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Multimodal approach for early prediction of COVID-19 disease using convolutional neural network

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ABSTRACT

The latest human coronavirus is COVID-19. Chest radiography imaging is essential for screening, early detection, and monitoring COVID-19 infections since the virus resides in the lungs. Classical real time reverse transcriptase polymerase chain reaction (RT-PCR) data and chest X-ray pictures will become more important for COVID-19 identification as the pandemic spreads due to their affordability, wide availability, and infection control benefits, which reduce cross-contamination. This work presents multi-modal hybrid automated approaches to classify COVID-19 illness into three clinical categories: normal, pathogenic, and COVID-19 utilising RT-PCR test data and online chest X-ray datasets. The RT-PCR and chest X-ray image datasets were processed using supervised machine learning and convolutional neural networks (CNN). Together, these measures help us separate COVID-19 patients, those with similar symptoms, and healthy persons. The author improved detection times and classification accuracy with extra tree classifier's feature selection and openCV's image sharpening. The proposed approaches were tested using a research dataset. The proposed methods allowed reliable COVID-19 disease categorization for clinical decision-making, with random forest (RF) classifier global precision values of 91.58% on the RT-PCR dataset and CNN model accuracy of 95.46% on improved sharpened images.

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1. INTRODUCTION

In December 2019, the extreme ARC 2 (SARS CoV-2) book was located in Wuhan, China. The World Health Organization (WHO) called it coronaviruse disease 2019 (COVID-19) in February 2020. The WHO declared COVID-19 an epidemic on 11 March 2020 after designating it a global public health concern on 30 January 2020 [1]. The virus swiftly spread, reaching 1.8 million cases and 114,698 deaths by April 12, 2020. The United States, Spain, and Italy had 22,115, 17,209, and 19,899 badly impacted by the epidemic.

Patients with infection may have fever, toux, respiratory issues, and flu. The infection can cause pneumonia, respiratory difficulties, multi-organ failure, and death [1], [2]. Many industrialized countries' healthcare infrastructure has disintegrated because to COVID-19's fast spread. Few ventilators and tests. Many governments have instituted lockdown and suspended meetings. Successful screening is needed to isolate and treat COVID-19-positive individuals. Real time reverse transcriptase polymerase chain reaction (RT-PCR) is the principal real-time COVID-19 screening tool [3], [4]. Patient respiratory samples may be tested in two hours or two days. Alternative PCR screening procedures include chest X-rays. Reviewing radiology journals [5], [6]. Chest imaging may help COVID-19. COVID-19 patients displayed ground-glass opacities and hazy darkish spots in their pulm [6], [7]. Chest radiation may help researchers measure and track COVID-19 cases. Many researchers released pre-print chest CT scan COVID-19 detection findings [8], [9]. Sensitivity techniques work well with small datasets but are rarely useful for development. These methods must be verified and polished before use. Because they learn from data fast, deep learning systems don't need custom features [10].

2. LITERATURE REVIEW

Previous in-depth learning categorised disorders using chest X-Rays. Deep neural network ChexNet [11] detects chest X-ray pneumonia. ChexNet has strong radiologists and outcomes. ChestNet uses chest X-rays to identify thorax disease [11]. With COVID-19 cases rising and artificial intelligent (AI)-based medical diagnostics, an AI-based detection system is needed. Recently, radiologists have found COVID-19. In conventional pneumonia-bacterial and pneumonia-via COVID-19 courses, Wang *et al.* [8]'s deep learning model COVID-Net is 83.5% accurateb [12].

Hemdan *et al.* [13] accurate computation: COVID-19 RT-PCR positive test dataset using stages classification through textual big data mining with machine learning," Apostolopoulos and Mpesiana scored 98.75%, 93.48%, and 98.48% on 224 COVID-19 images with pre-trained deep neural network models. Narin *et al.* [14] chest X-ray-trained ResNet-50 models found 98% COVID-19 in two groups. Undocumented multi-class efficiency. Individual convolutional neural network (CNN) models and a COVID-19 support vector machine (SVM) were used by Sethy and Behera [15]. Their survey found ResNet50 the best SVM classifier [16]. Ozturk *et al.* [9] most recently, a dark Net-based deep network was suggested. The 17-layer convolution model employs Leaky rectified linear unit (ReLu) activation.

The model scored 98.08% for binary and 87.02% for multi-class. All strategies except COVID-Net are binaurally graded (normal vs COVID-19) or three-class (normal vs pneumonia vs COVID-19) [8] others than COVID-Net don't discriminate bacterial and viral pneumonia. Ramnathan and Ramsundaram [16] machine learning was used to determine COVID-19 positive using the RT-PCR ribonucleic acid (RNA) viral expansion test. The proposed method uses machine learning and textual data mining to partition the clinical report into four pieces. The machine learning classification method extracts features from an efficient corona data set using cutting-edge term frequency - inverse document frequency (TF/IDF) algorithms. The three-way COVID-19 stages are categorized using machine learning using data recovery.

The TF/IDF quantifies and statistically tests COVID-19 patient file list text data for coronavirus prediction and classification. This study demonstrated that blood samples and machine learning may diagnose COVID-19-positive patients without RRT-PCR. Computers classify corona-positive patients as mild, moderate, or severe from the clinical record. Find measures using TF-IDF by comparing search similarities to study summary features. COVID-19-contaminated patient risk was measured by diagnostic levels. COVID-19 stages can be reliably diagnosed quickly, according to experiments [17]. A chest X-ray-based machine learning method by Chen *et al.* [17] swiftly and correctly identified COVID-19.

For quantitative COVID-19-based pneumonia identification using computed tomography (CT) imaging for automated, multiclass segmentation, Chen *et al.* [17] recommend residual attention U-Net. Chan and Adhikari [18] "auto diagnostic medical analysis" network helps doctors locate polluted areas and harmful components. Research employed CT and X-rays. A broad net network was recommended for lung pollution removal and labelling.

3. METHOD

The system we proposed in this paper is the hybrid approach to COVID-19 classification using chest X-ray images and RT-PCR data. Figure 1 represents the system architecture diagram. As represented in Figure 1, we developed the multimodal approach to detect the COVID-19 diseases with the help of two diverse datasets.

One dataset is the chest X-ray images andanother dataset is of RT-PCR dataset. The machine learning model had been applied to the RT-PCR dataset and CNN had been applied for the classification of the chest X-ray image dataset. The classification results are then ensemble at the final stage for identification of COVID-19 disease as normal, COVID-19 infected, and viral pneumonia.

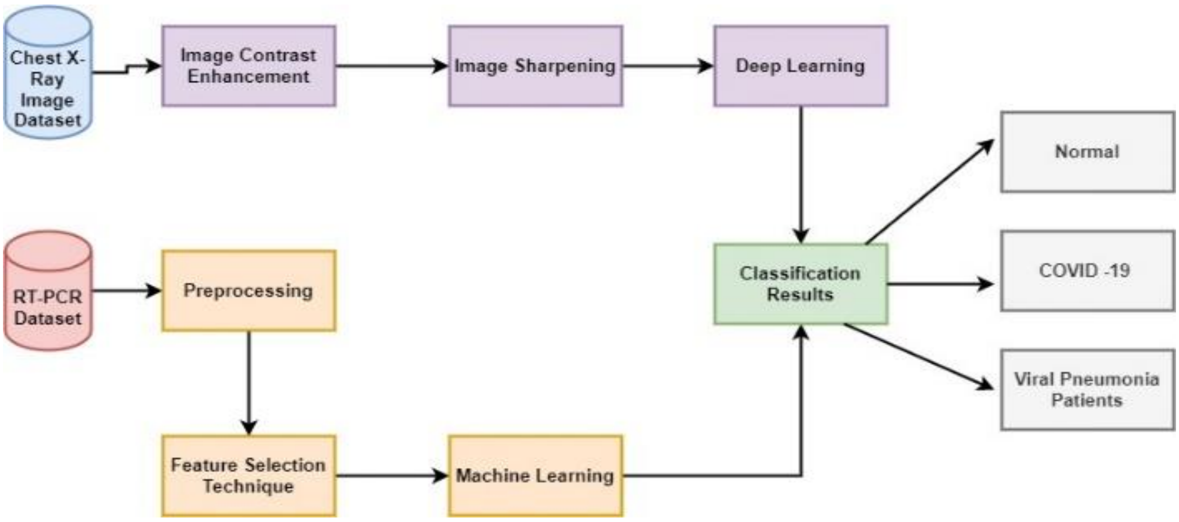


Figure 1. System architecture

3.1. Dataset description
3.1.1. Chest X-ray image dataset

The chest X-ray image dataset came from [18], [19]. It has two directories (train, test) and three subfolders (COVID-19, pneumonia, normal). Test data include 20% of data-set's 6432 X-ray pictures.

3.1.2. RT-PCR dataset

The Israeli Ministry of Health released SARS-CoV-2 RT-PCR nasopharyngeal swab testing data 11 [19]. The dataset provides daily initial records of all COVID-19-tested residents countrywide. Besides the test date and outcome, clinical symptoms, sex, and a binary diagnosis of age 60 or older are available. Total information shape is (1002063, 10). Figure 2 represents a sample image dataset obtained using chest X-ray for all three types sof classes. Figure 2(a) represents normal patient's chest X-ray image, Figure 2(b) represents pneumonia patient chest X-ray image where as Figure 2(c) represent COVID-19 patient's chest X-ray image.

(a) (b) (c)

Figure 2. Chest X-ray images (a) normal patient chest X-ray image, (b) Pneumonia patient chest X-ray image, and (c) COVID-19 patient chest X-ray image (left to right (a to c))

3.2. Pre-processing steps
3.2.1. RT-PCR dataset

The total dataset shape is (1002063, 10). After pre-processing, and considering only two classes for prediction i.e., COVID-negative and COVID-positive after dropping the records of COVID-19 other being they were very less in numbers compared to positive and negative test cases, we applied different machine learning algorithms i.e., logistic regression (LR), decision tree (DT) and random forest (RF). The train test split ratio waskept as 70:30.

3.2.2. Chest-X-ray image dataset

The original photos retrieved from the site above have noise because they are hospital X-rays. These photos may contain noise; thus, we utilised the OpenCV package for image enhancement to improve neural network classification. Contrast enhancement, contour detection employing clever edge detection, image blur, and image sharpening were used for study. We tested the aforementioned combination and got better image sharpening results.

3.3. Feature selection techniques for RT-PCR data

The main objective is to have anearly prediction for COVID detection, and the feature selection method had been implemented. The extra tree classifier model was chosen and top 5 features selected for further implementation of the machine learning model. Figure 3 represents the top 5 features fetched using extra tree classifier feature selection method. The top 5 features identified as headache, fever, cough, sore_throat, andshortness_of_breath.

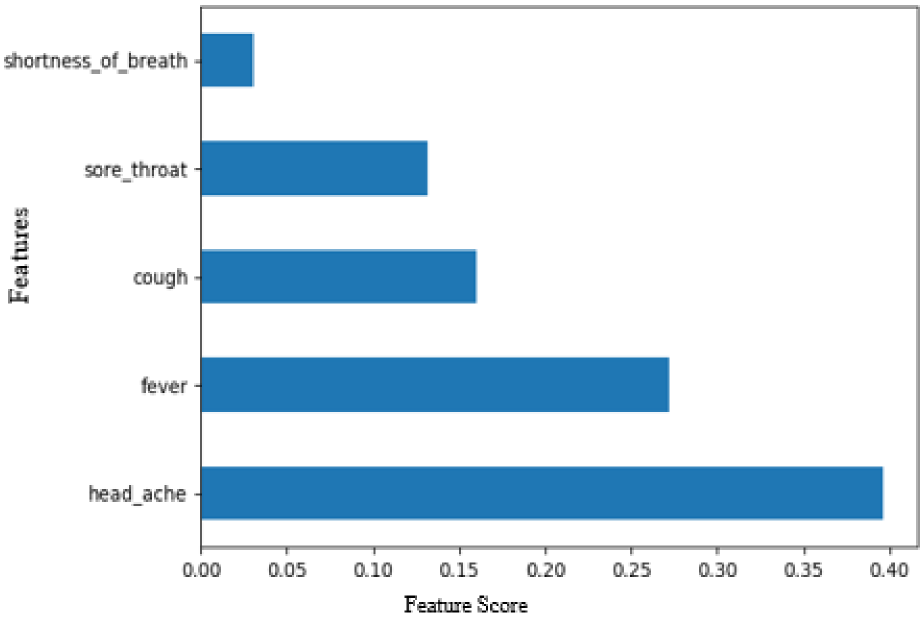


Figure 3. Top 5 feature selections using extra tree classifier

3.4. Machine learning models on RT-PCR data

Being the data is a supervised machine learning classification type, the author applied different machine learning classification algorithm for comparing the performance results. So that, final model can be selected based on best performance of accuracy of mode. For that, classification algorithms like LR, DT, and RF machine learning on the dataset had applied.

3.5. Neural network on chest-X-ray image dataset

Deep learning is prominent in artificial intelligence because it can detect complex patterns from input data. At several stages, deep learning algorithms learn data feature representation. Computer-aided detection/diagnostic systems and medical image analysis use these methods for accurate early detection, diagnosis, treatment, and monitoring of many pertinent illnesses [20]. This study uses a highly convolutional network design inspired by the keras sequential CNN, which was applied to our challenge because to its flexibility, simplicity, and promising results in previous pulmonary illness classification tasks. Figure 4 illustrates this study's keras sequential CNN architecture modification.

This architecture feed-forwards each layer within each dense block to maximise information flow. Layers examine feature maps from previous layers as inputs and send them to subsequent layers to preserve feed-forwardness. Each deep learning technique in this proposal classifies chest X-rays as normal, abnormal, or COVID-19. We changed the categorization layer to handle this output. To balance chest X-ray photos per category, the dataset was randomly divided into three mutually incompatible groups. Examples include 60% for teaching, 20% for validation, and 20% for testing.

4. RESULTS AND DISCUSSION

The training and testing were done on two diverse datasets (RT-PCR and chest X-ray images dataset) parallelly, and the methodologies of machine learning and CNN were applied to the above dataset as mentioned in the methodology's sections. The author collected results of both datasets separately, and since it is a multimodal approach, the ensemble classification results for COVID-19 disease classification were produced. After pre-processing, we performed LR, DT, and RF to the RT-PCR dataset. The train test split was 70:30. The full dataset was used for model training and testing in the first phase. The results got evaluated on accuracy, precision, recall and F1-score performance parameters. Table 1 shows findings from the full dataset without feature selection.

Table 1. Performance evaluation of complete features

Model	Precision	Recall	F1-score	Accuracy
LR	92	99	95	91.38
DT	92	99	95	91.41
RF	92	99	96	91.66

From Table 1, it is evident that the random forest model had performed marginally better than LR and DT. Figures 4 and 5 represents the confusion matrix for the RF model. The performance evaluation after the top 5 feature selection as shown in Figure 3 is mentioned in Table 2.

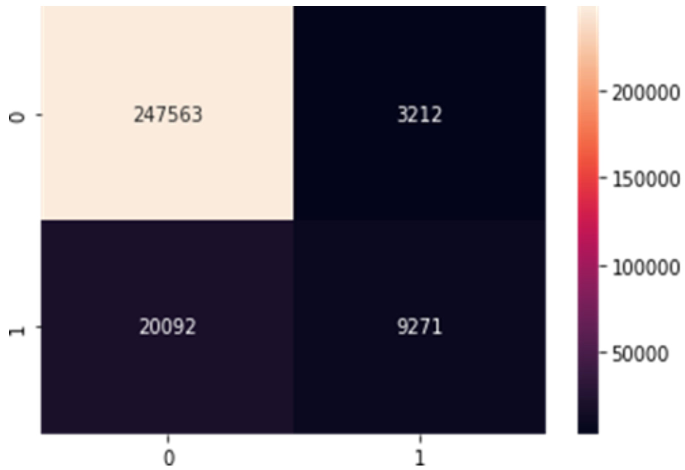


Figure 4. Confusion matrix RF

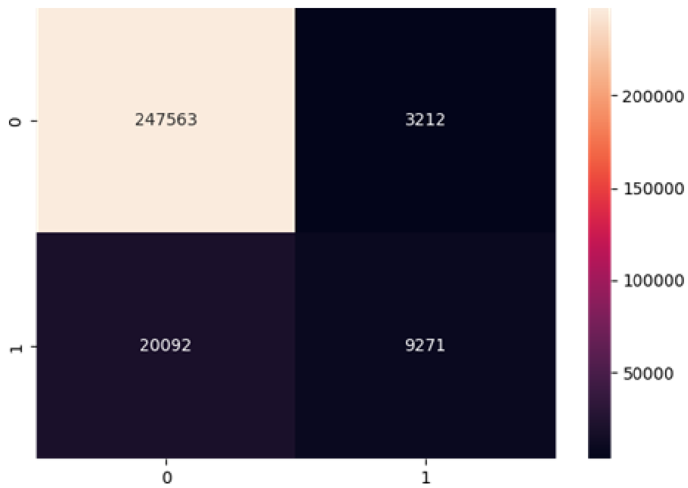
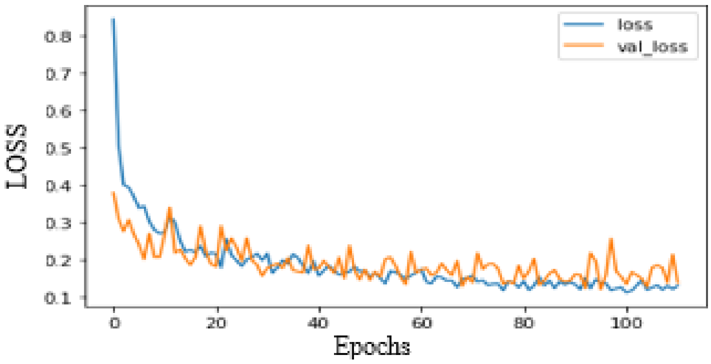


Figure 5. Confusion matrix RF after feature selection

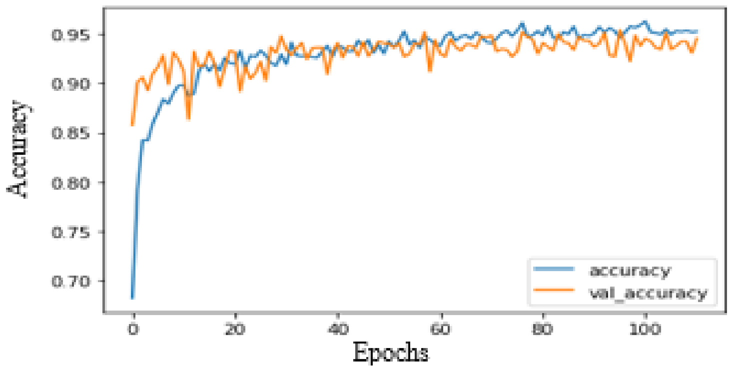
Table 2. Performance evaluation of top 5 features

Model	Precision	Recall	F1-score	Accuracy
LR	92	99	93	91.46
DT	92	99	95	91.41
RF	93	99	97	91.68

It is clear from Table 2 that even among the top five feature selection methods, the RF model outperformed LR and DT by a very small margin. The experimental setup used epochs 128. On the original dataset, training loss was 0.2982, accuracy was 0.8667, validation loss was 0.2142, and accuracy was 0.9024. Overall testing accuracy was 0.8446. Following openCV image improvement techniques, the author used the same CNN model to image enhanced chest X-ray pictures utilizing image sharpened methods. Applying the CNN with the same 128 epochs yielded training loss: 0.1782, training accuracy: 0.8971, validation loss: 0.1322, validation accuracy: 0.9624, and overall testing accuracy: 0.9526. Figure 6 showed the loss-accuracy graph of the model. Figure 6(a) show the loss against epochs graphs and Figure 6(b) show the accuracy graph against epochs for our CNN model. The classification report of the CNN model on sharpened image is shown in the Table 3.



(a)



(b)

Figure 6. Performance of CNN model (a) lossand and (b) accuracy graph of CNN model applied

Table 3. Classification report of CNN model

	Precision	Recall	F1-score
0	0.99	0.96	0.97
1	0.89	0.91	0.90
2	0.96	0.96	0.96
Accuracy			0.95
Macro avg	0.95	0.94	0.94
Weighted avg	0.95	0.95	0.95

The main objective of this research is to have the early detection of COVID-19 disease classification using a multi modal approach. Time taken comparison had been put in Table 4 and its graphical representation is shown in Figure 5. The preceding table shows that feature selection and sharpened image dataset saved 101.70 seconds. Overall accuracy increased from 88.07% to 93.47% with the multi modal model. Only with chest X-ray picture dataset after image sharpening enhancement approaches accuracy rose from 84.46% to 95.43%. This achieves the multimodal model's early COVID-19 illness categorization research goal. The experimental analysis shows that feature selection and image dataset sharpening saved processing time by 13%.

Table 4. Time taken by model

Methodologies	Time taken (in seconds)
Complete feature with RF model (A)	69.41
Top 5 features with RF model (B)	32.71
CNN model on the original dataset (C)	7450
CNN model on sharpens images (D)	7385
Time taken E=(A+C)	7519.41
Time taken F=(C+D)	7417.71
Time saved (E-F)	101.70

5. COMPARATIVE ANALYSIS OF PROPOSED WORK

Various researchers had worked on chest X-ray images COVID detection mechanism [21]. Different machine learning and deep learning models had applied for prediction of COVID [22]. Major performance parameters was the accuracy of the model. In this section, we are comparing our research work with most recent research work of COVID-19 prediction using chest X-ray images. Table 5 displays a comparison between the proposed system and current systems.

Table 5. Comparative analysis of proposed work

Author	Model	Dataset	Accuracy
Moura *et.al.* [23]	Deep CNN	Chest X-ray images from portable devices	90.27%
Marateb *et.al.* [24]	A combination of one-hotencoding, stability featureselection, over-sampling, and an ensemble classifierwasused	RT-PCR and CT-scan	96.00%
Swapnarekha *et al.* [25]	Mobile Net-V2	X-ray images	92.13
Proposed work	Hybrid methodology of machine learning and CNN	RT-PCR-chest X-ray images	RT-PCR data-91.68% chest X-Ray-94.60% (overall-93.47)

6. CONCLUSION

Due to its rapid spread, COVID-19, caused by the recently identified severe acute pulmonary symptoms of coronavirus 2 (SARS-CoV-2), is straining worldwide healthcare systems. Suspects should be identified quickly and monitored to prevent infection. COVID-19 detection was first limited to the defective RT-PCR test. Radiography analyses lung anomalies to diagnose and measure disease severity. This multimodal, automated research analyses patient RT-PCR data and chest X-ray images using machine learning and CNNs. The suggested method employs three complementary deep learning algorithms to better identify COVID-19-infected, similar-diseased, and healthy patients. COVID-19 and other lung diseases share symptoms because of this. Using RT-PCR dataset and chest X-ray image data, the proposed method distinguishes normal and COVID-19 patients. A innovative feature extraction technique on RT-PCR dataset and image enhancement using sharpen images with OpenCV enhanced classification accuracy. It also reduced prediction time by 110 seconds, demonstrating more accurate early COVID-19 identification.

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