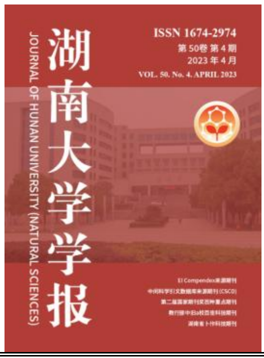

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Detection of Multiple Diseases from Chest X-Ray Using Machine Learning and Deep Learning Approaches

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Abstract: Diagnosis with Chest X-Rays and other forms of medical images has soared to new heights as an alternative Covid-19, pneumonia, TB infection detector. Radiographic images, primarily X-Rays images play massive roles in assisting radiologists to detect and analyses severe medical conditions. Computer-Aided Diagnosis (CAD) systems are used successfully to detect diseases such as tuberculosis, pneumonia, covid-19 and other common diseases from chest X-ray images. The main objective of this study is to develop a model capable of detecting multiple diseases from chest X-rays, with the aim of assisting radiologists and other healthcare providers in making more informed and timely diagnoses. The proposed framework includes four main steps to identify various clinical states such as analysis of the chest X-Ray image dataset and dataset preprocessing, feature extraction, classification with machine and deep learning classifiers and building an ensemble method that can aid in the diagnosis of various diseases using image processing and artificial intelligence algorithms to quickly and accurately identify COVID-19, pneumonia, TB and other diseases from X-Rays to stop the rapid transmission of the virus. The authors obtained a training accuracy of 98% to 100% across all models.

Keywords: convolutional neural network, VGG16, machine learning, deep learning.

使用机器学习和深度学习方法从胸部X光检测多种疾病

摘要:

作为替代新冠肺炎、肺炎、结核感染检测器，使用胸部X光片和其他形式的医学图像进行诊断已飙升至新的高度。射线照相图像，主要是X射线图像，在协助放射科医生检测和分析严重的医疗状况方面发挥着重要作用。计算机辅助诊断系统已成功用于从胸部X光图像中检测出结核病、肺炎、新冠肺炎和其他常见疾病等疾病。本研究的主要目的是开发一种能够通过胸部X光检测多种疾病的模型，以协助放射科医生和其他医疗保健提供者做出更明智、更及时的诊断。拟议的框架包括识别各种临床状态的四个主要步骤，例如胸部X射线图像数据集分析和数据集预处理、特征提取、机器分类和深度学习分类器以及构建有助于诊断各种疾病

的集成方法利用图像处理和人工智能算法快速准确地从X射线中识别出新冠肺炎、肺炎、结核病等疾病，阻止病毒的快速传播。我们在所有模型中获得了98%到100%的训练准确率。

关键词：卷积神经网络，VGG16，机器学习，深度学习。

Introduction

Chest ailments have historically been a very important health issue in people's lives [1]. The chest radiograph (CXR) is a frequently used imaging test for assessing thoracic pathology, trauma, and other pathologies. It has also proven useful in forensics investigations for establishing the age and gender of patients and victims [2]. The trachea, or windpipe, divides into bronchi, which develop into smaller tubes that run throughout lungs [3]. Images of heart, lungs, blood arteries, airways, and the bones in spine and chest are created by chest X-rays. X-rays of the chest can also show air surrounding a lung or fluid in or around the lungs [4].

The study of major diseases from x-rays becomes a most challenging task. In this study, the authors have considered 3 diseases Pneumonia, COVID-19, and Tuberculosis (TB) these diseases can be easily identified using chest X-rays and CT scans. Chest X-rays are normally painless and non-invasive radiological tests to screen and diagnose many lung diseases also other methods such as CT and MRI can be used. Chest Xray is fast, easy and inexpensive than CT and MRI and they are mostly used in emergency diagnosis and treatment of lungs, hearts, and chest wall diseases [1].

Pneumonia can be brought on by a number of different species, including bacteria, viruses, and fungus. Around 450 million people worldwide (7% of the population) get pneumonia every year, and it causes about 4 million fatalities. Survival has significantly increased since the 20th century with the development of antibiotics and vaccines [5]. An illness called pneumonia causes the air sacs in one or both lungs to become inflamed. Breathing becomes challenging as a result of the lungs swelling from pneumonia [1].

The vast virus family known as corona viruses can cause a variety of respiratory illnesses, from the common cold to more serious conditions like Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). The most typical signs of COVID-19 are fever, cough, breathing problems, and exhaustion. These symptoms can progress to pneumonia and could result in mortality [6].

Table 1 Dataset summary

Diseases	No. of Images
Normal	1583
COVID19	576
Pneumonia	4273
Tuberculosis	703

The results of this study demonstrate that combining deep qualities can significantly increase performance [1]. In this work, the authors used 1 datasets of disease chest X-rays, including Pneumonia, Covid-19, and Tuberculosis, to compare different CNN pre-trained models. Here is the list of what was contributed.

The authors developed and implemented CNN VGG16, which fully categorizes diseases by extracting their deep properties from X-ray pictures.

This technique entails the following three steps:

(1) Training the model with CNN models;

(2) Evaluating the pre-trained model's accuracy and losses;

(3) Selecting the ideal model for fine-tuning to achieve the best disease classification outcomes in chest X-ray images.

Our research work's primary contribution comprises two key steps:

- Firstly, creating a multi-class classification system capable of detecting multiple diseases from chest X-rays, employing both machine learning and deep learning classifiers;
- Secondly, developing a weighted average ensemble method to prevent model overfitting while simultaneously achieving the highest predictive performance.

1. Literature Review

In recent years, the field of lung disease detection from X-ray has seen significant advancements with the development of various deep learning techniques.

Mangeri et al. [1] developed a fully automated system to predict Pneumonia, COVID-19, and Tuberculosis from X-ray images using pre-trained CNN models, including VGG19, Resnet50V2, and Densenet201. They achieved state-of-the-art performance through three steps: training, comparing models, and selecting the top fine-tuned model. However, the study was limited to only two classes, neglecting the possibility of predicting outcomes across multiple categories.

Solaiman et al. [7] proposed an Ensemble model that combines Xception, InceptionResnetV2, VGG19, DenseNet-201, and NasNetLarge deep CNN architectures to accurately identify COVID-19 and other coronary diseases from X-ray images. They utilized a CXR dataset from various open sources and used image augmentation and focal loss to overcome data imbalance. Transfer learning using ImageNet weights and the focal loss function led to better results. They utilized both a max voting system and a linear averaging system for test predictions from all five models. However, they lacked sufficient iterations and did not compare with existing systems.

Tirth Mehta et al. [8], proposed an efficient method for classifying chest X-rays into six categories (COVID-Mild, COVID-Medium, COVID-Severe, Normal, Pneumonia, and Tuberculosis) using cGAN and deep transfer learning. They collected 1229 images and applied histogram equalization to minimize biases. Lung segmentation was done using the U-Net architecture, trained on the Montgomery County X-ray set and Shenzhen Hospital X-ray set. Images were normalized and a cGAN was used to generate additional images. The ResNet50, Xception, and DenseNet-169 models were trained for classification using feature extraction and a softmax classifier.

Rahib H. Abiye et al. [9], presented two convolutional neural network (CNN) models that were trained on two different datasets. The first model focused on binary classification and was trained solely on a dataset containing chest X-ray images depicting pneumonia cases and normal instances. Conversely, using transfer learning, the second model employed the first model as a base and trained on a separate dataset that included chest X-ray images of COVID-19, pneumonia, and normal cases, aiming to classify instances into three classes: COVID-19, pneumonia, and normal.

Michail Mamalakis et al. [10], developed DenResCov-19, a deep learning network for effectively classifying multi-class lung diseases. It consists of four blocks from ResNet-50 and DenseNet-121 with the same width × height × frames. Four layers of different kernel sizes concatenate information from both models, which is fed into a block of convolution and average pooling layers. The information is translated into convolution space using concatenation-CNN block techniques, and a soft-max regression layer delivers the classification decision.

2. Methodology

Using machine learning and deep learning, the authors have suggested a method in this research for categorizing hospital chest X-rays into four clinical states, such as normal, tuberculosis, COVID19, and pneumonia. The radiographer evaluates the image quality of each chest X-ray while it is being taken, before the CAD model can make any predictions. The suggested method begins by determining if the chest X-ray is normal or abnormal. The three states of tuberculosis, COVID19, and pneumonia are further characterized if an abnormal chest X-ray is discovered. The proposed methodology is illustrated in Fig. 1.

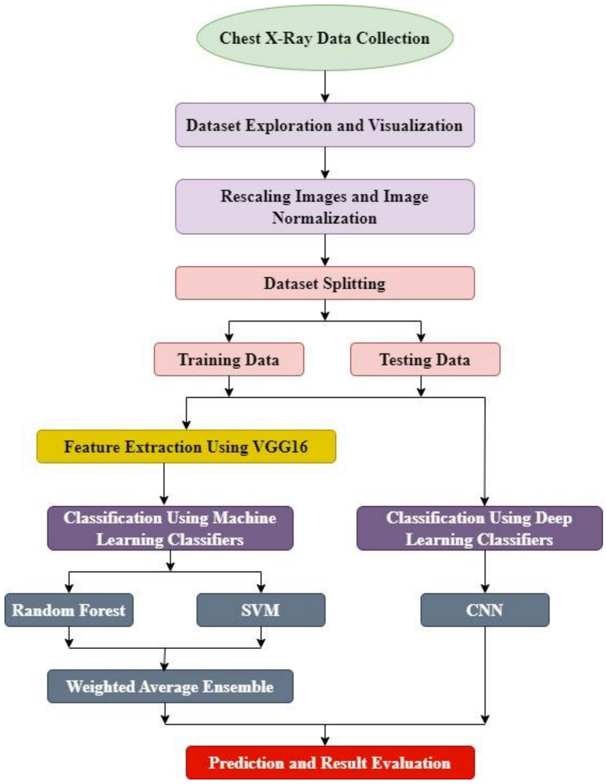

Fig. 1 Proposed methodology

2.1. Dataset Exploration and Visualization

The authors used the dataset Chest X-Ray (Pneumonia, Covid-19,Tuberculosis)

a. This dataset was created using four different dataset available in Kaggle and Github.

b. This dataset consists of 7135 Chest X-Ray images.

c. This dataset is divided into 3 folders (train, test, and val) and has a subfolder for each type of image (Normal/Pneumonia/Covid-19/Tuberculosis), according to how it is arranged.

Datasets from chest X-rays are accessible in a number of Kaggle projects. The authors have merged three datasets from Kaggle such as Chest X-Ray (Pneumonia, Covid-19, Tuberculosis), Montgomery County X-ray set and Shenzhen Hospital X-ray set. The authors can classify four medical conditions based on 7235 chest X-rays utilizing this data. These files contain labels created by medical professionals. Fig. 2 displays examples of images from the collection for each category of disease.

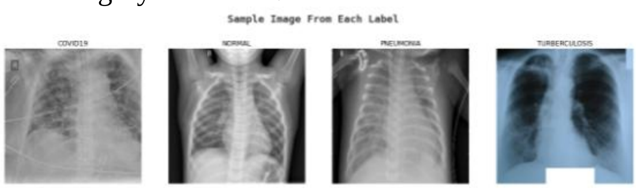

Fig. 2 Sample images of different clinical states

The quantity of chest X-ray images from four different medical conditions in the training and testing dataset is shown in Fig. 3 and 4 from the dataset.

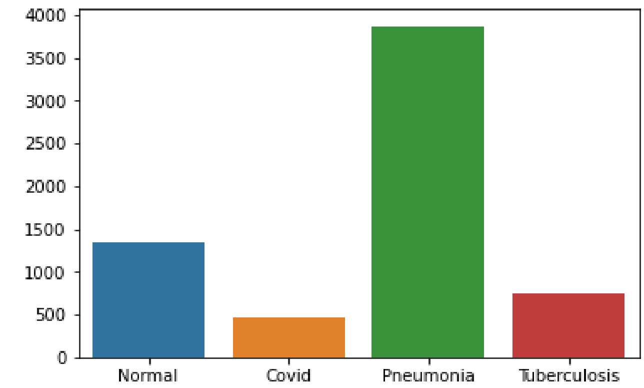

Fig. 3 Number of chest X–ray images in training set

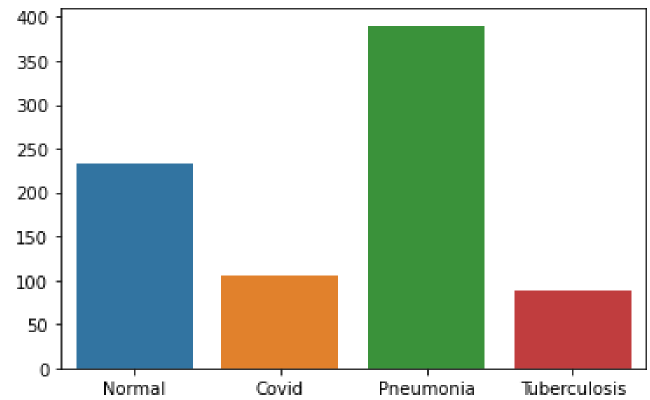

Fig. 4 Number of chest X–ray images in testing set

2.2. Dataset Preprocessing

In this work, the preprocessing procedures utilized are described below. As the approach primarily utilizes X-ray images, the quality of the images significantly affects the model's performance. Preprocessing of the images is necessary to enhance the model's robustness against noise, artifacts, and alterations in the input image during feature extraction. The approach outlined in this article aims to enhance the classification algorithms' ability to generalize. Thus, before presenting the images to the classification algorithms, the authors perform the following preprocessing steps.

2.2.1. Re-Scaling Images

The data set's images could come from a variety of places. As a result, each image contains a wide range of characteristics and pixel sizes. Prior to feeding the photos into the system, the number of parameters is reduced because a high number of parameters would result in a bigger demand for processing power. The photographs were all scaled down to 224x224 pixels.

2.2.2. Image Normalization

In image processing, normalizing is a technique used to change the range of pixel intensity values. Normalization is frequently used to create more recognizable or natural-looking images for the senses. Histogram stretching or contrast stretching are other names for normalization. There are various normalization methods, such as normalizing the range of pixel values between 0 and 1, normalizing the range between -1 and 1, and normalizing based on the mean and standard deviation of the dataset. To do this, the authors standardized the images between 0 and 1.

Using the train-test-split model validation method, it is possible to simulate how a model might behave given fresh, untested data. The train test split technique selects images at random for the model's training phase before evaluating the model's performance. 2000 images will be used to train the model in this study, and 1000 images will be used to test it.

2.3. Feature Extraction Using VGG16

Utilizing representations that a network has already learnt, the feature extraction method entails extracting valuable characteristics from samples. Then, these features are supplied to a fresh classifier that was trained from start. A convolution neural network model for image recognition, VGG16 is a VGG model with 16 weight layers. This model must initially master the detection of simple features like edges and color blobs in order to recognize more complex features. In the VGG16 model, a series of convolutional layers are followed by one or more dense (or fully connected) layers. The input layer through the final max pooling layer is regarded as the model's feature extraction portion, and the remaining layers of the network are called its classification layer. It was honed on countless numbers of pictures. It can recognize typical visual features present in image datasets because to its pre-trained architecture.

Following the convolutional layers, the visual properties are extracted from the output layer. Training and testing features are collected from the training and testing images using VGG16.

A large number of machine learning methods such as Random Forest, SVM, etc., work with three-dimensional feature vectors. Features of three dimensions are produced by the VGG16. As a result, in this stage, the feature vector is reduced to a one-dimensional feature vector.

2.4. Classification

Following the feature extraction process from VGG16, various classifiers are utilized to train the model. These include machine learning classifiers such as Random Forest, Gradient Boosting, and Support Vector Machine (SVM), along with a deep learning classifier, Convolutional Neural Networks (CNN), which is directly fed preprocessed images. Evaluation of the classifiers' performance indicates that Random Forest and SVM outperformed Gradient Boosting. Consequently, a weighted average ensemble approach is recommended, utilizing Random Forest and SVM as the base classifiers.

After many decision tree classifiers have been fitted to various dataset subsamples, a random forest is a meta estimator that uses averaging to improve predicted accuracy and decrease over fitting. Random Forest is used in classification and regression issues due to its adaptability, simplicity in determining the relevance of features, and lesser risk of over fitting. Working with a 1D feature vector is Random Forest Therefore, the model is tested and trained using The greedy algorithm gradient boosting has a propensity to overfit a training dataset very rapidly. It can profit from regularization techniques that punish various algorithmic components and enhance algorithm performance overall by lowering overfitting. Gradient boosting is a flexible technique that may be used for regression, multi-class classification, and other applications because it is based on minimizing a loss function, which allows for the use of many loss function types.

A supervised machine learning approach called the "Support Vector Machine" (SVM) is useful for both classification and regression tasks (30). To readily classify fresh data points in the future, the SVM algorithm seeks to identify the optimal line or decision boundary for categorizing n-dimensional space. The optimal choice boundary is a hyperplane.

The most popular deep neural network class for analyzing visual imagery is the convolutional neural network (CNN/ConvNet). Convolutional, pooling, and fully connected layers make up the three types of layers (or building blocks) that make up CNN. Convolution and pooling, the first two layers, extract features, while the fully connected layer, the third layer, transfers the extracted features into the final output, such as classification. Fig. 4 in this article illustrates the CNN architecture.

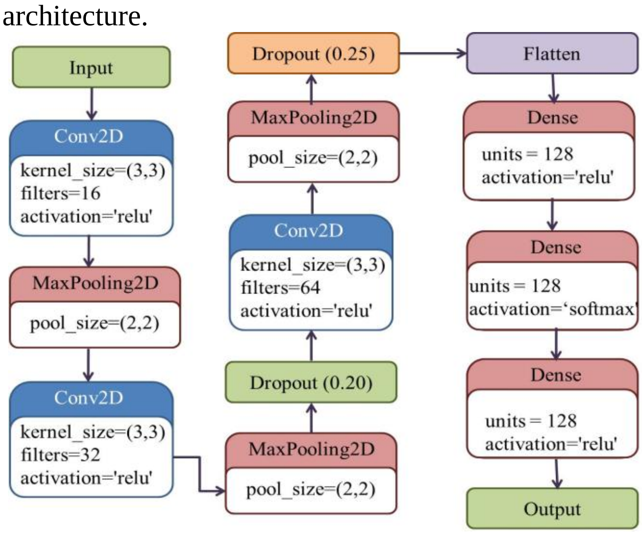

Fig. 4 CNN architecture used in this study

3. Result Analysis

In multi-class classification, various measures are used to assess each classifier's performance, including the confusion matrix, accuracy, precision, recall, f1-score, and support.

3.1. Confusion Matrix

A confusion matrix displays how well the authors' model predicts samples from various classes are called the confusion matrix (36). The predicted label and the actual label each have their own axes in the confusion matrix. It gives more details regarding a predictive model's performance, as well as which classes are correctly predicted, which are incorrectly forecasted, and what kinds of errors are created. Fig. 8 displays the confusion matrix produced by the various classifiers employed in this study.

True Positive (TP): True Positive (TP) data points are those that are both positive and the model predict they will be positive (37).

True Negative (TN): True Negative (TN) data points are those that are negative and that the model predicts would be negative (37).

False Positive (FP): False Positive (FP) data points are those that are negative but that the model predicts would be positive (37).

False Negative (FN): False Negative (FN) data points are positive data points that the model predicts will be negative (37).

For multi-class classification, confusion matrix is achieved for each of the class separately. Suppose in this study, while determining the confusion matrix for COVID19, each of its occurrences are replaced by positive and other classes are replaced by negative class label. Confusion matrix for different classifiers is depicted in Fig. 5.

87	0	13	12
1	248	24	0
0	9	731	0
0	0	1	158

Random Forest

64	0	15	33
2	201	67	3
5	41	681	13
19	3	17	120

Gradient Boosting

107	0	2	3
1	269	3	0
1	7	732	0
1	0	0	158

SVM

106	0	2	4
1	266	6	0
2	8	730	0
1	0	0	158

Weighted Average Ensemble

Fig. 5 Confusion matrix for different classifiers

Accuracy: Accuracy is calculated by dividing the total number of predictions by the number of right ones (38). Accuracy is equal to (TP+TN)/(TP+TN+FP+FN).

Precision: Precision is the ratio of true positives to all other true positives and false positives (38). Precision is equal to TP/(TP + FP).

Recall: According to (39), recall is the ratio of true positives to all other true positives and false negatives. Precision is equal to (TP + FN)/TP.

F1-Score: The F1-Score (20)] is a weighted average of recall and precision. F1-Score is equal to two times the product of recall and precision.

Support: Support is the number of real instances of the class in the provided dataset.

Table 2 displays CNN's performance, achieving a training accuracy of 99.30% and a validation accuracy of 79.37%, both with a loss of 1.24. Table 3 demonstrates the effectiveness of various machine learning classifiers in terms of accuracy, precision, recall, f1-score, and support. It is evident that Random Forest outperforms SVM and Gradient Boosting in terms of accuracy, with precision, recall, f1-score, and support values also outlined for all classifiers. Based on their higher accuracy, Random Forest and SVM are selected as the base classifiers for the weighted average ensemble method.

Table 2 Performance of different deep learning classifiers in terms of accuracy

Classifier	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
Convolutional Neural Network (CNN)	99.30%	1.24	79.37%	1.24

Table 3 Performance of different deep learning classifiers in terms of accuracy, precision, recall, f1-score and support

	Random Forest	Gradient Boosting	SVM
Accuracy	100%	83.02%	98.59%
Precision	0.95	0.83	0.99
Recall	0.95	0.83	0.99
F1-Score	0.95	0.83	0.99
Support	1284	1284	1284

Fig. 6 portrays the training versus validation accuracy curve and loss curve for each epoch of CNN. The training accuracy shows a higher increase than the validation accuracy. According to Fig. 7, the training loss reduces significantly for the first 2 epochs and then decreases at a slower rate.

On the other hand, the validation accuracy curve indicates a gradual increase with the number of epochs.

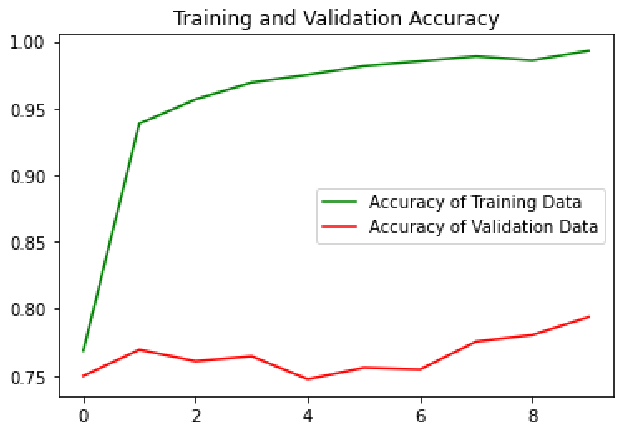

Fig. 6 Training vs. validation accuracy curve of CNN architecture

Fig. 7 Training vs. validation loss curve of CNN architecture

4. Conclusion

The authors proposed a combination of machine and deep learning models for the classification of X-ray chest images into three classes including COVID-19, in contrast with bacterial pneumonia, and TB, the normal healthy subjects. The authors finally created an ensemble method to prevent model overfitting and ensure higher accuracy. This work was motivated by the challenging conditions in low resource environments, where TB and COVID19 may be major healthcare problems. The authors explored the classification accuracy in three. This study is limited by the relatively small number of Pneumonia,COVID-19 and TB image but it shows the promise of a pipeline requiring low computational resources to contribute to the detection of COVID-19 and TB and pneumonia using X-ray images where other more advanced computationally demanding techniques may not be available.

Future prospects may include formulating new architectures based on CNN for the detection of COVID-19, pneumonia, TB alongside other diseases in the medical domain. The aforementioned models can be deployed in Web and Mobile applications, where patients can self-diagnose their ailments at their ease, thus saving valuable seconds in dire time. Such applications can also be extended towards hospital IT systems where patients can receive budget-friendly and quick COVID-19 diagnosis alongside the in-action RT-PCR tests. Future directions include to extend the proposed model to risk stratification for survival analysis, anticipating risk status of patients, and predicting hospitalization duration which would be valuable for triaging, patient population management, and individualized care planning.

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