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A Multi-Chest Disease Detection Using Multi-Scale Alignment Graph Capsule Binary Light Spectrum Dual Attention Neural Network

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Abstract
Internationally, the COVID-19 disease has badly affected both the healthcare system and the market. The complexity arises from the similarity in symptoms between COVID-19 and other chest diseases like pneumonia and lung cancer, making accurate diagnosis challenging. Dedicated frontline medical professionals and researchers are actively striving to develop a rapid and automated method for the initial stage recognition of COVID-19, with the goal of saving lives. Nevertheless, the clinical diagnosis of coronavirus remains subjective and variable. To tackle these issues, in this research propose a novel Multi-scale Alignment graph Capsule Binary light spectrum Dual attention neural Network (MACBDN) technique for efficiently classifying multi-chest diseases, including pneumothorax, pneumonia, tuberculosis, lung cancer and COVID-19. The methodology begins with the utilization of the adaptive guided multi-layer side window box filter for preprocessing, aiming to eliminate noise while preserving crucial details. Subsequently, a lightweight multi SegNet is employed for semantic segmentation. S-transform and fast discrete orthonormal transform are then applied for efficient feature extraction. The proposed MACBDN effectively classifies diseases using the binary light spectrum optimizer.
Keywords: *Chest x-rays, Coronavirus, Multi-class diseases, Multi-scale Alignment, Semantic segmentation*

I.INTRODUCTION

The research involved in the project is Multiple chest Disease Prediction using Machine Learning, Deep Learning " in this project we are interested in predicting various diseases: such as pneumonia,, heart disease, tuberclulosis, covid-19 disease, and breast cancer. lung cancer. The song playback prediction models are established by machine learning algorithms. where Support Vector Machine is included. Random Forest of Parkinson disease (SVM) and breast cancer, Neural Network heart disease, lung cancer and CNN. covid-19.. The project will start out with gathering the concerned data from Kaggle.com. is then pre-processed to be ready to be trained and be tested on the prediction models. A certain machine learning algorithm is selected in order to process each disease prediction. the most appropriate to that particular disease. There are five menus at the application interface. options, and each of them relates to a particular disease. When a user favors a certain disease, the application inquires parameters that are needed by the associated model of the disease outcome. The user gives the necessary parameters and the prediction result will be echoed on the app depending on the given input.

The detection of a chest disease especially in a situation where there are many diseases has even been turned into a challenge. important field of the medical imaging and diagnostic. Multiple chest diseases like pneumonia, tuberculosis, cancer of the lungs, and COVID-19 are prone to. overlapping symptoms, and at the same time, detecting them is a great challenge. stumbling blocks to medical practitioners. The progress of machine learning, deep learning, and medical imagery such as X-rays, CT scans and MRI. have proved to be promising with regard to the automation of detection and diagnosis of these diseases. This survey examines the new developments, problems and the remedies in the discipline of multichest diseases detection. Recognition of chest diseases, particularly in the case that when there is more than one condition concurrently, is one of the main focus in the research. diagnostics and medical imaging. Pneumonia and tuberculosis (TB) are some of the diseases. COVID-19 have overlapping symptoms with lung cancer, and it is hard to find the differences. so that they can be accurately diagnosed by the medical workers early enough.

Recent promises of machine learning, deep learning, and medical imaging liquid biopsies, which have had claims of success using newer technologies, e.g. X-rays, CT scans and MRIs. automation of detection and diagnosis of the diseases.

Summary of related work:

To seek a proper machine learning model of various diseases forecast, the key goals of the research work are Early Detection andand Diagnosis, Risk Assessment and Prevention, Personalized Medicine, Resource Optimization, Clinical Decision Support, Public Health Surveillance. Methodology The project Multiple Disease Prediction will be briefly explained as follows. methodology: 1. Data Collection: Kaggle.com is a popular data accessing site, so the data is collected at the following address: source of the data. Especially, the facts about diabetes and heart disease, lung The information about disease, Parkinson disease and breast cancer is collected. 2. . Data preprocessing Data preprocessing aims at ensuring that the collected data is qualified and appropriate. To train the machine learning models then preprocessing is done. This includes preprocessing of the missing values, removing the duplicates, and performing scaling features or normalization of data. 3. . Model Selection: Each disease prediction task requires another set of machine a learning algorithm is chosen. The techniques of most diseases are selected neural network and support vector machines (SVM) as well as logistic regression. random forest based on competence and applicability on the specific prediction tasks. 4. Training and Testing: Two datasets of preprocessed data are produced: one of them is training and the other testing. One has to be used in training and the other in testing. The models are evaluated with the help of the testing data. after being trained on the training data their performance is in terms of. The evaluation measure of assessing whether the performance of every model is accurate or not

II. Related Work

The article by Najam-ur Rehman[1] gives a model of able to detect 15 distinct types of chest diseases, such as COVID-19 on the basis of chest X ray images. The framework is the combination of Convolutional Neural Networks (CNN) with transfer learning and machine learning to boost the diagnostic It takes the help of an X-ray of the chest to detect various illnesses and improving predictability. of data quality and availability. Given a shortage of high when labeled data is present, the system might not deliver as per quality. Aditionally, although is possible, the although model performs well with chest X-ray, it may not perform that well with other forms of medical imaging, including CT scans or MRIs.

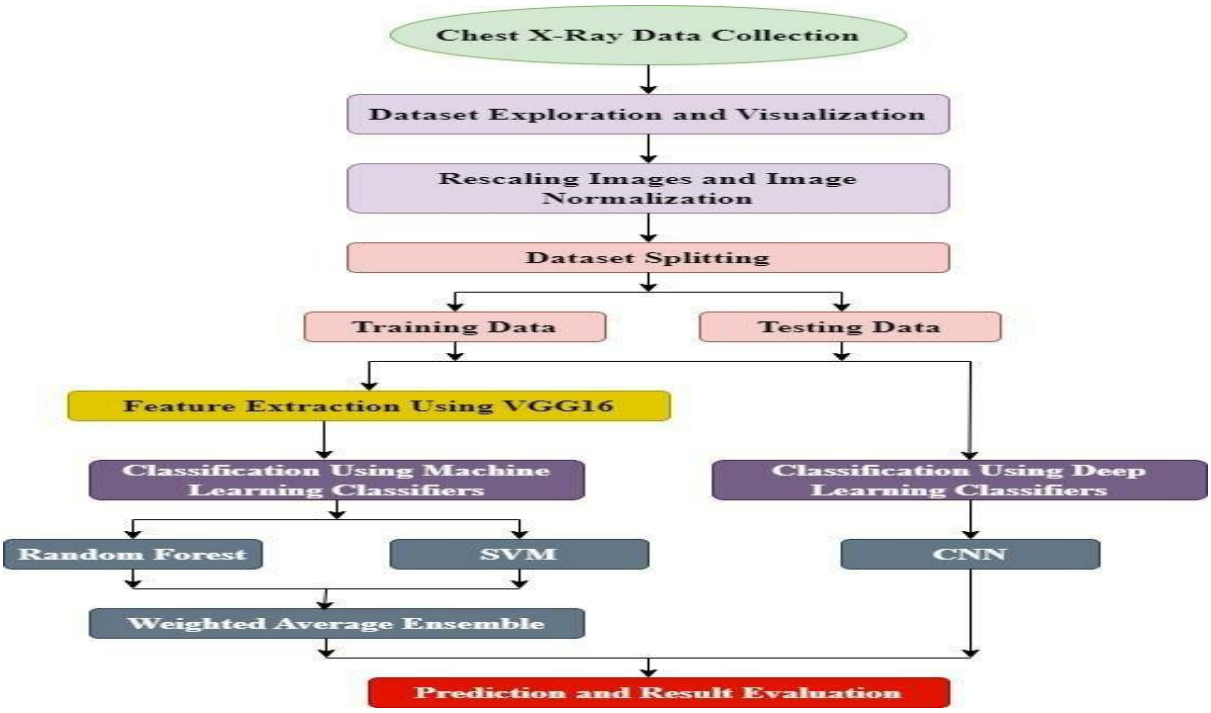


Fig 1: general flow prediction

The article by Dina M. Ibrahim[2] introduces the deep learning model that is aimed at identify three diseases of the chest, including COVID-19, pneumonia, and lung cancer. It tests four variants of deep learning models

in terms of performance on the disease model: VGG19-CNN, model built based on the VGG19 architecture; ResNet152V2 which is a deeper network; ResNet152V2 augmented with a Gated Recurrent Unit (GRU), assisting in the capturing of the patterns based on time; and ResNet152V2. Bi-GRU, is a more advanced variant which considers both types of data in the same way. instructions toward improved context. The model involves use of digital chest X-ray and CT scan datasets to diagnose those diseases very accurately and early. That offers extensive appraisal and extreme generalizing of various cases.

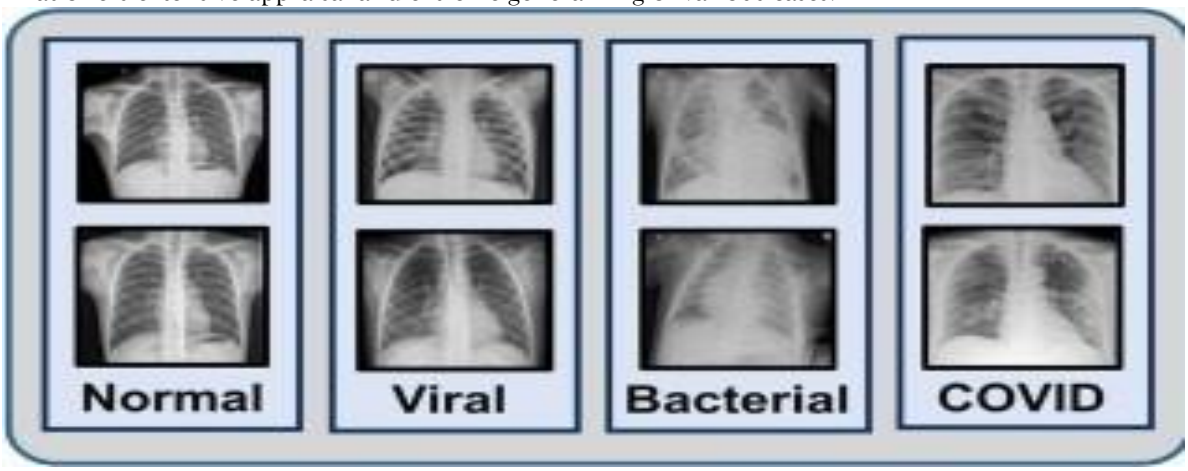


Fig.2: sample x-ray

The article of Goram Mufarah M. Alshmrani [3] introduces a deep learning an automatic model to identify various chest diseases based on chest X-ray (CXR) images. Diseases such as COVID-19, pneumonia, tuberculosis (TB), among others, affect the lung. the symptoms of cancer and lung opacity are similar, and so it may be hard to note. enable doctors to diagnose them accordingly. X-rays in the chest are widely applied in healthcare since they are rapid and effective and this model is to enhance the correctness. and rapidity of the diagnosis of these conditions.

The proposed system will employ the use of a VGG19 model that has been trained and has already been performing well when it comes to feature extraction of images. The model then appends three additional layers (known as CNN blocks) in order to enhance the extracted features and adjust it towards the identification of the chest diseases. Lastly, a fully connected layer assists in the classification of the diseases on the bases on which it learnt the features of the disease. This model is trained with more than 50000 pictures of chest diseases, which means that it is not short on data to predict properly.

The article of Vinayakumar Ravi proposed [4] a model that exposes lung diseases with the help of detection. Employs the combination of three machine learning methods: random forest, support The machine is a vector (SVM), logistic regression. Random forest In the first stage, the random forest is used. The data is analyzed using and SVM while in the second step the data will be analyzed using logistic regression. assists in I finalizing the diagnosis. A combination of these methods is expected to make the model. better and more precise in the diagnosis of lungs ailments.

The model by Tanvir Mahmud[5], CovXNet, is proposed in order to identify Chest X-ray images COVID-19 and various kinds of pneumonia with deep learning. It uses deep convolutional neural network (CNN) structure. extracts features efficiently with depth wise convolutions that have varying rates of dilation features of X-rays. First, the model learns with a big database of the chest X rays of patients with a regular lung and the various kinds of pneumonia (viral and bacterial). Following this the model is refined using fewer images of chest X-rays stemmed out of COVID-19 patients. The stacking algorithm is used to optimize CovXNet. works by integrating the output of several models into making better predictions. Moreover, the model combines gradient based discriminative localization, that assists in pointing fingers on the abnormal areas in the X-ray images. more convenient to detect the zones where the pneumonia occurs.

Table 1: Comparative Table

Ref. No	Proposal	Method Used	Dataset Used	Merits	Demerits

1	Detects 15 chest diseases including COVID-19 using X-ray images.	CNN, Transfer Learning, Machine Learning	Chest X-ray dataset	Multi disease Detection, Improved Accuracy	Dataset Dependency, Complex to Use, Transfer Learning Limitations
2	Classifies lung diseases like Pneumonia, TB, COVID-19 using a deep learning architecture.	Pre-trained VGG19, Fully Connected Network (FCN)	3615 COVID-19, 6012 Lung opacity, 5870 Pneumonia, 20,000 Lung cancer, 1400 TB, 10,192 Normal images	High Accuracy, Quick Diagnosis, High Recall and Precision	Dataset Bias, High Computational Resources
3	Proposes a multi-classification model for 3 diseases (COVID-19, Pneumonia, Lung Cancer).	VGG19-CNN, ResNet152V2, GRU, Bi-GRU	Digital Chest X-ray and CT datasets	High Accuracy, Early Detection, High Generalization	Dataset Limitations, Model Complexity
4	Multichannel deep learning approach for lung disease detection.	Stacked Ensemble Learning (Random Forest, SVM, Logistic Regression)	Pneumonia, TB, COVID-19 datasets	High Accuracy, Multichannel Feature Fusion	Lack of Dataset Details
5	Proposes CovXNet CNN architecture for efficient feature extraction from X-rays.	Depthwise CNN with Varying Dilation Rates	Chest X-rays (Normal & Pneumonia)	High Detection Accuracy, Transfer Learning Efficiency	Dependence on Chest X-ray Quality, Dataset Limitations

III. METHODOLOGY

This research introduces a new way to identify lung problems from X-ray images. It uses a special neural network called MACBDN to do this accurately. First, the system removes noise from the images using a technique called AGMWF. Then, it breaks down the image into important parts with a lightweight tool called LMSegNet. After that, it extracts useful features from the images using two methods, S-transform and SFDOT. Finally, it improves the classification results using BLSO, which helps make better predictions. The research also includes a website where people can upload their X-ray images and get quick, automatic results about their lung health.

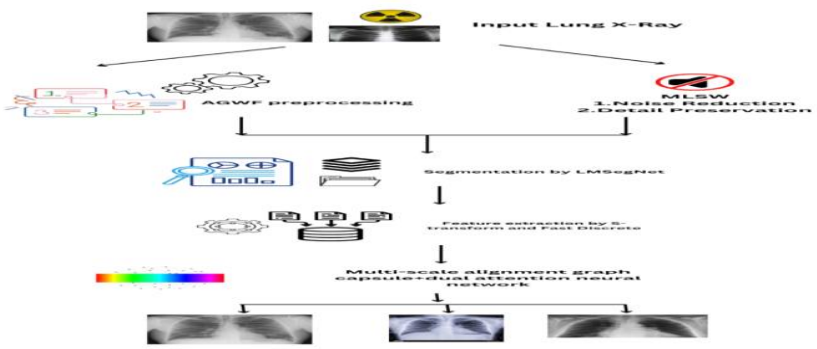


Fig: 3 proposed flow flow diagram

a. Removing Noise and Keeping Important Details with Adaptive Guided Multi-Layer Side Window Box Filter

To make the X-ray images clearer, we use a special two-step filtering process called Adaptive Guided Multi-layer Side Window Box Filtering (AGMWF):

1. Multi-Layer Gaussian Side Window Filtering (MLSW)
2. Multi-Layer Gaussian Side Window Filtering with Guided Strengthening (MLSW-GS)

The first step, MLSW, helps keep the edges sharp by focusing on the relationship between edge pixels and their nearby areas. This means the important lung edges stay clear while unwanted noise is reduced. This process can be described by these equations:

Next, the second step, MLSW-GS, improves the image further by using a "guiding" image that has more complex details to help enhance the simpler parts. This helps bring out weak details without adding noise. The guided strengthening is given by:

The goal is to clean up X-ray images by removing noise (unwanted spots or graininess) but keep important features like the edges of the lungs sharp and clear.

b. Semantic Segmentation with Light-weight Multi SegNet (LMSegNet)

LMSegNet is a fast and efficient method to find and outline important areas in chest X-ray images, such as lungs or abnormalities. This process is called semantic segmentation.

LMSegNet uses a two-part structure called an encoder-decoder:

- The encoder analyzes the image and extracts important features through several layers of convolution (which helps the system understand patterns).
- The encoder includes a step called max-pooling, which shrinks the image features to make the computation faster but can sometimes blur important edges.

Since edges and boundaries are very important to accurately identify lung structures, LMSegNet uses a special way to keep those boundary details during encoding.

Because the encoder works at different scales (or zoom levels), it produces multiple feature maps at different resolutions. LMSegNet collects these multi-scale feature maps, resizes them all to a standard size of 64 x 64 pixels using upsampling, and then joins them together into one combined feature map:

This combined map is then sent to the decoder, which reconstructs the segmented image, highlighting lung regions and abnormalities accurately.

c. Feature Extraction using S-transform and Fast Discrete Orthonormal Transform (SFDOT)

Feature extraction is an important step because it helps the system understand the most important details in the lung X-ray images to classify different conditions correctly.

In this research, a combined method called SFDOT is used. It mixes two techniques—the S-transform and the Fast Discrete Orthonormal Transform—to automatically pull out key features from the segmented lung images .This assists the system to have a better understanding of a disease such as Pneumonia and COVID-19. The method forms a breakdown of features by combining (high, low, and mean) all of them, so it gives a detailed breakdown of features. and multilevel image description of lungs in the X-ray pictures. This practice will minimize the volume of information that the system will need to process and still retain valuable ones. all the details preserved, which can simplify the process of distinguishing between various conditions of the lungs. The outcome of the extraction of those features is employed in the second step to establish the accurate classification of the lung diseases.

d. Multi-scale Alignment Graph Capsule Dual Attention Neural Network (MACBDN)

In the classification step, the research uses a powerful neural network called MACBDN to accurately identify different lung conditions from the extracted image features.

This network is special because it uses dual attention mechanisms — two ways to focus on the most important information in the features:

1. Channel Attention:

This looks at relationships between different feature channels (think of channels as different “types” of information or filters in the image). The network builds a similarity map to see how each pixel relates to all

others within each channel. This helps the network decide which features (channels) are most important for telling lung conditions apart.

2. Spatial Attention:

This focuses on the actual positions in the image, highlighting the key areas that are most useful for recognizing different lung diseases.

The information from both these attention parts is combined to improve the feature representation basically, helping the network "see" the important details better.

Besides attention, MACBDN also uses:

• Multi-scale alignment: It looks at the image features at different scales (or zoom levels), so it can understand both big patterns and small details.

• Graph capsules: This helps the network understand complex spatial relationships in the lungs, like how different parts relate to each other, improving recognition of abnormalities.

IV. RESULTS AND DISCUSSION

Once the loop is done, the algorithm sends the model parameter that minimise Results and Discussions: COVID-19, Viral, and Bacterial Pneumonia Classification

a. Dataset Description

The study involves three extensive chest X-ray databases to classify COVID 19, viral, pneumonia and bacterial pneumonia. These data have been amalgamated with different medical institutions and open-access repositories, making sure that there is a wide variety of conditions of radiographic imaging and patient demographics.

The COVID-19 dataset consists of 3,000 high-resolution chest X-ray images obtained from confirmed COVID-19 patients. These images were sourced from hospitals and publicly available medical repositories. The dataset covers various stages of COVID-19 infection, ranging from mild to severe pneumonia cases, allowing the model to differentiate between early-stage and critical conditions.

Each image was manually verified by radiologists to ensure diagnostic accuracy. The dataset maintains a balanced distribution across age groups (ranging from 10 to 90 years) and includes both male and female patients. Images with poor resolution or significant artifacts were excluded to maintain dataset integrity.

1 Viral Pneumonia X-ray Dataset

The viral pneumonia dataset comprises 2,500 chest X-ray images depicting different forms of viral respiratory infections. These images were collected from multiple hospitals and open-access medical databases. The dataset represents pneumonia cases caused by various viruses, including influenza and respiratory syncytial virus (RSV), ensuring a diverse range of infections.

A stringent quality control process was applied to remove low-quality or mislabeled images. The dataset provides a well-balanced representation across different age groups and severity levels, allowing the deep learning model to distinguish viral pneumonia from other lung conditions.

2.Bacterial Pneumonia X-ray Dataset

The bacterial pneumonia dataset includes 2,000 chest X-ray images of patients diagnosed with bacterial pneumonia. The dataset covers a wide range of bacterial pathogens, such as Streptococcus pneumoniae and Haemophilus influenzae. These images were obtained from various medical research institutions and open-access datasets.

The dataset is carefully curated to include images with well-documented medical reports, ensuring accurate labeling. It maintains a balanced representation of different patient demographics and infection severities, allowing for robust classificationthe classification error.

b. Data Preprocessing and Augmentation

Before feeding the chest X-ray images into the deep learning model, several preprocessing steps were done to improve image quality and make the data consistent. Intensity normalization Making sure pixel brightness levels are standardized across all images. Contrast enhancement Making lung details clearer and easier to see. Noise reduction: Removing unwanted artifacts or spots to improve image clarity. Adaptive histogram equalization Boosting contrast while keeping important diagnostic details intact.

To help the model learn better and avoid memorizing the training data (overfitting), the dataset as expanded using data augmentation Randomly rotating images up to 15 degrees. Flipping images horizontally and vertically. Zooming images in or out slightly (up to 10%).

c. Website for Chest X-ray Disease Detectio3

To make the developed model accessible to the public and healthcare professionals, a web-based application is being created. This website allows users to upload chest X-ray images and receive an automated diagnosis for COVID-19, viral pneumonia, and bacterial pneumonia. The platform leverages the trained deep learning model to provide real-time disease detection, helping in early diagnosis and treatment planning.

The website is designed with a user-friendly interface, ensuring ease of use for medical practitioners and general users. It aims to serve as a valuable diagnostic tool, assisting in the rapid identification of lung infections and improving patient care outcomes.

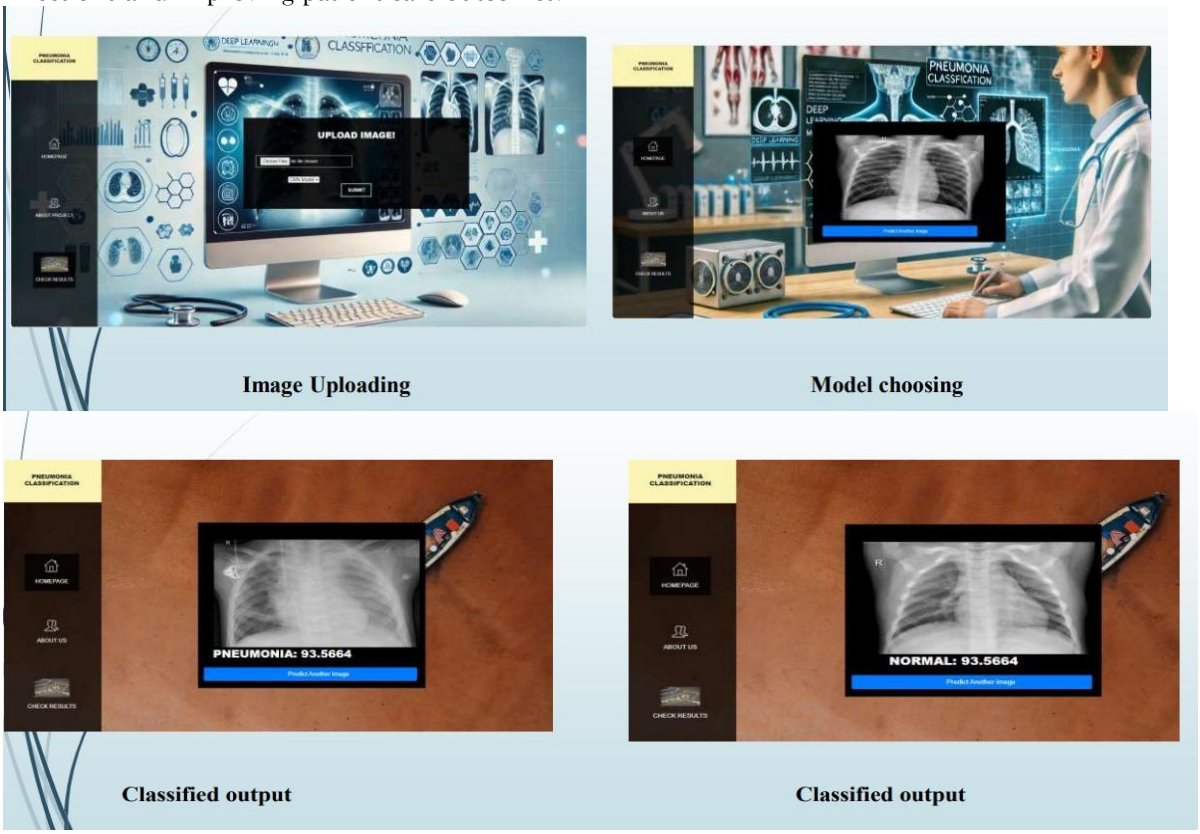
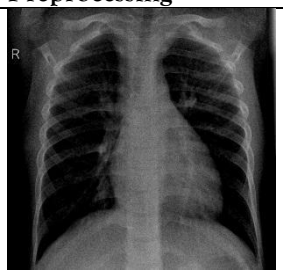
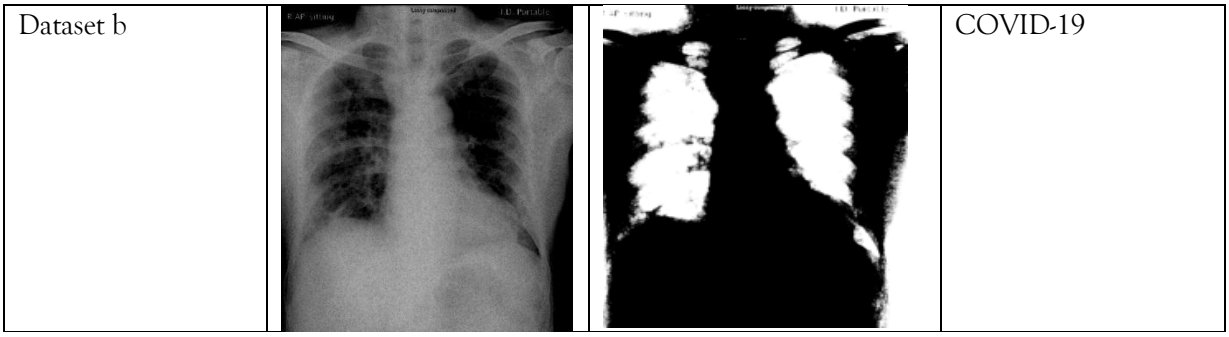


Fig 4 Results Obtained From the Website

Table 2 Visualization of output in terms of preprocessing and segmentation

Dataset	Preprocessing	Segmentation	Disease
Dataset a			Pneumonia



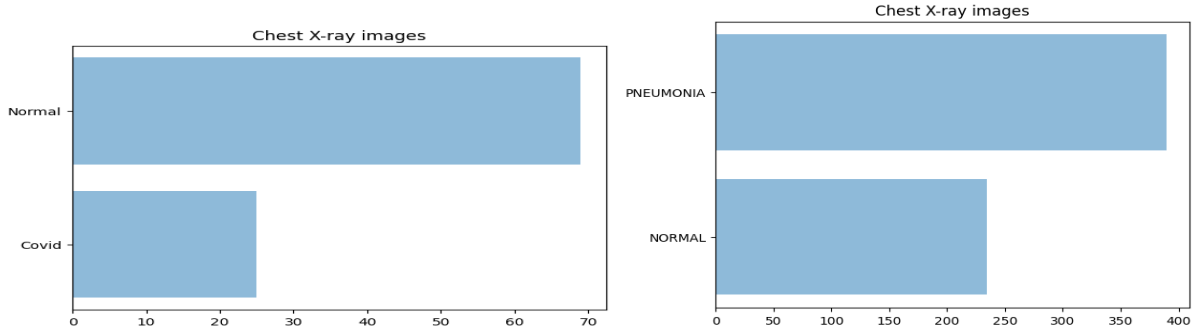


Fig 5 Classification report for (a)Dataset a (b) Dataset b

d. Performance Evaluation

The performance of the proposed model was evaluated using several key metrics to comprehensively assess its effectiveness in classifying lung conditions Such metrics were: accuracy, which is a level of overall correctness of the predictions; precision, that is, "How close are the predictions to the actual or target result"; and recall, which is the proportion of the actual or target results the predictions capture. the ratio of true positive prediction out of the total positive prediction; recall which measures achievement; the efficiency of the model to detect all real positive cases; as well as F1-score, which is a balance between precision. and recall to give one measure of performance. As well, the field of the receiver To measure the ability of the model to differentiate it was measured through operating characteristic (AUC) Among the classes of lung diseases. In order to make the results dependable and possibly standardizable, it was important to make sure that they were trustworthy and could be standardizable. statistical methods of validation, generalized, statistical, e.g., k-fold cross-validation and bootstrap resampling was used. Such ways aided in coming up with solid and repeatable results through training and testing the model on many subsets of data and the repeated sampling of the a dataset in order to approximate performance stability.

e. Visualization Techniques

Techniques of advanced visualisation provided the opportunity to know more about the functioning of the model and verify it better. performs. In the case of preprocessing, comparisons of original and enhanced images were made. portrayed, such as intensity distribution diagrams and activation maps of features to show what is significant. explains the specifics that the model addresses. To conduct segmentation, visual and highlighted areas of Semantic segmentation masks, probabilistic heatmaps and interests were produced. These the visualizations offer clear information on how the model makes its decision, and it is useful. describe the mechanism of its diagnosis of lung abnormalities. Complemented with the big data, vigilance is deployed processing, rigorous analysis, all these visualization techniques prove the high potential of the method. viability of the proposed method as a tool that can be used to support clinical diagnosis with respect to reliability in computation. the integration of state-of-the-art machine learning with analysis of medical imaging

f. Clinical Significance

The MACBDN method is one of the significant developments in the automated investigation of the lungs. Diseases like COVID-19, viral pneumonia and bacterial pneumonia. Prompt and quality It is critical to detect these conditions in order to treat them and avoid severe complications. It is a diagnostic improvement that this approach achieves because it uses deep learning to precisely analyze X-ray images of the chest. accurate, decreases mistakes, and lowers the interdependence on professional radiologists, hence rendering it

particularly useful in resource poor healthcare settings. The approach is also effective in that it could also help to facilitate the localization of the innovation. separates various types of pneumonia and COVID-19, which is essential in making an appropriate diagnoses. patient care. Speedy, automated identification helps clinicians make improved therapy choices, eventually, improving patient outcomes and providing optimal hospital resources. To increase accessibility, a special site is under development, where it will be possible to put chest X-rays into it. get automatic detection of diseases, providing a comfortable option to sick-care specialists. patients have homogenized and facilitated remote diagnosis and early intervention..

V. CONCLUSION

In the present work, MACBDN a new multi-type classification model of chest diseases was introduced the main purpose of the development of which is to have an efficient instrument to properly diagnose Pneumothorax Pneumonia (PNEU), (PNEUTH) Lung Cancer, Tuberculosis (TB) and COVID-19. The model seeks to help both physicians and radiologists to have early diagnoses of such life-threatening chest conditions. In reaching this, the AGMWF preprocessing method is incorporated in the proposed framework. successfully eliminates noises, but retains valuable details on an image. Following preprocessing, Accurate segmentation of Regions of Interest (RoI) utilizing LMSegNet is adopted to increase computational speed. efficiency. The segmented is then subjected to feature extraction via the STFDO method. outputs. The MACBDN architecture achieves the classification work and further optimizes it using Binary Light Spectrum Optimizer (BLSO) algorithm in order to increase accuracy. robustness. This model was keenly tested against five benchmark data sets speaking of its respective targeted disease, with outstandingly higher performance on most of the major markers, and with its usage of unique crystal formulations, such as its 510 crystal and 511 crystal, it has found a niche in the markets of Europe, North America, and China. to already known state of the art solutions. The work to be done in the future will be aimed at improving the MACBDN model, confirming its practical application in a clinical context, and increase up the scope of its application. cover more chest diseases but it would ultimately hope that it would have a better focus in terms of actual effectiveness medical diagnostics

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