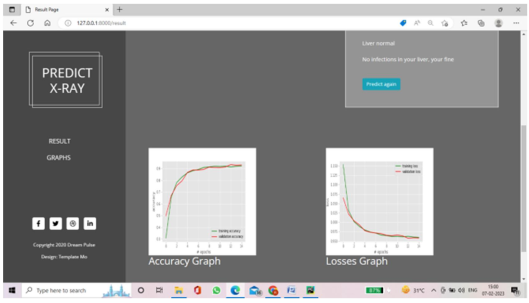

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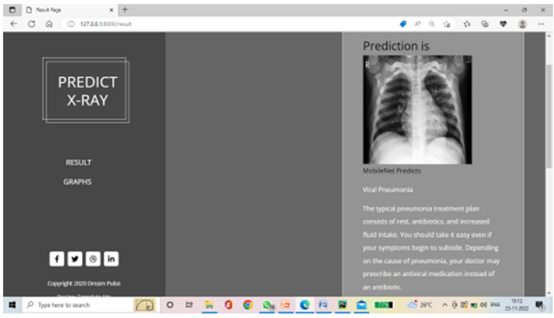

Fig (ix)

Graph:

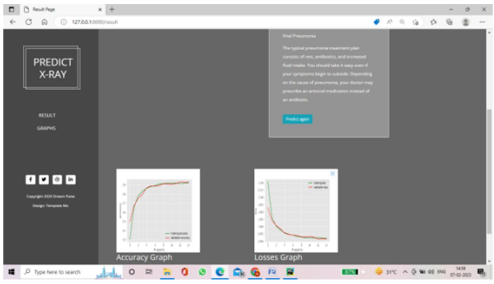

Fig (x)

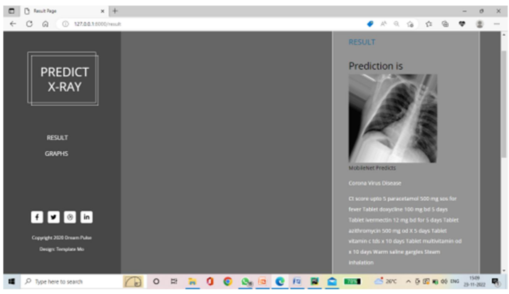

Fig (xi)

Graph:

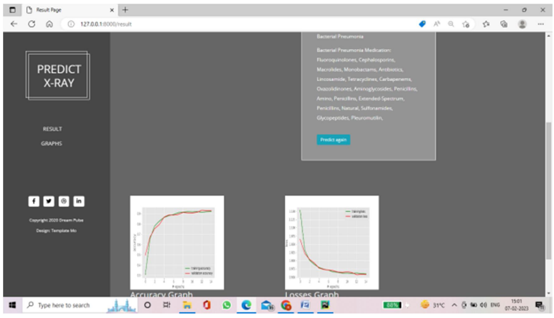

Fig (xii)

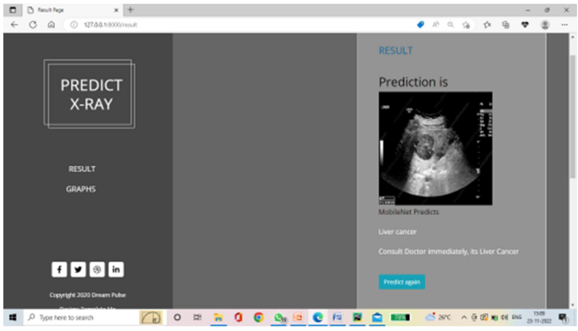

Fig (xiii)

Graph:

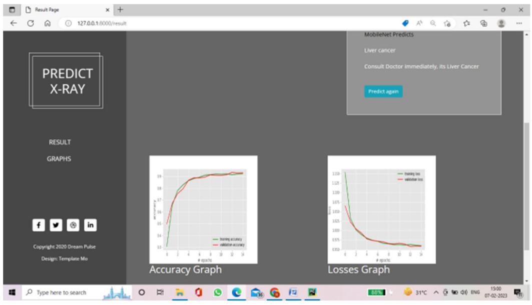

Fig (xiv)

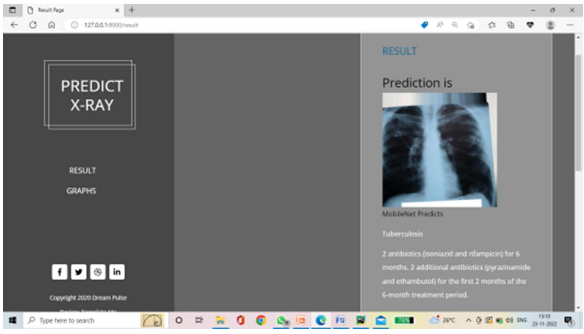

Fig (xv)

Graph:

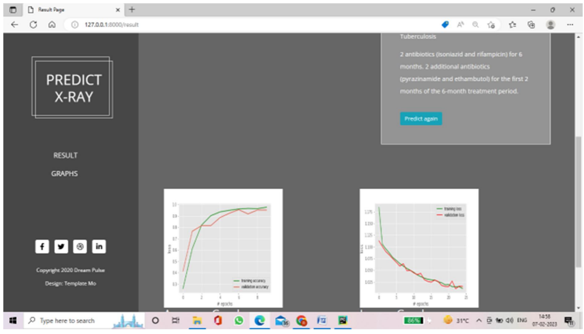

Fig (xvi)

IV. **Conclusion**

In this project we have successfully classified the images of lung and liver image classification, are either diseased with the lung or liver diseases items name using the deep learning and Transfer learning. Here, we have considered the dataset of Lung and Liver diseases which will be of different types trained using Mobile-Net and Resnet-50, transfer learning method. After the training we have tested by uploading the image and it classified as either the image is lung disease or liver disease identification using Convolution Neural Network CNN Mobile-Net Resnet50 of deep learning along with the deep learning methods .The accuracy of the model is above 95%. This model is more helpful for the doctors to diagnose Lung and Liver diseases for a patient.

V. **References**

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