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Detection of COVID-19 using chest X-rays enhanced by histogram equalization and convolutional neural networks

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ABSTRACT

The persistent global health crisis initiated by the COVID-19 pandemic continues to demand robust and high-throughput diagnostic solutions. While gold-standard methods, such as polymerase chain reaction (PCR) testing, are accurate, their scalability and turnaround time remain limitations in high-volume settings. This paper introduces a novel deep learning framework designed for rapid and accurate detection of COVID-19 from chest X-ray (CXR) imagery. Our methodology leverages a convolutional neural network (CNN) architecture, augmented by a crucial pre-processing stage: histogram equalization. This step is vital for enhancing the subtle contrast features inherent in CXR scans, there by significantly improving the quality of the input data and facilitating superior feature extraction by the CNN. The model was trained and rigorously validated on a dedicated dataset. Performance was systematically quantified using a comprehensive confusion matrix, yielding key metrics such as precision and specificity, alongside the receiver operating characteristic (ROC) curve. The achieved results are highly encouraging, demonstrating a classification accuracy of 98.45%. This innovative approach offers a substantial acceleration of the diagnostic process, providing a non-invasive and highly effective complementary tool for clinicians. Ultimately, this advancement has the potential to streamline patient management protocols and alleviate diagnostic pressures on global healthcare infrastructures.

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1. INTRODUCTION

Healthcare systems across the globe have been heavily strained by the COVID-19 pandemic [1]. Its fast spread and severity, particularly among vulnerable populations, have placed immense strain on diagnostic resources [2]. Chest X-rays (CXR) have emerged as a vital tool for initial diagnosis, but manual analysis can be time-consuming and susceptible to human error [3], [4].

Deep learning, specifically convolutional neural networks (CNNs), presents a promising solution for automating medical image analysis [5], [6]. These powerful networks can extract features from images and leverage them for classification tasks [7]. CNNs have already demonstrated success in detecting various pathologies like tumors and cancers [8]. This paper proposes a lightweight CNN model designed specifically for detecting COVID-19 from CXRs [9]. The model is trained on a publicly available dataset (COVID-QU) and utilizes histogram equalization as a pre-processing step [10]. This technique improves image quality, similar to how other image processing techniques, like lung segmentation, can be integrated for further analysis in medical imaging tasks like lung nodule detection [11]. Our findings are encouraging, with the model achieving an accuracy of 98.45%. This efficient model has the potential to contribute to faster and more accurate COVID-19 diagnosis [12], [13]. By automating analysis, such models can alleviate pressure on medical personnel and contribute to optimized patient management [14], [15].

2. THE COMPREHENSIVE THEORETICAL BASIS

Following the exploration of CNNs for COVID-19 detection in CXR images by various studies, this research proposes a novel method that incorporates both CNN and long short-term memory (LSTM) networks [16]. As of today, COVID-19 is still a global concern. This combined architecture aims to achieve even more accurate automatic diagnosis of COVID-19 from CXR images [17].

3. METHOD

3.1. CXR image database

Our model was trained on a selection of the COVID-QU database [18]. This database contains 1,823 images divided into three categories:

- COVID-19 positive: 536 images; normal: 668 images; lung virus: 619 images

For our study, we focused on the three categories this represents a total of 1,823 images.
Justification for the choice of categories:

- COVID-19 positive: allows the model to learn the distinctive characteristics of the disease [19].
- Normal: serves as a reference for comparison and discrimination.
- Exclusion from other categories: pulmonary virus: features may overlap those of COVID-19, which may cause confusion in the model [20].

The sets of images in database are distributed: the difference between Figures 1 and 2 is that Figure 1 shows a chest affected by COVID-19, with ground-glass opacities, consolidation, and infiltrates. These hazy areas in the lungs can appear white on a CXR [21], [22], and are caused by fluid buildup in the lungs.

The diagram in Figure 3 illustrates the approximate number of people affected by the COVID-19 pandemic compared to those who were not infected. It shows that the number of affected individuals is close to that of the unaffected population [23].

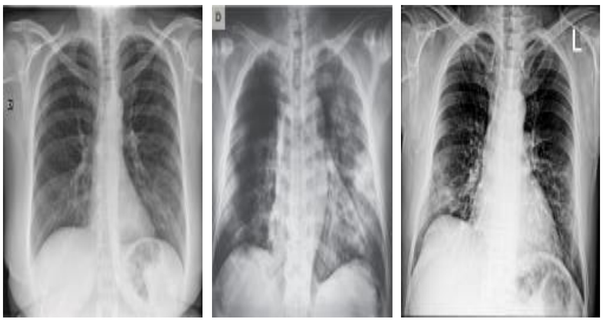

Figure 1. Images from the dataset used positive COVID-19

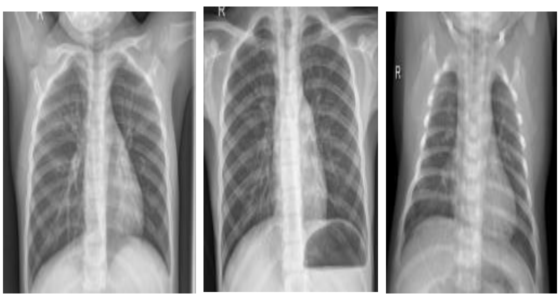

Figure 2. Images from the dataset used normal

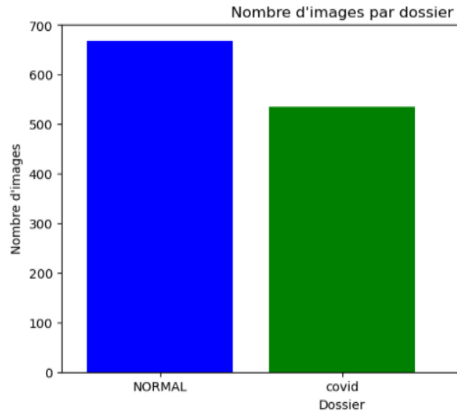

Figure 3. count of images for database used

3.2. Proposed approach

The study was organized in eight main stages:

– Image size standardization: all images have been resized to a uniform size to ensure consistency in learning.

$$p_x(x_k) = p(x = x_k) = \frac{n_k}{n}, 0 \leq k < L \quad (1)$$

x_k : discrete intensity level (gray level);
L: total number of possible intensity levels
n_k: absolute frequency (pixel count) and n is total number of pixels in the image
$p_x(x_k)$: probability mass function (PMF) or normalized frequency

– Convert images to grayscale

The grayscale conversion allowed focus on texture and brightness information, while reducing data complexity with function grayscale in python [24]. Breakdown of data into learning and validation sets: 80% of the data were used for model learning (learning set). 20% of the data were used to assess the reliability of the model (validation set) [25], [26].

– Design of the CNN architecture

The CNN architecture was defined by specifying the number and type of convolutional and fully connected layers [27]. The CNN architecture plays a crucial role in its ability to effectively detect COVID-19 from CXRs [28], [29]. This architecture Figure 4 is defined by specifying several key elements: number and type of convolutional layers and fully connected layers [30].

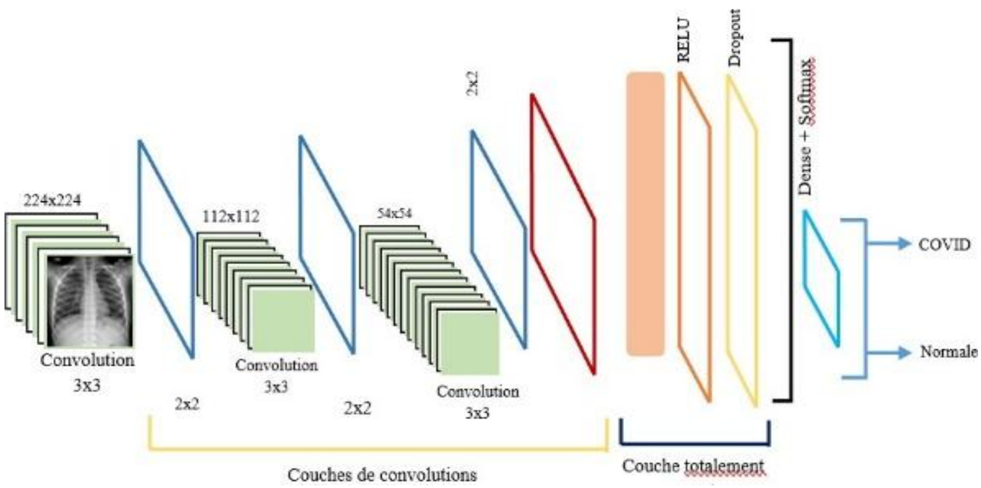

Figure 4. Architecture CNN used

4. RESULTS AND DISCUSSION

Model drive setup, the hyperparameters of the model, such as the learning rate and the number of eras, have been optimized to obtain the best results [30]. While defining the CNN architecture is essential, achieving optimal performance often requires fine-tuning the model's hyperparameters [31]. These are settings that control the learning process but aren't directly learned by the model itself [32].

Model training launch, the model was trained on the learning set and its performance was evaluated on the validation set [33]. By following these steps, we were able to develop a CNN model capable of detecting COVID-19 from CXRs with high accuracy and reliability [34]. Optimizing these hyperparameters can significantly improve the model's ability to detect COVID-19 in CXRs [35]. In Figure 5 which show the graph or accuracy and Figure 6 which show evolution of loss value [36].

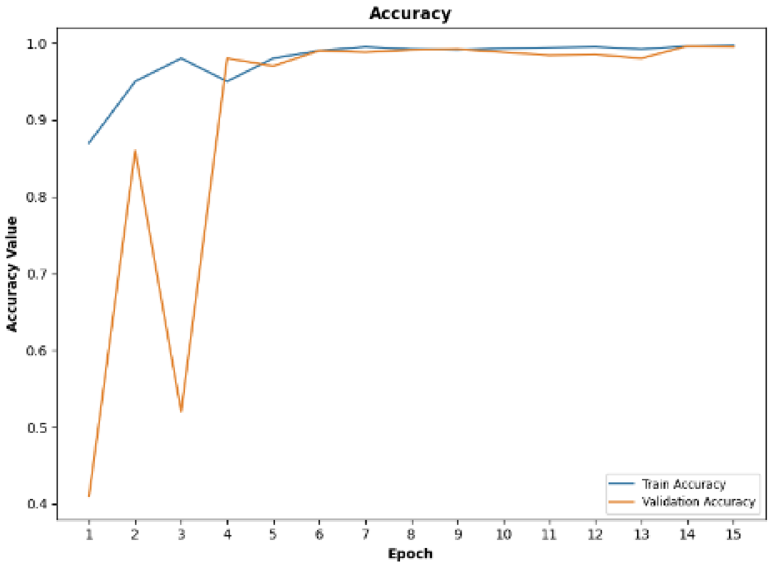

Figure 5. Accuracy value

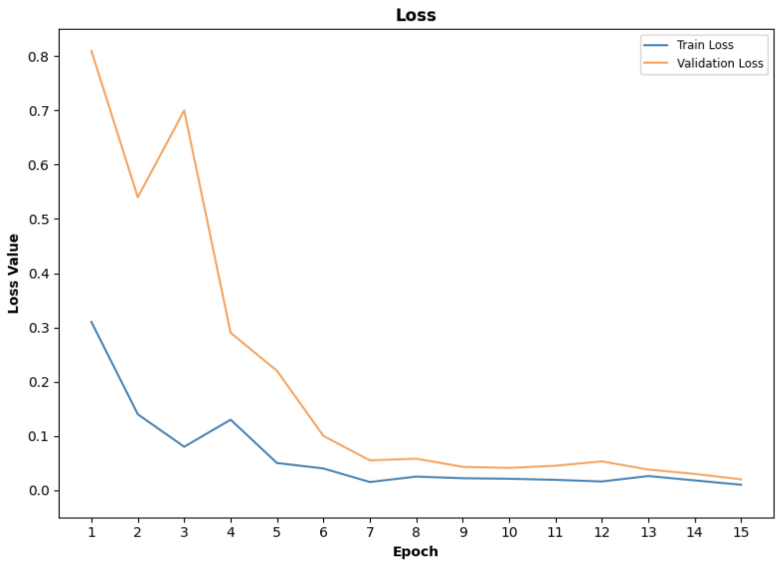

Figure 6. Loss value

Last phase of the study, upon the completion of the CNN training phase, two subsequent critical steps are undertaken to rigorously quantify and validate the model's predictive performance on the unseen test data:

4.1. Visualize the confusion matrix

The confusion matrix serves as an essential diagnostic tool for visualizing a model's predictive accuracy by mapping forecasted outcomes against actual ground truth values. This structured representation facilitates a comprehensive evaluation of performance, as it highlights specific patterns of successful classifications and systematic errors across different categories [36]. Furthermore, by isolating these predictive discrepancies, researchers can derive critical secondary metrics such as precision, recall, and the F1-score to gain deeper insights into the algorithm's reliability in complex decision-making scenarios.

4.2. Display the receiver operating characteristic (ROC) curve

The ROC curve illustrated in Figure 7 depicts the relationship between the true positive rate and the false positive rate across various threshold settings. This graphical representation serves as a critical diagnostic tool to evaluate the model's fundamental capacity to discriminate effectively between positive and negative classes [36]. By analyzing the area under this curve (AUC), researchers can quantify the overall diagnostic accuracy and determine the optimal balance between sensitivity and specificity for the given classification task.

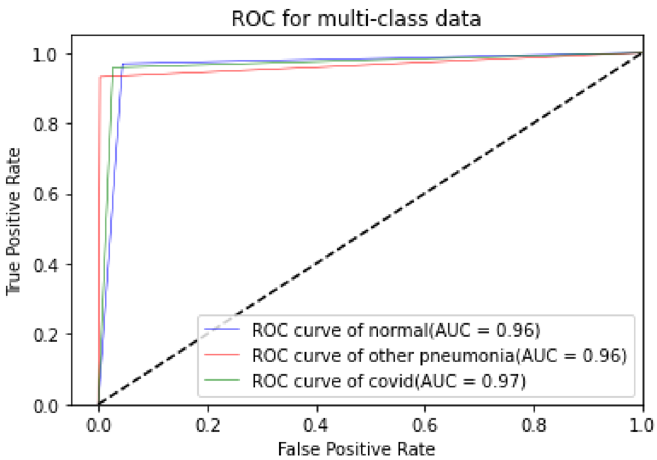

Figure 7. Graph of the ROC

5. CONCLUSION

This research demonstrates a robust and efficient approach to COVID-19 detection through the optimization of CNNs and advanced image processing techniques. By balancing architectural simplicity with high diagnostic precision, the proposed system offers a viable solution for rapid screening in resource-constrained environments. Ultimately, this study contributes a scalable methodology to the field of medical imaging, providing a foundation for future automated diagnostic tools in respiratory health.

The proposed method achieved an accuracy of 98.4%, confirming its effectiveness. Future work will require a more extensive image database to refine evaluation and enhance robustness. Additional techniques such as segmentation may further improve accuracy and resilience. In terms of future perspectives, we aim to strengthen the model with larger image datasets and advanced preprocessing and learning methodologies, integrate the approach into clinical diagnostic systems for early COVID-19 detection, and explore broader applications for other lung pathologies. By addressing these directions, we anticipate further advancements in COVID-19 detection and meaningful contributions to medical imaging research.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Ahiod Belaid	✓			✓			✓			✓				✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, NAZIF TCHAGAFO, upon reasonable request.

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