Lung Disease Detection using Convolution Neural Network

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Abstract - Computer vision and deep learning (DL) have completely changed the world over the past ten years. So-called deep neural networks, which capitalise on advancements in processing power and data availability, have dominated the area of deep learning. This study looks at using convolutional neural networks (CNNs) for image classification in the diagnosis of lung diseases such tuberculosis (TB), pneumonia, and Covid-19. In a big data environment, this study employs the EfficientNetB1 architecture with global average pooling (GAP) layers, in a big data environment. The Apache Spark environment is used to develop the system. The effectiveness of the EfficientNetB1 architecture in identifying illnesses in a dataset of 7747 chest X-ray (CX) images was used to forecast the model's performance. Two datasets are created by breaking down the dataset. The model produced a high f1-score, accuracy, and precision when its performance was evaluated and compared to other models. We have a 99% accuracy rate in our work.

Keywords - Convolutional neural network, Deep learning, Deep learning, Spark system.

I. INTRODUCTION

The medical industry is among the areas that the advancement of technology has impacted. Among these is medical imaging, which has become a vital information resource for medical personnel. Every year, It produces many images each year, these images produce a large amount of data «the data of medical images» [1].

A prediction system's primary goal is to provide estimates or forecasts using the data at hand. To make predictions about unknown data, prediction systems employ artificial intelligence models, like DL, that are trained on historical data to generate predictions about unknown data. Usually, these systems employ algorithms to take correlations and patterns out of training data, and then use those patterns to predict outcomes on new data.

Deep Learning is meant by the machine's ability to learn on its own [2]. Deep learning's overarching goal is to autonomously learn data without the involvement of humans. Convolution networks are used to process a wide range of images, including medical imaging.

We propose a model for the classification of medical images for lung diseases such as Pneumonia, COVID-19, and TB, which was developed using a neural network model in a spark system environment. We used a dataset available on Kaggle. The process of diagnosing diseases will be faster and smarter and will help reduce the burden on medical staff.

Our objective is to help doctors in the diagnosis of lung disease through image processing and machine learning techniques and offer a tool exploiting inexpensive methods (in terms of money) and early detection of disease types in patients. In addition, the speed of prediction of the type of disease and its severity helps physicians make quick decisions and give effective treatments.

II. RELATED WORK

Various recent works on medical image analysis show that deep learning (DL) models boost computer-aided medical diagnosis for CX. In the following, we summarize the recent works on the diagnosis of COVID-19, Pneumonia, and TB.

According to Masadeh. M and al in 2022, to alleviate personal detection costs of Covid-19 disease and time again, used chest X-rays of three categories and deep learning exactly CNN. For this, they used 2,905 X-rays and their results were 97.44% accurate in detecting Covid-19 [3]. The benefit of this approach is that it applies diagnostic motor diseases, for example, in remote locations impacted by COVID-19. In addition, they can use it to diagnose other lung diseases. The limitation of this work is the use of a limited number of X-ray images labelled for COVID-19. Awan. M. J and al [4] proposed a binary classes classifier (COVID-19 and Normal X-rays) and a three-class classifier (COVID/Normal/ pneumonia) for the detection of the COVID-19 and CX images from the Kaggle. They used Apache Spark of Big Data and used three convolutive neural networks (CNN) InceptionV3, ResNet50, and VGG19 architectures. They evaluated three models in binary classes with 100% accuracy. But in three-class, the accuracy of the detection, was as follows 97% for inceptionV3, 98.55% ResNet50, and 98.55% for VGG19. The disadvantage is that these models are not used in the real world.

According to Sitaula et al. [5] The resolution of CX images varies in practical applications, and single-scale deep bag-of-visual-words (BoDVW)-based features are insufficient to capture detailed semantic information on lung infection regions. They perform max-pooling convolutions on a fourth pooling layer using three different kernels (1 × 1, 2 × 2, and 3 × 3) to obtain multi-scale bags with deep visual word-based features. After evaluating the proposed features using a support vector machine (SVM) classification algorithm, their strategy achieved significant classification accuracies of 84.37%, 88.88%, 90.29%, and 83.65% on four public CX datasets. In [6], the authors predicted the number of COVID-19 infections for the next 7 days. They created a cloud-based short-term predictive machine learning model for Bangladesh. The model uses various regression-based machine learning models to analyze data on infected cases. By using sample data recorded in the web application for the past 25 days, the method was able to accurately predict the number of infected cases. The results can be used to develop and evaluate prevention methods and identify factors that impact the spread of the COVID-19 virus in Bangladesh.

Qaqos et al. [7] used stochastic gradient descent to train a DL model with 6587 CX images. Using 128 × 128 images and 100 epochs, the model was able to achieve 94.53% accuracy while classifying CX images into four categories (COVID-19, pneumonia, and tuberculosis). Transfer learning for VGG16 was developed by Mostofa et al. [8] for tuberculosis recognition on CX images. They fine-tuned the model using 1324 CX images and achieved 80% accuracy in classifying CX images into TB and Health categories. Shastri et al. [9] used a DCNN-based pre-trained Inception V3 model and transfer learning. A total of 3532 CX images in the collected dataset are augmented, and each image is resized to 299 × 299 × 3. The model was 93% accurate. However, the study did not classify TB in CX images. Artemi et al. [10] used 14 pre-trained CNN models for feature extraction followed by five-fold cross-validation. Based on a dataset of 2186 CX images, the study showed a recognition accuracy of 91.6%. To improve the effectiveness and accuracy of the diagnostic capabilities of computer-aided diagnostic systems (CAD), the authors used a capsule neural network model to classify CX images showing COVID-19 infection [11]. The model was trained using 6310 CX, classified into three categories: normal, pneumonia, and COVID-19. Compared with traditional CNN (Convolutional Neural Network) models, CapsNet has many advantages worth noting, including position invariance, fewer parameters, and better generalization ability. During the model training process, the accuracy of the proposed model exceeds 95%.

In addition to CX image analysis, DL models have recently been explored for identifying tuberculosis, COVID-19, and pneumonia based on computerized tomography images (CTM). For example, Li et al. [12] used a pre-trained ResNet50 model to distinguish between COVID-19 and pneumonia in CTM. They trained the DL model on 4356 CTM samples, achieving 95%

accuracy, and used Grad-CAM to visualize important regions in the CTM to better interpret the model. However, heat maps are not sufficient to identify the unique characteristics that a model uses to make predictions.

III. PROPOSED APPROACH

Our system employs the Convolutional Neural Network (CNN) approach, a type of acyclic artificial neural network. It begins by taking an image input tailored to the patient's case. Using this image, our system can determine whether the patient is healthy or ill. If the patient is diagnosed as ill, the system can identify the specific disease, including three types of lung diseases: Covid-19, pneumonia, and tuberculosis. Figure 1 illustrates the proposed system.

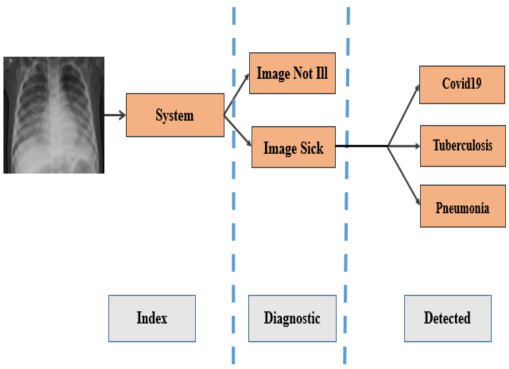

Fig. 1. Proposed approach.

IV. GENERAL ARCHITECTURE

Figure 2 shows the various steps we have gone through to achieve our system.

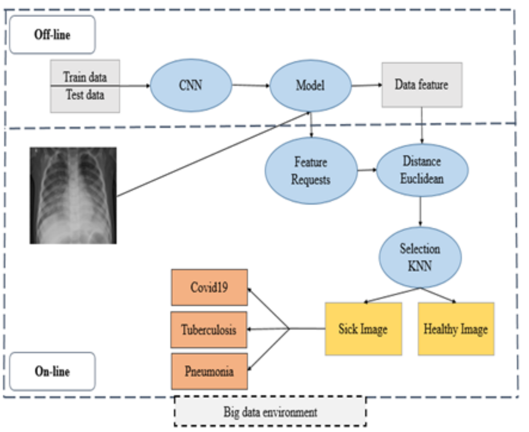

Fig. 2. General architecture

A) *In the offline phase*

To conduct the learning process, we have tested and trained the data sets (image bases). Our system employs CNN (Convolutional Neural Network) architecture and utilizes the EfficientNetB1 model, chosen based on the computer's capability. Convolutional networks are widely used for image processing tasks, including satellite imagery, medical imaging, visual identification, and object detection. These networks are designed to analyze images, extract their features, and categorize them into various groups based on the research subject [13].

Computers interpret the input image as a set of pixels, with accuracy depending on the image's resolution, represented as Height Width Dimension (d=3 for RGB images, d=1 for grayscale images) [14]. We employ EfficientNet for our model, designed by Adam Paszke in 2019. Our model stands out for achieving state-of-the-art accuracy in typical image classification and transfer learning tasks [15]. Figure 3 illustrates the EfficientNetB1 (ENetB1) topology [16].

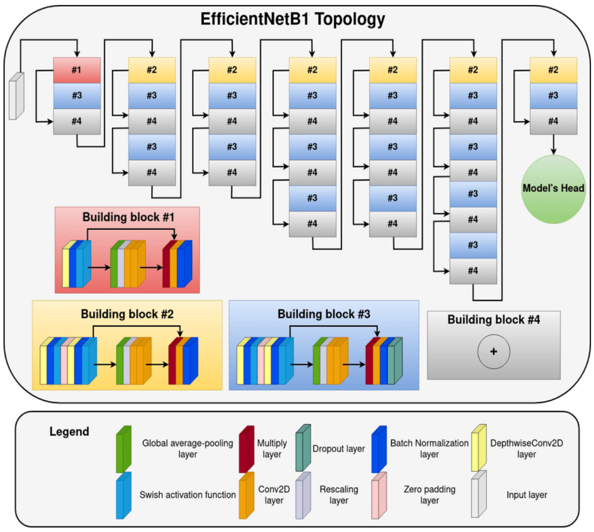

Fig. 3. ENetB1 topology.

Computers interpret the input image as a set of pixels, with accuracy depending on the image's resolution, represented as height*width*dimension (d=3 for RGB images, d=1 for grayscale images) [14]. We employ EfficientNet for our model, designed by Adam Paszke in 2019. Our model stands out for achieving state-of-the-art accuracy in typical image classification and transfer learning tasks [15]. Figure 3 illustrates the EfficientNetB1 (ENetB1) topology [16].

The model extracts features, and after that, we save data features of image data.

B) In the online phase

We take a query image of the lung as input and feed it directly into the model, which extracts the image's attributes. We then calculate the Euclidean distance between the characteristics of the base image and those of the query image. Using KNN selection, the patient's image is classified as either healthy or ill. If the result indicates the patient is ill, the specific type of lung disease is identified.

V. EXPERIMENTATION AND DISCUSSION OF RESULTS

A) DATASET

Four sets of public CX image data are used in this work. These are:

The normal dataset processes healthy lungs and contains 1341 images, including jpg or png. The image resolution is either 1484x1399 pixels or 2180x1955 pixels.

The covid-19 dataset treats sick lungs and contains 460 images, including jpg or png. The image resolution is either 1168x1161 pixels or 1024x1024 pixels.

The pneumonia dataset treats sick lungs and contains 3875 images, including jpg or png. The image resolution is either 1276x1110 pixels or 1080x840 pixels.

The TB data set treats diseased lungs and contains 650 images, including jpg or png. The image resolution is 512x512 pixels [17].

B) Experimentation and Results

In this part, we used the Epoch variable to do an experiment and the measurement is Accuracy. The activation function to use is SoftMax. SoftMax function or exponential function normalized allows to generate a strictly positive activation whose sum of activations on all parameters of the function will be equal to 1 [18].

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad (1)$$

The SoftMax function assigns probabilities to each class, ensuring that all output values fall within the range of 0 to 1 and sum up to 1.0. It is commonly used as the activation function in the final layer of a neural network to categorize among several options [18].

The primary performance metric is accuracy (Acc), which is calculated as the ratio of correctly predicted observations to the total number of observations [19]. Other evaluation measures are shown in Figure 4.

$$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (2)$$

Here's a concise explanation of these classification metrics:

- True Positive (TP): The number of times the model correctly classifies a positive sample as positive.

- True Negative (TN): The number of times the model correctly classifies a negative sample as negative.

- False Positive (FP): The number of times the model incorrectly classifies a negative sample as positive.

-False Negative (FN): The number of times the model incorrectly classifies a positive sample as negative.

These metrics are essential for evaluating the performance of a classification model, helping to understand its accuracy and where it might be making errors. Table 1presents the experimental results.

TABLE 1. EXPERIMENTAL RESULTS

Epoch	05	10	15	**20**
Accuracy	0.96	0.99	0.99	**0.99**

From Epoch 10 there is a stabilization in Accuracy by Epoch variable ratio. In the rest of this work, we use Epoch = 20, Accuracy = 0.99.

C) Results and Discussion

We used several evaluation measures for example precision, recall, f1-score, etc. The objective of these measurements is to evaluate the performance rate of our system.

Precision: is the report of true positive number TP and FP false positive number. The accuracy is intuitively the capacity of the classifier.

$$Precision = \frac{(TP)}{(TP+FP)} \quad (3)$$

Recall: Recall is finding all positive samples.

$$Recall = \frac{(TP)}{(TP+FN)} \quad (4)$$

F1-score considers precision and recall. It is the harmonic mean(average) of the precision and recall.

$$\text{f1-score} = 2 \times \frac{recall \times precision}{recall + prcision} \quad (5)$$

Support: is the number of occurrences of each class.

Macro avg: is the average of each one (precision, recall, f1-score).

Weighted avg: For example, the weighted average F1 score is calculated by taking the average of all F1 scores per class while considering the support of each one.

$$\text{weighted avg} = \frac{((P0 \times C0)+(P1 \times C1)+(P2 \times C2)+(P3 \times C3))}{(C0+C1+C2+C3)} \quad (6)$$

	precision	recall	f1-score	support
0	1.00	0.97	0.98	129
1	0.97	0.98	0.98	317
2	0.99	0.99	0.99	842
3	0.97	1.00	0.99	132
accuracy			0.99	1420
macro avg	0.98	0.98	0.98	1420
weighted avg	0.99	0.99	0.99	1420

Fig. 4. Results of the evaluation measures used.

Figure 5 shows the comparison training and validation (Accuracy/Loss) by Epochs in the graph following:

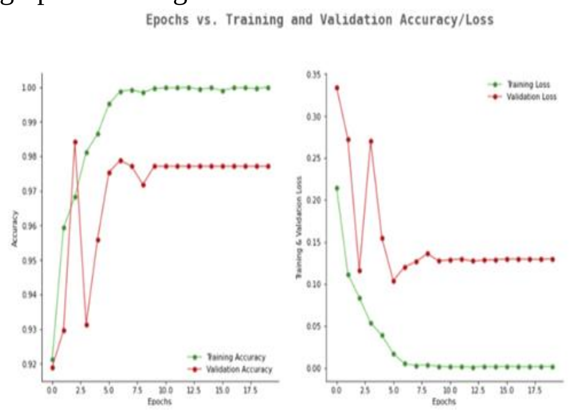

Fig. 5. Comparison of training and validation (Accuracy/Loss) by Epochs.

The graph on the left represents the Accuracy rating against the Epoch. The good result is if Accuracy increased to 1. The right graph represents the error minimization compared to the Epoch. Good results if loss decreases to 0.

Then, we have the confusion matrix (error matrix) in Figure 6 which represents a table that presents different forecasts and test results, comparing them with real values.

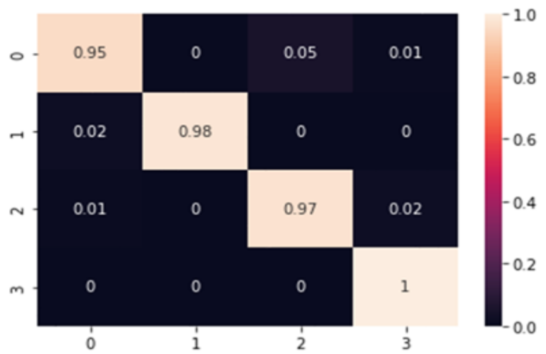

Fig. 5. Confusion matrix.

It represents the percentage of the prediction of the true images in the diagonal square and the other for the false prediction. For example, in the square (3, 3) =1 and another 0, therefore, the percentage of the prediction of the true images of tuberculosis is 100%.

We presented a comparison between the proposed system and related works in TABLE II. This comparison highlights the algorithms used for each task, specifically the CNN algorithms, as shown in the table. Furthermore, the table includes a comparison of the dataset sizes used in related works and in our study. As TABLE II demonstrates, our work achieves the highest overall accuracy compared to other related works.

Table 2. A COMPARISON BETWEEN THE PROPOSED SYSTEM VS. THE RELATED WORK

Author(s), Year, Ref	Dataset	Method used	Performance
Masadeh. M and al, 2022 [3]	2905 images CX	-CNN	Accuracy =97.4%.
Javed Awan. M and al, 2021 [4]	1063 images CX	-Apache Spark -CNN: InceptionV3, ResNet50, VGG19.	InceptionV3: accuracy=97%. ResNet50: accuracy=98,5%. VGG19: accuracy=98,5%.

Wang. L and al, 2020 [20].	13,975 CX	COVID-Net	Accuracy=93.3%
Hwa. S and al, 2020 [21]	800 CX	-CNN: VGG16, InceptionV3.	VGG16: Accuracy=91.03% InceptionV3: Accuracy=82.05%
Khan. E and al, 2022 [22]	21 165 CX	-CNN: EfficientNetB1, NasNetMobile, MobileNetV2	EfficientNetB1: Accuracy = 92% NasNetMobile: Accuracy=89.30% MobileNetV2 Accuracy=90.03%
Our approached	7747 Images CX	-Apache Spark - CNN: EfficientNetB1	**Accuracy = 99%. Recall = 98%. Precision =98%.**

VI. CONCLUSION

The main objective of this work is to achieve high detection accuracy for image classification in lung disease detection, including COVID-19, pneumonia, and tuberculosis (TB). Our proposed approach was implemented using TensorFlow and Keras in Python, and Apache Spark for its efficiency in rapid computation. The CNN-based model aids doctors in accurately diagnosing lung diseases. The novelty of our work lies in the utilization of EfficientNetB1 within the Spark system. Experiments have demonstrated that EfficientNetB1 achieves a 99% accuracy rate in Apache Spark. In conclusion, the proposed strategy proves highly effective for classifying various lung diseases.

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