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Deep-Learning-Based Mobile Application for Detecting COVID-19

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Abstract

Patients infected with the COVID-19 virus develop severe pneumonia, which typically results in death. Radiological data show that the disease involves interstitial lung involvement, lung opacities, bilateral ground-glass opacities, and patchy opacities. This study aimed to improve COVID-19 diagnosis via radiological chest X-ray (CXR) image analysis, making a substantial contribution to the development of a mobile application that efficiently identifies COVID-19, saving medical professionals time and resources. It also allows for timely preventative interventions by using more than 18000 CXR lung images and the MobileNetV2 convolutional neural network (CNN) architecture. The MobileNetV2 deep-learning model performances were evaluated using precision, sensitivity, specificity, accuracy, and F-measure to classify CXR images into COVID-19, non-COVID-19 lung opacity, and normal control. Results showed a precision of 92.91%, sensitivity of 90.6, specificity of 96.45%, accuracy of 90.6%, and F-measure of 91.74% in COVID-19 detection. Indeed, the suggested MobileNetV2 deep-learning CNN model can improve classification performance by minimising the time required to collect per-image results for a mobile application.

Keywords: *Deep learning; CNN; MobileNet-V2; image processing; COVID-19; lung opacity; mobile display*

1. Introduction

On December 31, 2019, the COVID-19 pandemic officially started after the first pneumonia report with unidentified aetiology appearing in Wuhan, China [1,2]. Initially known as SARS-CoV-2, the World Health Organization (WHO) later designated it as COVID-19 owing to its infectious nature. On January 30, 2020, the WHO formally categorised the COVID-19 pandemic as a Public Health Emergency of International Concern [3]. On July 21, 2020, the WHO classified around 9 million of the 15 million confirmed COVID-19 cases worldwide as active. Tragically, the virus has claimed the lives of 614,208 individuals globally [4]. The predominant manifestations of COVID-19 include pyrexia, nasal discharge, paroxysmal expulsion of air from the respiratory tract, pharyngeal discomfort, inflammation of the throat, cephalalgia, diminished physical strength, general discomfort, and respiratory distress [5].

The timely identification of sickness enhances the likelihood of effective treatment for afflicted individuals and concurrently diminishes the risk of transmission amongst the community, particularly in the case of a communicable ailment such as COVID-19 [6]. Many countries also offer laboratory tests that use real-time reverse-transcription polymerase chain reaction (RT-PCR), the most widely used technology for COVID-19 detection [7]. However, the RT-PCR test sensitivity is only 60%–70%. Therefore, identifying the harmful consequences of COVID-19 by looking at patient lung images can ensure early treatment.

Chest radiological imaging such as X-rays and computed tomography (CT) scans plays a significant role in the early detection and therapy of this illness. One advantage of X-rays is their ease of use with portable X-ray tools, leading to a faster and more effective diagnosis of COVID-19. With the help of artificial intelligence (AI), X-rays may be able to find COVID-19, causing less bodily damage than CT scans [2,8]. Various AI-based techniques have assisted in recent efforts to locate COVID-19 using images [2].

AI techniques are currently being discovered to be exceedingly advantageous for the purposes of testing, training, and evaluation. Prediction models are frequently constructed using neural networks. However, neural networks continue to possess constraints, such as their learning capacity and delayed convergence [9]. Deep learning enhances diagnostic speed by facilitating clinical decisions and predictions within the medical system. Researchers are currently investigating deep learning, a subfield of machine learning, for its ability to automatically extract significant characteristics from datasets using neural networks like artificial neural networks, where recurrent neural networks and convolutional neural networks (CNN) play key roles. They are particularly useful for categorising data because they enable computers to learn from it and deliver accurate answers [10].

Recently, image classification with CNNs has effectively diagnosed common chest disorders, including tuberculosis screening and mediastinal lymph nodes in CT images. Numerous real-world applications such as pattern recognition and intuitive picture categorisation have extensively used CNN, one of the most effective deep-learning architectures [11]. CNNs can function in many ways using pre-trained CNNs with feature extractors [12]. Nevertheless, the use of deep-learning approaches to identify and detect new COVID-19 in X-rays up to this point is rare [9].

Using radiological images such as X-rays or CT scans, medical imaging can be considered a critical technique for diagnosing COVID-19 infections and assisting doctors in evaluating the disease, as well as in optimising prevention and control measures, as early as feasible. Therefore, medical images with the diagnostic parameters are a highly effective approach that can enable physicians to diagnose patients with the help of big data [13]. However, researchers have found anomalies in the form of ground-glass opacities in the chest CT scans of COVID-19 patients [14]. Research has demonstrated that developing a system using chest CT imaging can diagnose and quantify COVID-19 cases [15]. However, X-ray images can be used instead of CT scans to detect COVID-19. X-rays can be obtained without the enhanced danger of propelling the pathogen through the air. The X-rays may help sort out the patients into the highest risk group, high-risk group, and low-risk group for the rest of the complications, apart from helping in assessing the severity of disease on one or more occasions. Nevertheless, compared with X-ray imaging, CT imaging is significantly more time consuming and necessitates a rigorous sanitation process before patients can be switched. Even so, high-quality CT scanners may not be readily accessible, so a timely chance to screen for viral pneumonia may not exist. Therefore, Covid-19 medical imaging and diagnostics are important for the fast diagnosis of COVID-19 [16].

Medical images such as X-ray images can be analysed to provide relatively immediate diagnostic information by identifying potential patterns that can result in the automatic diagnosis of the disease. The chest X-ray (CXR) is the most frequently used imaging modality in the diagnostic examination of patients with thoracic abnormalities. The reason is its rapid imaging speed, low radiation, and low cost [17]. Expert radiologists frequently perform interpretation without assistance in emergency and hospital settings, where it is universally available.

Indeed, the COVID-19 pandemic is characterised by a rapid spread rate, and RT-PCR is the standard diagnostic procedure for viral nucleic acid detection [18, 19]. Nevertheless, this test has suboptimal sensitivity and specificity. Numerous hyperendemic regions and countries are also unable to provide adequate RT-PCR testing for tens of thousands of suspected subjects within a brief period. Additionally, concerns exist regarding the discomfort associated with RT-PCR, the absence of swabs, the necessity of reagents, delays in the production of results, and substantial false-negative rates. These concerns warrant the investigation of alternative diagnostic methods [12]. For the purpose of rigorous detection, contact tracing, and isolation of infected subjects during the primary stage of infection, all such methods must be precise, rapid, and effective instruments for detecting COVID-19 infection.

In this research, efforts were exerted to implement efficient network architectures and transfer learning techniques; thus, MobileNetV2 was used as a computational tool to autonomously predict the presence of COVID-19 based on CXR images. The most comprehensive collection of CXR pictures ever assembled for classification was utilised. These images included healthy individuals, COVID-19 patients, and patients with other lung illnesses.

The performance of the MobileNetV2 is best suited for applications that deal with real-time processing and classification of COVID-19, non-COVID-19 lung opacity, and normal control. Given that it is comparatively lightweight, it carries out inference in a short time, which is essential in a mobile application where response time can influence a clinician's decision. Furthermore, the model uses depthwise convolutions and thus operates with a considerably smaller number of parameters than typical convolutional networks. This enables deployment on devices with low computational capability and makes the app fast as well. Additionally, MobileNetV2 has a built-in library, and a user can start with prior knowledge from large datasets. This capability enhances the model's performance, especially when there is little data available because COVID-19 detection may be specific in some instances. MobileNetV2 can also be scaled up easily owing to the optimised architecture. The size of the models can be easily scaled up or down depending on the available processing power; and hence, they can be conveniently used across the broad range of devices that exist in the mobile platforms. Lastly, the outcomes achieved based on MobileNetV2 can be compared with other deep-learning architectures that are extensively used in medical image analysis, including ResNet, DenseNet, and Inception [20,21].

Conversely, ResNet can handle very deep networks with relative ease by virtue of the residual connections. However, it is slightly slower and may not be as efficient when used on a mobile device. Meanwhile, MobileNetV2 is designed to perform adequately for mobile platforms not necessarily high performing. DenseNet includes the use of feature reuse because the gradients can flow freely during the training process. Nevertheless, owing to its heavy information-processing functionality, memory usage can also be enhanced. MobileNetV2 follows a less complex architecture to be more portable on mobile devices. Inception models are accepted to be designed for multi-scale feature extraction on the given images, but they are often costly in terms of computation. MobileNetV2 has similar efficiency in feature extraction owing to its more simplistic architecture making it more preferable for real-time use. Thus, despite the plethora of models available, for our research, we opted for MobileNetV2 owing to its efficiency, small number of parameters, ability to use transfer learning, and scalability. Thus, when comparing it to other architectures, we want to emphasise the benefits of the proposed architecture for the context of mobile applications for medical image analysis. To further improve the depth and practicality of the article, we integrate this comparative discussion for increased coverage of depth and practicality for the users, as well as clinical decision making [22,23].

The present study aimed to enhance the capacities of medical practitioners by leveraging CNN. COVID-19 diagnosis was improved through radiographic image analysis, making a significant contribution to the development of a mobile application that promptly detected COVID-19, thereby saving medical professionals time and resources and facilitating timely preventative actions. Moreover, this work explored the possibility of integrating MATLAB with the Telegram messaging platform by developing a Telegram bot that can communicate with MATLAB to conduct intricate computations. Additionally, it performed detailed analyses, thereby improving user experience and accessibility. Collectively, the purpose of these contributions was to enhance the application of AI in medical diagnostics. Therefore, in the context of COVID-19, these contributions offered highly dependable, user friendly, and efficient tools for early detection and analysis. Furthermore, the objective of this research was to provide a comprehensive examination of CNN's use in the analysis of radiographic visual images. This can enhance the ability of seasoned medical practitioners and researchers to develop models relevant to the COVID-19 domain.

Applying the deep MobileNetV2 CNN model is less time consuming than PCR with delays caused by machine availability or the challenges faced by clinicians when extracting details from CT scans of large dimensions. Thus, deep-learning-based mobile applications have a positive impact on healthcare delivery and may also aid in the early detection of COVID-19.

The utilisation of the MobileNetV2 model and transfer learning techniques to construct a computational tool within this manuscript clearly articulates the contributions of the paper. This tool aims to autonomously predict the presence or absence of radiological indications consistent with COVID-19 in patients based on analysis of CXR images. The authors make these contributions to the best of their knowledge. Moreover, this dataset represents the most extensive collection of CXR images ever compiled and used for classification. The dataset comprises COVID-19 patients, non-COVID lung-opacity illnesses, and healthy-control individuals.

2. Related Works

AI, particularly deep learning, is applicable for the automatic diagnosis of various diseases in the human body [20–21]. Deep learning is applied as a feature extractor that improves classification choices based on reported classification accuracies [22]. Despite the fact that chest radiology imaging systems are commonly found in hospitals and can be performed quickly, the interpretation of radiography images by radiologists remains a significant concern owing to the human capacity to detect the subtle visual features present in the images.

The field of image analysis and processing in the biomedical field has seen very spectacular results. Deep-learning algorithms and CNN models have recently been utilised. Several studies have been performed utilising deep-learning approaches to automate the diagnosis of COVID-19. The majority of deep-learning-based models are hierarchical, with each layer extracting information unique to COVID-19 that may be used to distinguish COVID-19 photos from other kinds of images. The most popular learning technique that can effectively interpret images and videos, across a range of computer vision applications [23, 24].

In recent years, numerous have been published about the diagnosis of COVID-19 from X-ray images of lungs with the help of various AI tools. New approaches to fine tuning using transfer learning approaches, different network architectures, and ensemble techniques were applied to enhance the network performances and thus distinguish COVID-19 from normal lung and other lung diseases. Nevertheless, the results obtained are optimistic because the developed deep-learning models can be built based on a small dataset for COVID-19 detection. Khan et al. [25] compared a limited number of machine-learning algorithms specifically for a four-class classification problem with the dataset used in the current study: COVID-19, bacterial pneumonia, viral pneumonia, and normal. Through the ResNet50 classifier developed by Goldstein et al. [26], the accuracy and sensitivity for detecting COVID-19 is 89.7% and 87.1%, respectively. For instance, Wang and Wong integrated about 14k CXR images but only achieved an 83.5% accuracy rate by using a deep CNN referred to as COVID-Net. Moreover, Motamed et al. [27] introduced a generalisation of the above idea called randomised generative adversarial network, which is capable of identifying images of an unseen class (COVID-19) from specified and labelled classes (normal and viral pneumonia) without requiring any labels and training data of the novel class (COVID-19), achieving an accuracy rate of 0.77 AUC. When comparing the results of utilising the described approaches separately, their combination enabled higher levels of COVID-19 detection to be attained.

Therefore, many studies have used deep-learning techniques to examine different datasets containing lung images from COVID-19 patients healthy individuals and those with non-COVID pulmonary diseases. For instance, Saeed et al. evaluated the performance of deep-learning models, with particularly focus on VGGNet, GoogleNet, and ResNet. These models are used to process X-ray and CT-Scan images of COVID-19 patients' lungs [28]. Moreover, Alwawi et al. have introduced a deep-learning-based model for expanding and detecting COVID-19 cases by using X-ray images. The model comprises a CNN architecture in which the network was trained to classify images into positive or negative COVID-19 [29]. Other studies have proposed a deep-learning approach by using CNN for binary X-ray images for COVID-19 classification in which the dataset of X-ray images is trained to diagnose COVID-19 as positive or negative [30]. Moreover, deep learning has become a prominent topic in computing and is extensively applied in medical applications. It proves effective for the automatic diagnosis of COVID-19. Another research has implemented a CNN model with fewer layers and optimised parameters to obtain an implementation resulting in reduced training time for the binary classification of COVID-19 using by X-ray images [31].

Khaleel et al. [32,39] focused on training VGG CNN models such as VGG16 and VGG19 using X-ray images to identify COVID-19. Zahra et al. [33] have suggested a COVID-19 prediction infrastructure that makes use of deep learning with a CNN model to identify the presence of COVID-19. Researchers suggested a two-step transformer model for COVID-19 detection [34] using pre-trained CNN models, including InceptionV3 and

Efficient Net. Al-Qazzaz et al. have used automatic deep CNN model to detect COVID-19 [40].

This work introduced a CNN model to identify COVID-19 infections from CXR images. We aimed to use a distinctive CNN model to automate the identification of COVID-19 through the utilisation of CXR images with a dataset of three groups containing more than 18000 X-ray images. Our study evaluated the efficacy of MobileNetv2 models to improve model generalisation and prevent overfitting. Comprehensive evaluations were performed using training–validation–testing, and results demonstrated high effectiveness.

3. Methodology

Figure 1 presents an overview of the primary phases used in this investigation. The academic process began with the acquisition of CXR pictures, followed by a preprocessing step. Subsequently, CNNs were used to analyse the images. Finally, the classification stage was executed to categorise the X-ray findings.

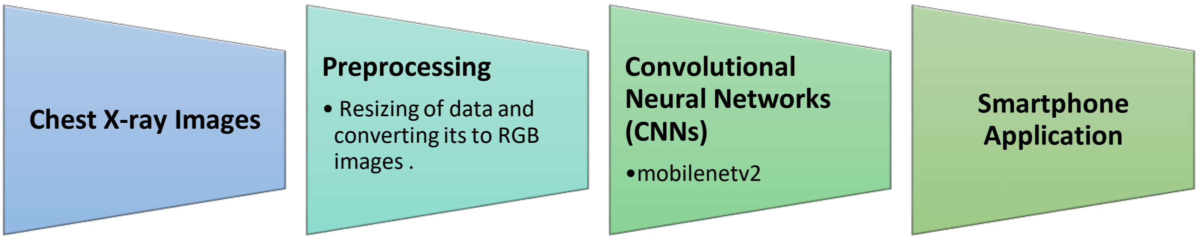

Fig. 1. Work block diagram

3.1. Dataset

This study aimed to create a new huge dataset on the coronavirus family by combining different CXR datasets that are freely accessible to the public. Three categories make up the combined dataset. These categories include lung masks and the X-ray dataset (COVQU), which is the largest freely available COVID positive database. This study included 18,479 CXR pictures, amongst which 8851 were normal, 6012 were non-COVID lung infections, and 3616 were COVID-19 CXR images, together with their accompanying ground-truth lung masks (Figure 2).

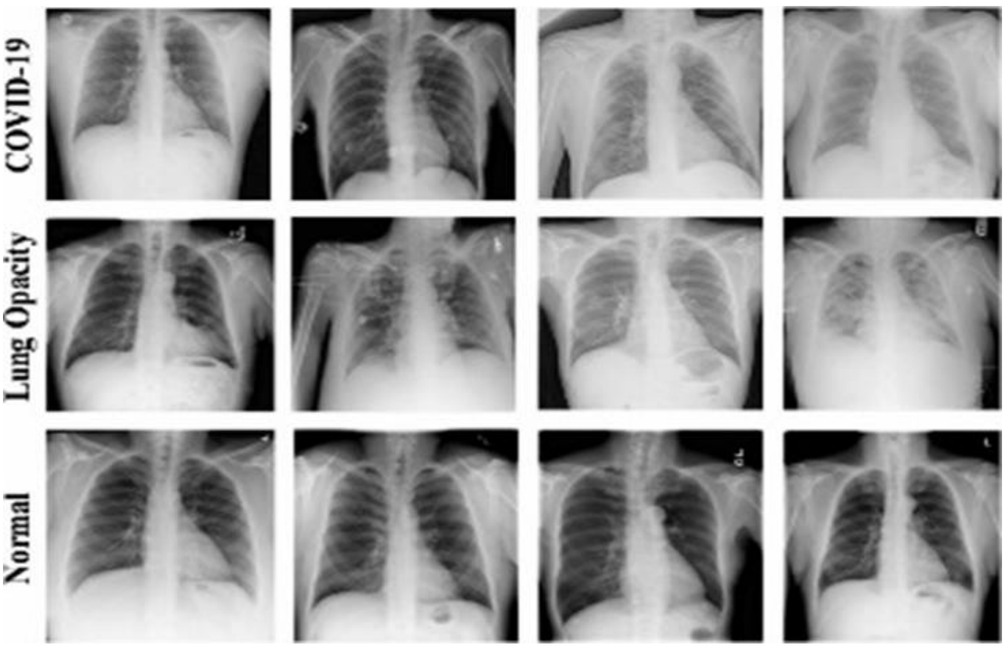

Fig. 2. Chest X-ray images.

3.2. Preprocessing

Preprocessing X-ray data is an important step in preparing the data for use in neural network models, such as MobileNetV2. One possible preprocessing technique that has been used in some studies is resizing the X-ray images to RGB images so that they can be used in MobileNetV2. This neural network architecture is designed to work with RGB images.

The X-ray pictures were initially greyscale. To obtain the RGB input, the greyscale values were copied three times for the red, green, and blue channels. The outcome was an RGB image where all the three bands had the same values, so the integrity of the intensity was maintained with an addition of image format into RGB format After converting the images into RGB format, the quantitative value of images of different sizes were interpolated into 224×224 pixels by using bilinear technique. This step ensured that the dimensions of the images, or at least their aspect ratios, remained intact to reduce the chances of the model receiving images of an undesired size. It also retained the images qualifying for the MobileNetV2 model's input size.

The data were divided into training/validation and testing sets at a ratio of 70:30. The training/validation set was divided into training and validation sets at a ratio of 70:30. The models were built by the training set and assessed with the validation set to measure the performances of the models in terms of accuracy and then tested by the testing set to measure again and confirm the accuracy.

3.3. MobileNet-V2

MobileNetV2 is a mobile-oriented architecture exhibiting reduced complexity and size owing to its utilisation of depth-wise Separable Convolution. This design choice renders it well-suited for execution on devices possessing limited processing capabilities. The MobileNetV2 architecture extended the feature-extraction capabilities and incorporated a novel inverted residual structure. The model architecture comprises a convolutional layer followed by a succession of residual bottleneck layers. The kernel size for all spatial convolution operations is determined while utilising ReLU6 as the non-linearity function, in conjunction with batch normalisation and dropout techniques during the training phase. The bottleneck block has three layers: an initial (1 × 1) convolutional layer, a subsequent (3 × 3) depth-wise convolution layer stated above, and a final (1 × 1) convolutional layer without ReLU6 activation [27]. The MobileNetV2 model is currently widely utilised because of its exceptional ability to extract features and its compact size [37]. The Mobilenet-V2 model is a pre-trained model that has been developed specifically for the purpose of picture categorisation, as shown in Figure 3. Pre-trained models refer to deep neural networks that have undergone training using a substantial dataset of images. By utilising pre-trained models, developers are able to avoid the necessity for constructing and training neural networks from the ground up, resulting in time savings throughout the development process.

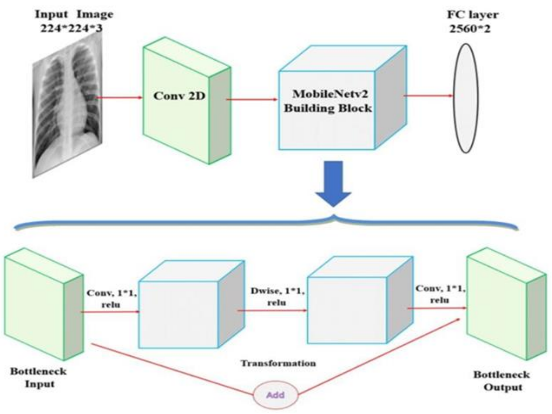

Fig. 3. MobileNetV2 architecture

MobileNetV2 expects images of 224 × 224 pixels with three colour channels. In other words, it expects an input of shape (224, 224, 3). You can pass multiple images at once to the model. This means that the input should actually consist of four dimensions, where the first dimension corresponds with the index of the image [27]. The output of MobileNetV2 is a probability distribution over a set of predefined classes. The number of output classes depends on the specific task for which the network was trained. If the model is designed to classify, for example, 1000 classes, then the output vector should have 1000 values, where each value represents its input image probability for a specific class [34]. Thus, the highest probability value is referred to the predicted class [37]. In summary, classification can be defined as the process of categorising observations for which the corresponding category has been determined using the knowledge obtained from a dataset.

Lastly, the MobileNetV2 model was modified by reducing the number of classes from 1000 to 3 in this research to classify the x-ray dataset into three classes; normal, ling opacity, and COVID-19. This deep-learning model is popular and widely used, primarily in mobile and resource-constrained environments. Owing to its effective design (i.e., speed and accuracy on mobile devices), it is recommended as a perfect choice to develop a mobile application for diagnosing lung diseases like COVID-19 [36].

3.4. Mobile Display

The progress in various technologies is massive. These technologies include integration with message platforms to improve the conventional access of the user interface to powerful computational capabilities. Specifically, this work introduced the integration of Telegram application (a popular messaging platform) with MATLAB software (an extensively used computational tool) by developing a Telegram bot. The main objective of this integration was to leverage data-processing capabilities and robust MATLAB algorithms to offer users with interactive and unified experience while executing complex analyses and computations. Several advantages were provided by this integration. Firstly, the integration of MATLAB and Telegram enabled users to interact with MATLAB functionality in the familiar messaging environment. The Telegram bot incorporated the MATLAB toolbox and extensive algorithm library to perform a wide range of statistics such as visualisation, machine learning, and data analysis Secondly, users who may not have experience or access to MATLAB can be a complex mathematical accessible and used just man. Thirdly, Telegram can provide a multi-purpose medium for sharing and communicating results. For example, users can easily add images, statistics, and other relevant information to the Telegram bot, which allows them to integrate seamlessly with MATLAB algorithms to use data sources, and images with all calculated results. The bot can then respond directly through the Telegram interface. Finally, the need to switch between different interfaces or applications to perform mathematical tasks was eliminated, thereby enhancing the user experience. The essential steps of our process of integrating MATLAB with a Telegram bot was explained in detail. Hosting the integrated system, connecting MATLAB to the Telegram platform, developing the MATLAB code to handle user interactions, utilising the MATLAB Telegram Bot Toolbox, and setting up the Telegram bot are the essential steps. We also explored the benefits, challenges, and potential applications of this integration, as well as provided examples and demonstrations to illustrate its functionality. However, the first step was the creation of a bot account and obtaining an API token for authenticating and communicating with the bot. A special bot called BotFather was the easiest way to create the Telegram bot.

3.4.1. Python–Telegram-Bot library

A Python wrapper for the Telegram Bot API is the Python–Telegram-Bot library. It offers a simple and suitable interface to interact with the Telegram Bot API and enables developers to create Telegram bots using Python. Conversely, the Telegram Bot API contains a collection of interfaces and techniques offered by Telegram to develop bots. These bots are exclusive Telegram accounts for interacting with users and automated tasks. By providing high-level classes and functions and then abstracting the underlying API details, this library simplifies the process of developing Telegram bots. Moreover, it provides an event-driven architecture for handling updates and user interactions. It also handled the communication with the Telegram Bot API.

We developed a Python code that interacted MATLAB with Telegram and can communicate with the Telegram Bot API, perform computations, processes command, and handle user interactions. This code set up the Telegram bot using the Python–Telegram-Bot library and the Telegram Bot API. Meanwhile, users can run a MATLAB script and send an image through the bot. The code overview is as follows:

- Importing Required Modules:

A module in Python language is defined as a file that involved the Python code (incorporating variables, functions, and classes). Other Python programmes can use it. The module is required to interact with the Telegram Bot API and to perform other operations.

- Configuring the Bot:

As mentioned earlier, the BotFather function creates the Telegram bot token, which is then assigned to the TOKEN variable. This token is required for authenticating and communicating the script with the Telegram Bot API.

- Handler Functions:

- The handler for the /start command is the start (update: Update, context: CallbackContext) function, which is triggered when the user sends the /start command to the bot. This function sends a welcome message to the user with the keyboard and creates a static keyboard with two buttons: ‘Run MATLAB Script’ and ‘Send a Picture’.

- The handler for the 'Run MATLAB Script' action is the test (update: Update, context: CallbackContext) function, which is triggered when the user clicks the 'Run MATLAB Script' button. This function runs a MATLAB command and sends a reply to the user, indicating that the MATLAB script is being executed.
- The handler for the 'Send a Picture' action is the save picture (update: Update, context: CallbackContext) function, which is triggered when the user sends a picture to the bot. This function checks if the 'images' folder exists or not. If no such folder exists, this function creates one. If the folder already exists, it removes its contents and creates a new folder. Then, it retrieves the highest resolution photo from the received photos array, downloads the photo as a byte array, and saves it with the filename set as the user's chat ID.
- The text_handler (update: Update, context: CallbackContext) function handles text messages received when the user clicks the buttons. If the received text message is 'Send a Picture', it sends a reply asking the user to send a picture. If the message is 'Run MATLAB Script', it calls the test () function.

• Running the Bot: The main () function is called when the script is executed, initiating the setup and execution of the Telegram bot. In the flowchart, the steps of programming code are presented. When the user sends /starts, the start function is run and by that, and then the bot sends a message welcoming the user. The user should choose an action from the handlers. If the user chooses to send a picture handler, the bot gives him excess to the pictures gallery to pick a picture, and then the programme receives the picture and saves it in the image folder. The run MATLAB script handler sends a message to the programme to run the function of running the MATLAB code.

3.4.2. Performance Measure

The validation curve helped evaluate the model's performance on unseen data during training. It measured the validation accuracy and loss, computed on a separate dataset called the validation set. The validation set contained examples that the model had not seen during training, allowing us to estimate its ability to generalise to new, unseen data. The validation accuracy represented the model's performance on the validation set, whereas the validation loss reflects the discrepancy between - 27 - predicted and actual values for the validation data. Monitoring the validation curve was critical to identifying overfitting or underfitting. The suggested network was trained with 50 epochs using mobileNetV2 and 2400 iterations with 48 iterations per epoch and 3 rounds of validation. After several epochs without validation accuracy increase, training was ended. Developers and academics can evaluate the deep-learning framework and mobile app for COVID-19 identification from CXR pictures by using these performance measures. The quantitative findings were promising and demonstrated the success of the suggested strategy, but the qualitative outcomes must be examined. Any segmentation technique should be compared against hand delineations to determine qualitative performance. Manual delineations needed domain expertise, making them difficult. It is complex and time consuming, so the manual ground-truth segmentation for the COVID-19 picture collection was tough to achieve. However, segmented results may be visually examined to assess performance. The suggested method segmented the X-ray image areas well. The extensive qualitative and quantitative research showed that the suggested technique outperformed most current approaches. The suggested strategy produced better segmented results than current methods, helping clinicians analyse suspected patients non-invasively. This technique can help undertake large testing with realistic segmented outputs to inhibit COVID-19's rapid spread. Image types may respond differently to a given technique [37]. The suggested system was assessed using average classification accuracy and confusion matrix.

4. Results

4.1. Results of Performance Measures

Accuracy or performance metrics are crucial measures for evaluating the effectiveness and reliability of a trained neural network, Performance metrics provide quantitative measures that quantify how well a neural network performs on specific tasks such as classification and object detection. These metrics serve as benchmarks for evaluating the quality of predictions made by the network and help in comparing different models or algorithms. One of the most fundamental performance metrics is accuracy, which measures the proportion of correct predictions made by the neural network over a given dataset. A notable deep-learning framework, MobileNetV2, was used in this work to develop a system with an average classification accuracy of 90.6% for COVID-19 detection.

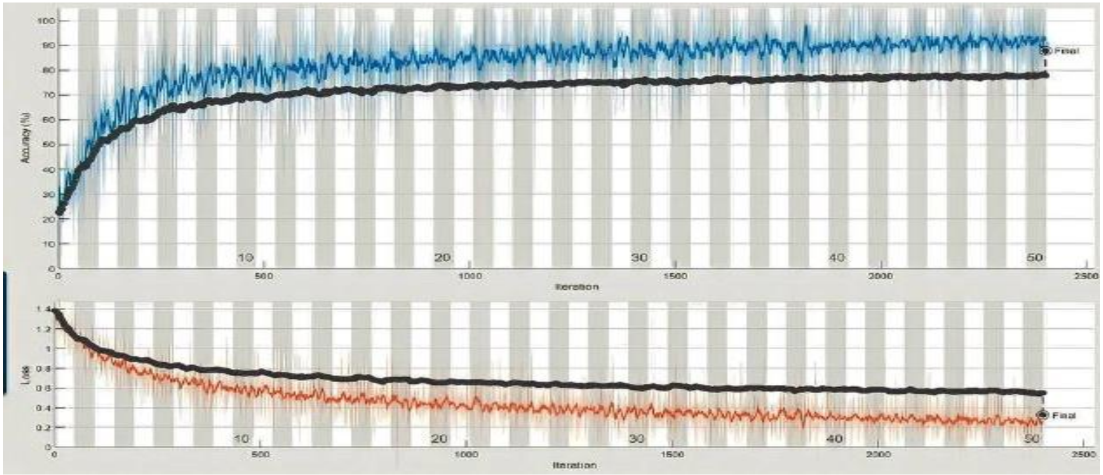

Fig. 4. Process of training the MobileNetV2

The proportion of accurate classifications produced by the MoibleNetV2 network is depicted in Figure 4. It shows normal, non-COVID lung opacity, and 983, 1720, and 196 of COVID-19, respectively. Additionally, COVID-19 was accurately identified with a non-COVID lung opacity of case 61 and a normal lung opacity of case 14, respectively. A total of 101 lung opacities were erroneously categorised as normal, whereas 90 non-COVID lung opacities were erroneously classified as COVID-19. Moreover, normal are accurately categorised with 12 and 23 are mistakenly labelled as COVID-19 and non-COVID lung opacity patients, respectively. The test was conducted by saving an X-ray image on the computer and then importing the image into MATLAB. Afterwards, we processed the image, such as resizing it to fit the network. Preprocessing was applied to the image based on MATLAB code, and then the specific test code was applied to display the results within seconds.

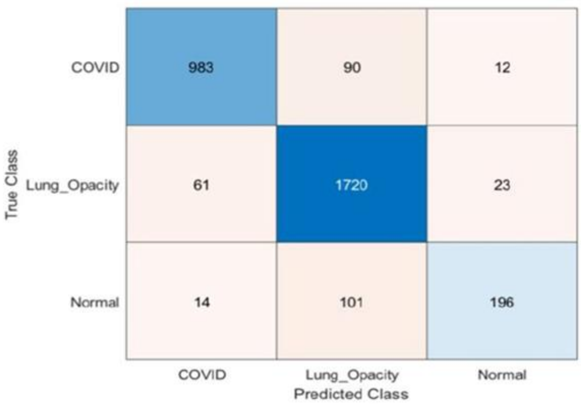

Fig. 5. Confusion matrix for normal subjects, lung opacity, and COVID-19 patients by using MobileNetV2.

Table 1 presents key performance metrics of the MobileNetV2 deep-learning model for detecting COVID-19 from CXR images, categorised into three classes: COVID-19, lung opacity, normal images. The analyses of precision levels showed that the developed model had high accuracy in defining true positive cases of disease detection with COVID-19 precision level reaching 92.91%. This finding indicated that the model reduced false positives, which is useful in the clinical context to reduce anxiety and further testing in patients.

The sensitivity, which showed the accuracy percentage of the proposed model for positive samples as COVID-19, was 90.6%. Thus, although the model worked, it did not catch every single case of COVID-19, which may leave some false negatives. This performance was crucial to eventual early detection, particularly in a pandemic setting that positively reacted to the timely identification of cases and subsequent containment.

Therefore, the model specificity, which was 96.45% for COVID-19, showed that normal cases are well differentiated from actual COVID-19 cases while reducing on the cases of false positives, where otherwise healthy people were incorrectly diagnosed. This is more so at a time that patients and healthcare providers needed to have confidence in diagnostic technologies.

The calculated accuracy of the model was 90.59%, indicating that the model produced almost accurate universal results for all classes. The F-measure of 91.74%, which was obtained in identification of COVID-19 compels the effectiveness of the proposed model as it combines both the precision and the recall.

Applying this model to a mobile application improved patient access to care because diagnoses can be made rapidly using the app without requiring complex laboratory support. Regarding the work's implementation of the model, the authors pointed out in the Abstract that the model supported quicker diagnosis and also reduced the pressure on healthcare facilities, indicating its usefulness in combating COVID-19.

Table 1,
Performance metrics of MobileNetV2 for COVID-19 detection from CXR Images.

Masseurs	COVID-19 (%)	Lung opacity (%)	Normal
Precision	92.91	90.01	84.85
Sensitivity	90.6	95.34	63.02
Specificity	96.45	86.32	98.79
Accuracy	90.59	90.59	90.59
F-measure	91.74	92.6	72.32

4.2 Results of testing the network

The test was conducted by saving an X-ray image on the computer and then importing the image into MATLAB (Figures 6, 7 and 8). Afterwards, we processed the image, such as resizing it to fit the network. The image was preprocessed based on MATLAB code, and then the specific test code was applied to display the results within seconds.

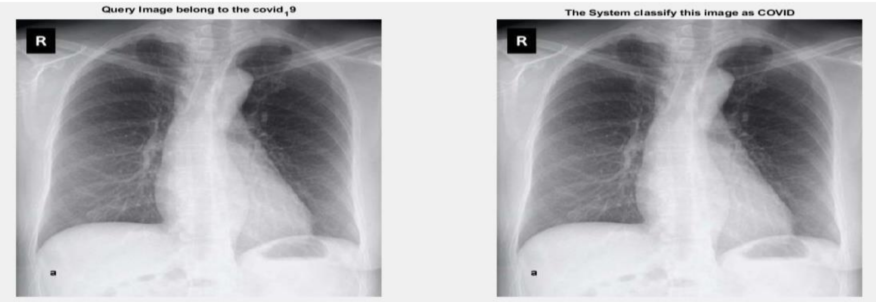

Fig. 6. Result of covid-19 CXR test.

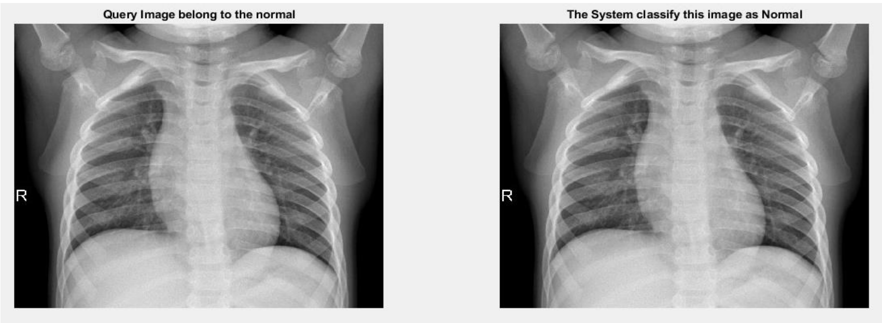

Fig. 7. Result of normal CXR test

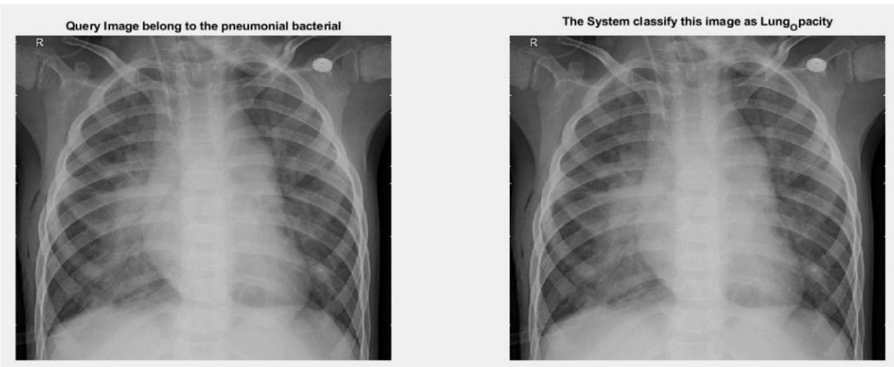

Fig. 8 Result of pneumonia bacterial CXR test

4.3 Mobile-display results

The test was conducted by accessing the Telegram bot and clicking on 'Start'. Then, a welcoming message appeared, and the desired CXR image for testing can be sent. A message was received from the bot confirming that the image had been received. The phrase 'run MATLAB script' was typed to automatically execute the test code in MATLAB. The test result was sent as a text message in the bot within a few seconds.

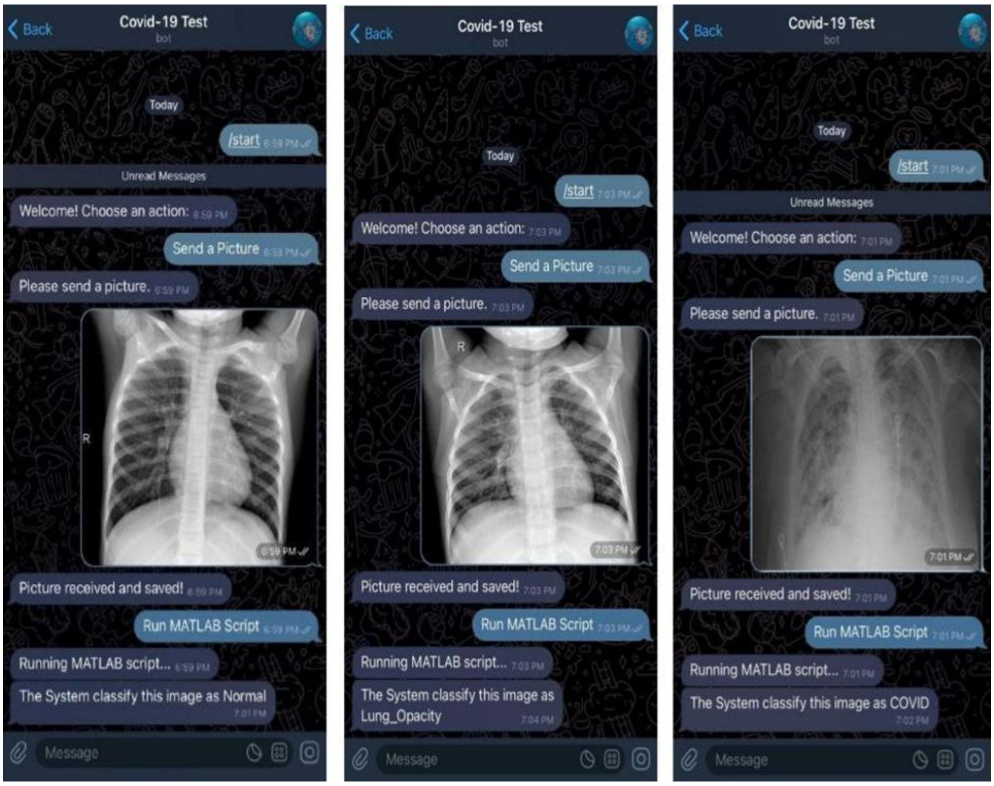

Fig. 9. Mobile-display results of three different CXR cases

Through COVID-19 diagnosis from CXR by using deep-learning algorithms via a mobile application, we focused on the acquisition and preprocessing of the dataset. The list had three categories: COPD, normal, and lung opacity. We firstly collected a set of CXR images superimposed by the categories. Data collection played an important role in training our deep-learning model to accurately classify X-ray images. Secondly, after obtaining the dataset, we performed preprocessing steps to ensure that our chosen deep-learning model was compatible with MobileNetV2. The acquired X-ray images were initially greyscale. However, given that MobileNetV2 was designed to work with RGB images, we had to convert greyscale images into RGB format. These changes allowed us to use the full capabilities of the MobileNetV2 framework for our distribution project.

5. Conclusion

COVID-19 infection is likely to cause persistent lung damage, which can lead to death. This study aimed to classify CXR images into COVID-19, non-COVID-19 lung opacity, and normal control. COVID-19 detection was conducted utilising MobileNetV2 deep-learning models because it was critical to detect COVID-19, which spreads rapidly and internationally.

Numerous researchers have used AI-based X-ray image processing to detect COVID-19. Various approaches, new network designs, and ensemble solutions were proposed for improving COVID-19, normal, and other lung-disease classification. Goldstein et al. [26] identified COVID-19 by using a pre-trained deep-learning network (ResNet50) that achieved 89.7% accuracy and 87.1% sensitivity. Wang and Wong [38] achieved 83.5% accuracy by using COVID-Net, a deep CNN.

Furthermore, Motamed et al. [27] suggested a randomised generative adversarial network that detected COVID-19 images from known and labelled classes (normal and viral pneumonia) without labels or training data from the unknown class, with an AUC of 0.77.

One of the innovative characteristics of the proposed approach was subjecting the photographs to preprocessing. Preprocessing procedures can extract more features efficiently from image data. The stacking approach involved superimposing each pixel of equivalent images and increasing the pixels with low efficiency. The proposed technique resulted in the development of an efficient mobile application for COVID-19 detection based on the MobileNetV2 model. The model was designed to provide faster and more accurate results. We also illustrated the applicability of our approach to smart mobile devices with the MobileNetV2 model, which can be examined on mobile devices without the use of any hospital devices.

In conclusion, our COVID-19 detection method outperformed those reported in recent literature for COVID-19 and other lung infection detection. The classification of COVID-19 data, opacity lung disease, and normal pictures yielded a precision of 92.91%, sensitivity of 90.6, and specificity of 96.45%, accuracy of 90.6%, and F-measure of 91.74% for COVID-19 detection. A detailed investigation of CXR image-enhancement techniques for COVID-19 detection was provided, and the results were reliable and generalisable because training and validation were conducted on a large dataset. This study had certain limitations. Firstly, we included a large dataset of over 18000 images, but it may not fully represent COVID-19 populations worldwide, including age, gender, ethnicity, and comorbidities. The model may not be generalisable across demographic groups. Secondly, the quality of CXR pictures can also vary depending on the imaging device, patient posture, and artifacts, which can affect model accuracy. In real-world applications, this variability may influence model resilience. Thirdly, this study focused on immediate detection. Thus, future work should evaluate the model's potential to detect long-term COVID-19 lung injury.

In future investigations, deep-learning-based analyses will be performed utilising data images of other organs impacted by the virus according to COVID-19 experts. We intend to develop a future approach using various organising strategies to improve the datasets. As data on the factors influencing the virus in human chemistry (e.g., blood group, RNA sequencing, age, gender, etc.) become accessible, we will conduct a solution-oriented study with AI.

Overall, our research showed that X-ray devices can depict pictorially which portions of input data such as images shaped the outcomes of the model. This can help various individuals understand why the model arrived at the given results. Even after applying preprocessing to lessen its impact on the final decision, the significance of MobileNet features became evident. It can help doctors determine how accurate the model's outputs are or how reliable the software is. In this scenario, the application interface's final visualisation tools for determining the final choice based on the models is enhanced. The beneficial effects include safety and non-invasiveness for users, as well as improved decision making for doctors by providing statements with more background information. All these factors indicate the high potential of our app for testing and as an easily available, open platform for the doctors.

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اكتشاف COVID-19 من الأشعة السينية للصدر باستخدام إطار عمل التعلم العميق عبر تطبيق الهاتف المحمول

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المستخلص

يصاب المرضى المصابون بفيروس كوفيد-19 بالتهاب رئوي حاد، مما يؤدي عادةً إلى الوفاة. أظهرت البيانات الإشعاعية أن المرض ينطوي على اصابة الرئة الخلالي، وعتامة الرئة، وعتامة الزجاج الأرضي الثنائية، والعتامة غير المكتملة. تهدف هذه الدراسة إلى تحسين تشخيص COVID-19 من خلال تحليل صور الأشعة السينية للصدر الإشعاعي (CXR)، مما يساهم بشكل كبير في تطوير تطبيق الهاتف المحمول الذي يحدد COVID-19 بكفاءة، ويوفر على المهنيين الطبيين الوقت والموارد ويسمح بالتدخلات الوقائية في الوقت المناسب باستخدام أكثر من 1800 CXR صور الرئة مع شبكة CNN العصبية MobileNetV2. يتم تقييم أداء نموذج التعلم العميق MobileNetV2 باستخدام الدقة والحساسية والخصوصية والدقة وقياس F لتصنيف صور CXR إلى COVID-19، وعتامة الرئة غير COVID-19، والطبيعي. أظهرت نتائج هذه الدراسة دقة 92.91٪، وحساسية 90.6، وخصوصية 96.45٪، ودقة 90.6٪، ومقياس F 91.74٪ في اكتشاف COVID-19. في الواقع، يمكن لنموذج CNN المقترح للتعلم العميق MobileNetV2 تحسين أداء التصنيف من خلال تقليل الوقت المطلوب لجمع نتائج كل صورة لتطبيق الهاتف المحمول.