ISSN: 2584-0495 Vol. 2, Issue 4, pp. 767-775

International Journal of Microsystems and IoT

ISSN: (Online) Journal homepage: https://www.ijmit.org

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Cite as: Rajalakshmi, R., & Kumar, T. (2024). Corona-Virus Detection Using Web Management Platform for CT scans. International Journal of Microsystems and IoT, 2(4), 767-775. https://doi.org/10.5281/zenodo.12200812

Published online: 22 April 2024

DOI: https://doi.org/10.5281/zenodo.12200812

International Journal of Microsystems and IoT
Vol. 2, Issue 4, pp. 767-775; DOI: https://doi.org/10.5281/zenodo.12200812

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Corona-Virus Detection Using Web Management Platform for CT scans

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ABSTRACT
Disease spreads from viruses, like COVID-19, stem from agents like SARS-CoV-2. Common symptoms associated with this virus include fever, cough, indigestion, muscle pain, and fatigue. Across many nations, the RT-PCR test stands out as the predominant molecular test employed for tracking virus transmission. There is, however, a long processing time, and the ingredients are in short supply. This work proposes to use chest CT scan images as input to identify patients with COVID-19 by utilizing a deep neural network architecture. The stages like feature extraction, where the features of the picture are extracted using a pre-trained model called VGG16. The second phase in which a multilayer neural network classifies the image based on its COVID classification and NO COVID classification. Implementing a Web platform that makes our architecture easy for interested people to understand, access, and use. Using Python libraries for neural network design, the deep learning algorithm was implemented.

KEYWORDS
Artificial Intelligence (AI); Convolution Neural Networks (CNN's); COVID-19; Deep Learning Algorithm; Neural Network Design; Under-Fitting and Over-Fitting; X-ray Chest Images

1. INTRODUCTION

The most widely used evaluation metric in predictive analysis is when a model is applied to a dataset, its overall performance is represented as N×N matrix, and in the scenario of a classification task, N denotes the count of distinct class labels assigned to various categories [1]. The only effective method of protecting humans from COVID-19, as there are currently no vaccinations or treatments, is to stop the viruses spread through early population testing and isolation of affected people.

This infection can be diagnosed by a chest CT scan in conjunction with specific health signs. Radiologists can use a chest CT scan as a visual sign of corona-virus infection. This resulted in-creation of several deep learning models, and experiments indicate that there is a high probability of accurately identifying COVID-19-positive patients using chest radiography pictures [2].

The efficiency of generalization is proportional to the size of the labeled data since CNNs' huge number of parameters make them susceptible to overfitting on short datasets [3]. Small datasets pose the greatest obstacle in the field of the medical imaging due to their limited quantity and a variety of samples. Researchers and radiologists must take part in the time-consuming and a costly process of gathering medical images.

Furthermore, it is challenging to collect enough data from the chest CT scan (CXR) pictures because to the current COVID-19 outbreak. This proposal is to use synthetic data augmentation to mitigate the shortcomings.

The training dataset is artificially expanded through the use of data augmentation techniques. Present-day data augmentation methods add affinity through straightforward alterations like scaling, flipping, converting, enhancing contrast or brightness, sharpening and blurring, white balancing, and so on. This traditional data augmentation method is simple, dependable, and quick. However, the changes are limited because the purpose of this augmentation is to convert an existing sample into a slightly modified sample. Put otherwise, traditional data augmentation does not generate entirely hidden data. Synthetic data augmentation is a cutting-edge, contemporary type of augmentation that gets around the drawbacks of traditional data augmentation [4]. The World Health Organization provided a range of quick and thorough diagnostic tests for COVID-19 identification, such as Cobas SARSCoV-2 for use with Cobas 6800/8800 systems and Genesis RTPCR Coronavirus (COVID-19) testing. While the COVID-19 tests can be costly and time-consuming, CNN can be a major factor in automatically identifying positive patients. What can ultimately save a life by saving money and time? Furthermore, as no existing test can guarantee 100% accuracy, it can provide an additional layer of validation. To reiterate prefer to use the preferred model as a triage tool to determine whether a patient with SARI is suitable to undertake the test for COVID-19 infection rather than as a replacement for the traditional diagnostic testing for COVID-19 infection.

2. LITERATURE SURVEY

S. Yadav and R. Kumar, "RT-PCR Result Based Covid-19 Prediction Using Voting Classification Approach," 2021. The ongoing global health crisis stemming from addition to creating enormous obstacles, and society's socioeconomic conditions [5]. Efficient and perfect identification and tracking of COVID-19 patients is essential to handling this crisis and allowing for prompt decisions about their care and treatment.

Studies are being conducted to provide rapid substitutes or enhancements for RT-PCR techniques. When compared to the above study, this paper quickly tests patients for COVID-19. This work focuses on building effective deep learning models using pictures from the chest CT scans. Using publicly available adult COVID-19 patient PA chest CT scan pictures, artificial intelligence (AI)-based classification algorithms covering a range of serious viral illnesses were trained. This approach surpasses the effectiveness of previously published methods, marking a significant advancement towards implementing AI-based solutions for biomedical imaging classification challenges related to COVID-19.

Hira, S., Bai, A. & Hira, S. (2021) "Automated Detection of Covid-19 Disease from Chest X-ray Images Using CNN Architecture", (2021), [6]. The COVID-19 has swiftly spread, impacting approximately 215 countries, with reported cases reaching around 11,274,600 worldwide, according to the World Health Organization. The escalating daily caseload is placing an overwhelming burden on hospitals, highlighting the challenge of managing the spread of COVID-19 with limited resources. Comparatively this study underscores the critical need for a precise diagnosis of COVID-19, emphasizing the paramount importance of early detection to curb the disease's transmission. The study introduces a strategy focused on deep learning that is intended to distinguish COVID-19 patients from those suffering from bacterial pneumonia, viral pneumonia, and normal cases.

A study of Liu, Y., Lee, J.M. & Lee, C, "The challenges and opportunities of a global health crisis: the management and business implications of COVID-19 from an Asian perspective", 2020, [7]. In this, the international health system will bounce back swiftly, and governments, business, and science including social science will work together to revitalize the global economy.

A. Thyagachandran, et al., (2023), "Identification and Severity Assessment of COVID-19 Using Lung CT Scans", [8]. The driving force behind this scientific study originates from the limited availability of datasets for COVID-19, particularly in the domain of chest CT scan images. The methodology involves aggregating the existing COVID-19 images available up to the research period and leveraging GAN networks to generate additional images, thereby improving the accuracy of virus detection in the available CT scans.

B. Xiao et al., (2022), "PAM-DenseNet: A Deep Convolutional Neural Network for Computer-Aided COVID-19 Diagnosis", [9]. Three deep transfer models AlexNet, GoogLeNet, and ResNet18 are chosen for examination due to their architecture featuring a modest number of layers, thereby reducing complexity, memory usage, and execution time for the proposed model.

3. MATERIALS AND METHODS

The process of defining a system's interface, modules, and data in order to specify the needs that must be met is known as system design. One way to think of system design is as the system theory applied [10]. The primary goal of system design is to create the system architecture by providing the data and knowledge required for system implementation as seen in below Figure 1.

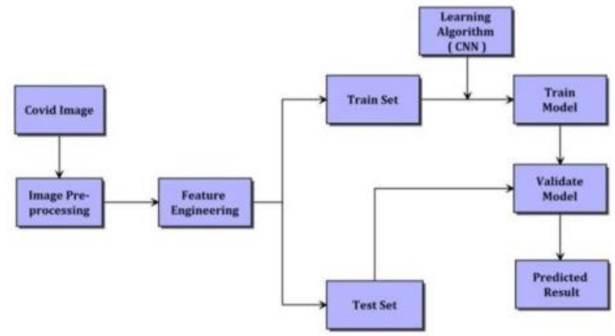

Fig. 1 Proposed System Implementation [10]

3.1 Dataset Preparation and Data Pre-processing

The cornerstone of any deep learning project lies in its data. The subsequent phase of project implementation is intricate and encompasses the meticulous selection, preparation, and manipulation of data [11]. Each of these stages can be further dissected into various steps as seen in Figure 3.

3.1.1 Data Collection

Chest CT scan pictures used in this investigation were gathered from several publicly available databases, websites, and published publications.

Chest CT scan pictures taken in the poster-anterior (PA) orientation. There are 668 chest CT scan photos of patients without a Covid-19 infection and 1155 CT scan pictures of infected individuals' chests. As a result, the dataset contains 1823 images [12].

Patients with a Covid-19 infection have been assigned a label of 1 on their chest CT scan images, while those without a Covid-19 infection have been assigned a label of 0.

There are two categories in this dataset and details about the dataset are:

a) Covid
b) Normal

3.1.1.1 Covid

There are 3,615 photos in all in the Covid data. It shows 183 CXR photos from a German medical school and 2,473 CXR images from the pad-chest dataset are gathered. 400 CXR photos from another GitHub source, and 559 CXR images from GitHub, Tweeter, Kaggle, and SIRM.

3.1.1.2 Normal

The 10,192 photos that make up the Normal data were taken from two distinct datasets. It uses RSNA 8851, Kaggle 1341.

It's time for a data analyst to take charge and steer the team towards the deployment of deep learning. In Figure 2, finding methods and resources for gathering thorough and pertinent data, analyzing it using statistical methods, and reporting findings are the duties of a data analyst.

Fig. 2 Front End Module Diagram [13]

Depending on what you hope to forecast, the type of data may vary.

Determining the exact amount of data required for the machine learning problems is subjective, as each problem possesses unique characteristics [13]. The selection of attributes by data scientists during the construction of a predictive model hinges on the predictive value inherent in those attributes.

While adopting a 'the more, the better' mindset is a reasonable approach during this phase, a proposition put forth by some data scientists suggests that less than one-third of the gathered data might ultimately prove to be valuable.

The challenge lies in predicting which portion of the data will contribute most effectively to accurate results, a task that becomes clearer as model training commences [14]. Therefore, it is crucial to gather and store all types of data, whether internal or open, structured or unstructured.

The tools employed for collecting internal data vary based on industry and business infrastructure. For instance, businesses operating exclusively online aiming to launch a personalization campaign can explore web analytic tools such as Mix panel, Hotjar, Crazy Egg, as well as well-established options like Google Analytics. Additionally, web log files serve as a valuable source of internal data, storing information about user behavior online, including details like time and duration of visits, viewed pages or objects, and user location [15].

3.2 Data Pre-processing

The process of transforming raw data converted into a machine learning-friendly format. When the data is clean and well-organized, a data scientist can apply an applied machine learning model to get more precise results. Sampling, formatting, and data cleaning are all steps in the process.

3.2.1 *Data Formatting*

A data scientist's top goal is to standardize record formats. An expert verifies that variables that correspond to each attribute are recorded consistently. Variables include things like product and service titles, prices, date formats, and addresses [16].

3.2.2 *Data Cleaning*

Data discrepancies can be fixed and noise can be eliminated using this set of techniques. An expert also finds observations known as outliers, which differ noticeably from the remainder of the distribution. A data scientist removes or amends the data if an outlier suggests that it contains errors.

3.2.3 *Data anonymization*

A data scientist may need to remove or anonymize characteristics that contain sensitive information, such as when working with banking and healthcare data.

3.2.4 *Data sampling*

The analysis of large datasets takes longer and requires more processing power. If a data set is too large, the best course of action is to apply data sampling [17]. A data scientist can select a more manageable yet representative sample of data to work with by applying this strategy. allowing for faster model building and execution while maintaining accuracy.

3.3 Image Pre-processing

The manipulation of digital images through computer algorithms done by digital image processing. Positioned as a branch of digital signal processing, digital image processing surpasses analogue image processing in several aspects. The objective of digital image processing is to enhance image data (features) by mitigating undesirable distortions and/or amplifying crucial image features [18]. This improvement enables AI-computer vision models to derive greater benefit from the refined data, enabling the application of a broader spectrum of algorithms to the input data.

a) Read Images: This stage involves after setting and putting the path to picture dataset in a variable allows us to import photos from folders into arrays using a process.
b) Resize Image: In this phase, two methods are creating for showcasing photos: one designed to display a single image and another tailored for presenting two images to visualize any changes. Following that, construct a function named "processing" that takes the photos as input. Here, by performing a resize since not all of the images that are supplied into AI algorithms have the same size. This is because some of the photographs that are taken with a camera and fed into AI system have different sizes.

3.4 Data Augmentation

To build a new augmented data set, rotate and mirror the photos. Data augmentation, as used in data analysis, describes methods for generating new synthetic data from existing data or adding slightly altered copies of the current data in order to increase the quantity of data [19]. It serves as a regularize and reduces overfitting during machine learning model training. By altering the photos' height, rotation, horizontal flip, and breadth during the augmentation process.

3.5 Data Splitting

Training, test, and validation sets are three subsets into which a data-set used for machine learning should be divided [20].

3.5.1 The Training Set

A data scientist trains a model and defines the optimal parameters that the model should learn from the training set.

3.5.2 The Test Set

This is essential to evaluate the trained model's ability to generalize. The latter refers to a model's capacity, after training over training data, to spot patterns in fresh, unknown data. Using distinct subsets for training and testing is essential to prevent model over-fitting, which leads to the previously discussed inability to generalize.

3.6 Modeling

A data scientist trains a number of models at this step-in order to determine which one produces the most accurate predictions [21].

3.6.1 Model Training

With this small collection of photos, it's time to train the model. Transfer learning is really simple to employ with the variety of architecture that fast.ai offers.

a) To construct a convolution neural network (CNN) model, opt for the efficiency and accuracy of pre-trained models that prove effective across various applications and datasets. In this instance, choose the ResNet architecture, specifically resnet18, where the numerical suffix indicates the actual number of layers within the neural network.
b) To assess the model's predictive quality using the validation set from the data loader, and incorporate the metric parameter, with the selected metric being error rate. This metric provides insights into the frequency of incorrect predictions made by the model.
c) The finetune method employed here is analogous to the fit() method found in the machine learning libraries. To commence training the model, which need to specify the number of epochs, representing the iterations during which the model learns from each image.
d) CNN, a neural network type widely utilized for image recognition and classification, operates on supervised learning principles. The CNN architecture comprises filters or neurons equipped with biases and weights. These filters take inputs, perform convolutions, and contribute to the four layers of the CNN classifier [22].
e) Convolutional layer: This layer extracts the characteristics of the applied picture. The neurons convolve the input picture to produce an output image with a feature map, which is then fed into the next convolutional layer.
f) Pooling layer: With the use of this layer, the feature map's dimensions can be reduced while keeping all of its significant features. Typically, two convolutional layers are positioned before this layer.
g) ReLU layer: This is a non-linear operation that adds zero to each of the feature map's negative values. It is an operation based on elements.
h) Fully Connected layer: FCL denotes a link between each filter in the layer above and each filter in the layer below. In accordance with the training dataset, this is utilised to classify the input image into several groups.

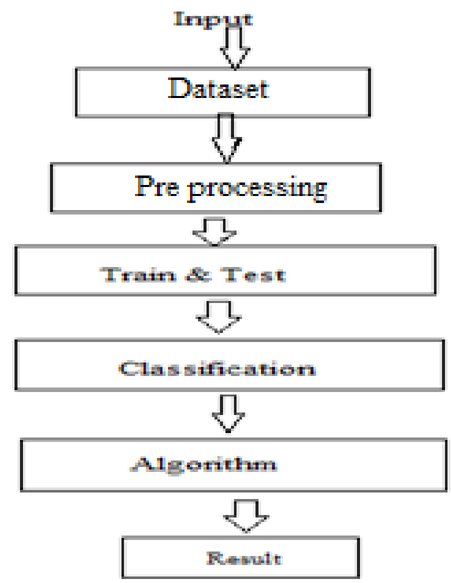

Fig. 3 Back End Module Diagram [22]

Algorithms for machine learning are essential for building models. In the instance of this project, convolution neural networks were used. Model training is the next step after model construction. In this case, training data and the anticipated output for the data are used to train the model. Conducting model testing is feasible once the model has been trained. A second set of data is loaded in this phase. Since the model has never seen this data set, its actual correctness will be confirmed. The saved model can be put to use in real life once the model training is finished. This stage is called "model evaluation".

3.7 VGG16 model

In Fig. 4, transfer learning broadly refers to a technique wherein a model initially trained on a specific problem is leveraged in some capacity for a second, related problem. In the realm of deep learning, transfer learning involves training a neural network model on a task closely related to the problem at hand. Subsequently, one or more layers from the pre-trained model are incorporated into a new model, which is then trained specifically for the target problem.

One notable advantage of transfer learning lies in its ability to significantly reducing inverse relationship between training duration and generalization error is seen for neural network models. The weights in recycled layers function as an initial starting point for the training process, allowing for fine-tuning to adapt to the nuances of the new problem. In Figure 4, this approach views transfer learning as a form of weight initialization scheme, particularly beneficial when the initial related problem boasts a more extensive labelled dataset than the problem of interest. This becomes particularly advantageous when there exists a structural similarity between two problems, allowing the knowledge gained from the first task to be effectively applied in the context of the second task.

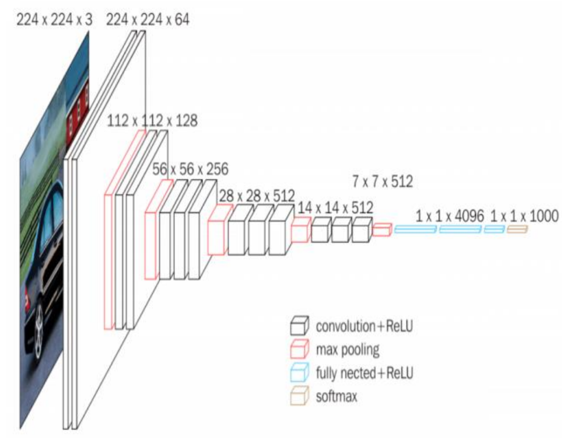

Fig. 4 VGG 16 [25]

In 2014, the convolution neural network (CNN) model VGG16 proved its prowess by securing victory in the ILSVR (Image-net) competition, establishing itself as one of the most advanced vision model architectures. VGG16's noteworthy characteristic lies in its consistent use of the same padding and a max pool layer featuring a 2x2 filter with a stride of 2. Rather than relying on an abundance of hyper-parameters, VGG16 focuses on employing convolution layers with a 3x3 filter and a stride of 1 throughout the entire model [25, 26, 27]. The model concludes with a soft-max output, succeeded by two fully connected (FC) layers. The designation "16" in VGG16 signifies the presence of 16 weighted layers in the model, which boasts approximately 138 million parameters, rendering it considerably large.

3.8 Performance Metrics

The dataset was split into two segments: a training subset, which encompassed 70% of the total data, and a testing subset, which constituted the remaining 30%. Using En-thought Canopy, these two algorithms were run on the same data-set, and outcomes were shown.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{P} + \text{N}) \qquad (1)$$

The primary evaluation criterion employed in this work was prediction accuracy as seen in Figure 5. In the Equation (1), it can be used to defy accuracy. The algorithm's overall success rate is its accuracy.

3.9 Confusion Matrix

Its ease of comprehension and its ability to calculate other crucial metrics like Accuracy, recall, precision, among others, contribute to making it the most extensively employed set of evaluation metrics in predictive analysis. An NxN matrix is used to see how a model performs overall when applied to a given data collection. N is the total number of class labels required to complete the categorization operation.

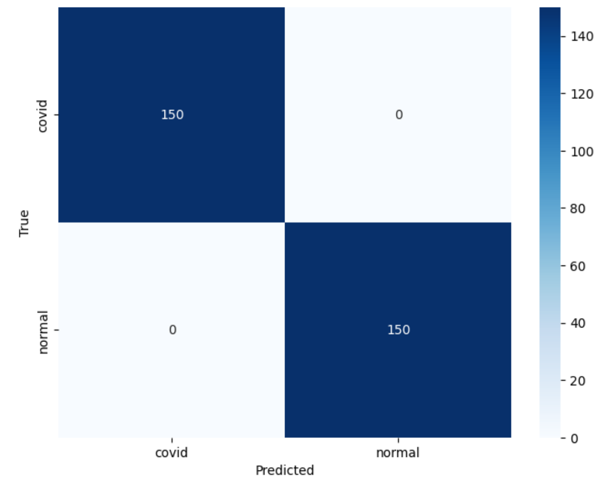

Fig. 5 Prediction Accuracy Rate [28]

The table displays the frequencies of True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP) instances predicted by all algorithms. True Positive (TP) signifies that the positive class is correctly predicted as positive, reflecting the instances where the model accurately identified positive class samples [28].

a) Conversely, False Negative (FN) denotes cases where the positive class is inaccurately predicted as negative, indicating instances where the model failed to recognize positive class samples.
b) False Positive (FP) corresponds to situations where the negative class is erroneously predicted as positive, representing instances where the model incorrectly identified negative class samples as positive.
c) True Negative (TN) indicates correct predictions of the negative class as negative, reflecting instances where the model accurately recognized negative class samples.

3.10 Simulation Tools

These are essential for training and testing machine learning models used in COVID detection from chest X-ray images. Some notable simulation tools include:

a) Python Libraries: Libraries like TensorFlow, PyTorch, and scikit-learn provide tools for developing and training machine learning models. They offer various functions for data preprocessing, model building, training, and evaluation.
b) Medical Image Analysis Frameworks: Frameworks such as MONAI (Medical Open Network for AI) provide specialized tools for medical image analysis, including pre-processing, augmentation, and evaluation specific to medical images like X-rays.
c) Simulation Environments: Platforms like Google Colab, Kaggle, and various cloud-based services offer free or affordable environments for running simulations and training machine learning models on large datasets.

3.11 Hardware

Efficient hardware accelerates the training and inference processes, enabling faster development and deployment of COVID detection systems. Hardware options include:

a) Graphics Processing Units (GPUs): GPUs excel at parallel processing and are well-suited for training deep learning models on large datasets. They significantly speed up model training compared to traditional CPUs.
b) Tensor Processing Units (TPUs): TPUs, developed by Google, are specialized hardware accelerators designed specifically for machine learning workloads. They offer even faster training speeds than GPUs in many cases.
c) Cloud-based Solutions: Cloud service providers like AWS, Google Cloud Platform, and Microsoft Azure offer access to powerful GPU and TPU instances on a pay-as-you-go basis, enabling researchers to scale up their computational resources as needed without investing in expensive hardware infrastructure.

Combining simulation tools with suitable hardware accelerators can greatly facilitate the development and optimization of accurate COVID detection models using chest X-ray images.

4. RESULTS AND DISCUSSION

In Figure 6, information is provided regarding the total number of COVID cases and non- COVID cases, with 69 instances of COVID cases and 25 instances of non- COVID cases. However, this data-set is deemed inadequate for ensuring accurate training and testing of the model. To achieve accurate model training and testing, it is essential to have a nearly equal number of datasets for both COVID and non- COVID cases [29]. Failure to balance the data-set may lead to issues such as under-fitting and over-fitting.

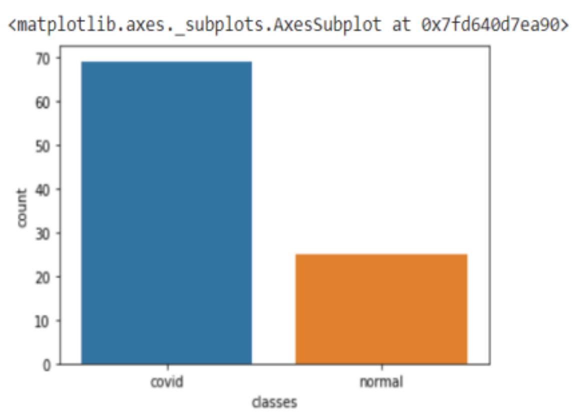

Fig. 6 Covid And Non-Covid Cases Prediction [29]

The problem occurs then will get the result in-accurately. To solve the problems to train and test with almost a equal number of Covid and non-Covid dataset. Then only will get accurate result. And solve problems like overfitting and underfitting.

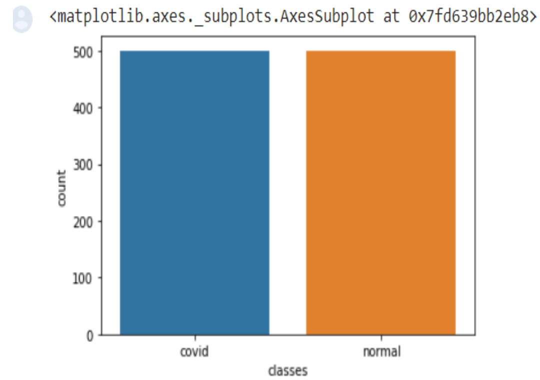

Fig. 7 Covid and Non-Covid Cases Prediction Using Re-Sampling Technique [20]

In Figure 7, solve the problem by using a resampling technique are making a equal number of datasets for both Covid cases as well as non-Covid cases. So that we will have balanced dataset of both Covid as well as non-Covid cases. There will be no in-balance in the dataset after resampling, are taking equal number of datasets which is 500 Covid case dataset and 500 non-Covid dataset and train and test the model. In this case thus can expect accurate results.

In Figure 8, out of 1000 dataset, have used 700 datasets for training and 300 for testing. i.e., 30% of the dataset is utilized for testing and 70% of the dataset for training. Here using the CNN method for training. There are 300 datasets in all, of which 150 are Covid and the remaining 150 are not. These 300 datasets are used for testing.

Out of 1000 dataset, have used 700 datasets for training and 300 for testing. Here, 70% of dataset is used for training and 30%of dataset is used for testing. Here, trained using VGG 16 algorithm as seen in above Figure 9. Here total 300 dataset is present in which 150 datasets are Covid and the remaining 150 datasets are non-Covid or normal cases. These 300 datasets is used for testing.

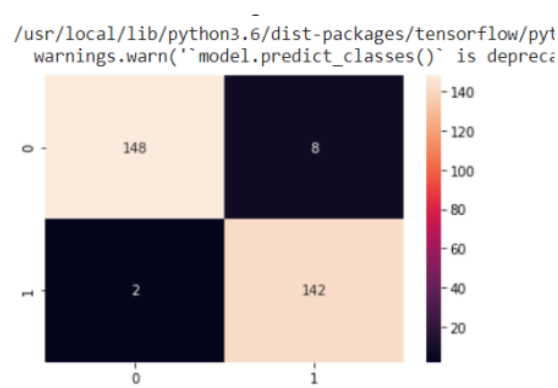

Fig. 8 Prediction Using CNN Algorithm [30]

Out of 150 Covid cases the computer able to predicate 148 Covid cases correctly and remaining 2 Covid cases, it has predicated wrongly. Additionally, the computer was able to properly predict 91 out of 150 normal cases, mis predicting the remaining 59 normal cases and use confusion matrix to represent the output by using CNN algorithm [30], are able get

80 % accuracy.

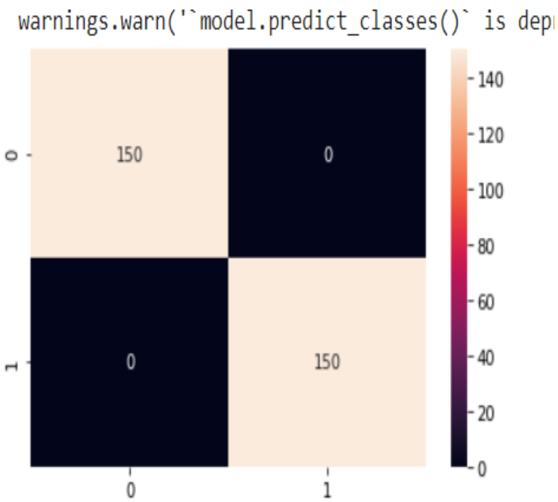

Fig. 9 Prediction Using VGG16 [23]

Out of 150 Covid cases the computer able to predicate 150 Covid cases correctly. Out of 150 normal cases the computer able to predicate 150 normal cases correctly and does not predicate anything wrongly. By using the confusion matrix to represent the output by using VGG16 algorithm are able get 100 % accuracy. CNN and Vgg16 algorithm are used to implement this model. Using these two algorithms can compare the accuracy of each algorithm as shown in Figure 10 and Figure 11.

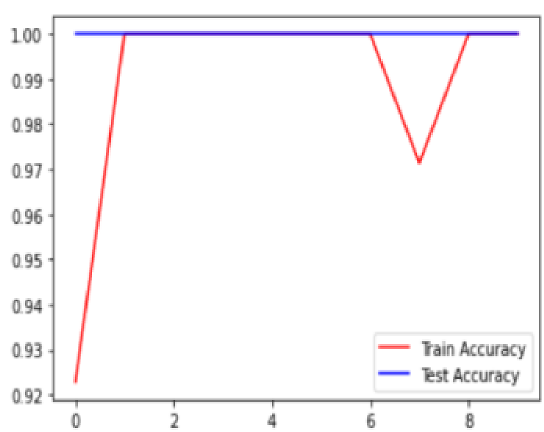

Fig. 10 Training and Testing Accuracy Using VGG16 Algorithm [24]

The above graph represents the test accuracy and train accuracy of vgg16 algorithm.

In the below graph, which represent the test accuracy and train accuracy of CNN algorithm. The web development platform for COVID-19 detection based on X-ray chest images has demonstrated promising results in the quest for early and accurate identification of the virus. This section discusses the key findings, implications, and future considerations stemming from efforts.

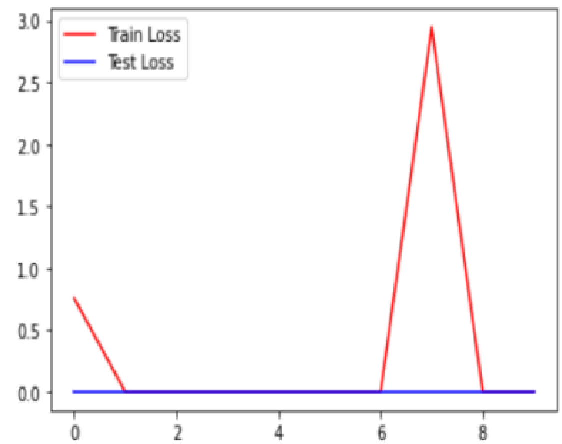

Fig. 11 Training and Testing Accuracy Using CNN Algorithm [27]

a) Interpretation of Results: A platform has exhibited a commendable accuracy in detecting COVID-19 from X-ray images. The algorithm successfully identifies characteristic patterns associated with the virus, showcasing its potential as a valuable diagnostic tool. For CNN 98% accuracy and for vgg16 algorithm getting 100% accuracy.

Table. 1 Comparison Between Existing And Proposed Work

S. No	PROPOSED	EXISTING	DOI NO
1	Using the same CNN and vgg16 algorithm but in this accuracy is more and getting 98% of accuracy for cnn and vgg16 100% of accuracy.	Algorithm is used are CNN and vgg16. The accuracy is 94% for CNN and 97 percentage for vgg16.	10.1109/ICAIS50930.2021.9395851
2	Algorithms using here are very good at deep understanding and recognizing of patterns of the dataset, which will not predicate other diseases or wrong results instead of Covid 19.	The algorithms are not that efficient in deep understanding and recognizing of patterns of the dataset, which may predicate other diseases or a wrong result instead of Covid 19.	10.1007/s10489-020-01902-1

The above Table 1, shows the comparison and accuracy between the proposed and existing research of the papers [23,24].

b) Comparison with Existing Methods: Comparing platform with traditional diagnostic methods, such as RT-PCR, reveals its efficiency in providing rapid and accessible results. The speed and accessibility make it particularly beneficial in scenarios where timely detection is crucial for effective containment. This model provides more accuracy than existing models.

c) Practical Implications: The practical implications of this platform extend beyond its diagnostic capabilities. By providing a user-friendly web interface, to ensure accessibility for healthcare professionals, even in resource-constrained environments. This aligns with the global imperative of widespread testing.

d) Integration with Healthcare Systems: To maximize the impact of this platform, seamless integration with existing healthcare systems is crucial. This could streamline the diagnostic process, allowing for real-time collaboration between medical professionals and the platform.

e) Ethical Considerations: As with any diagnostic tool, ethical considerations must be addressed. Ensuring patient privacy, obtaining informed consent, and establishing guidelines for the ethical use of the platform are paramount.

f) Accessibility and Global Reach: The user-friendly web interface enhances the accessibility of this platform, enabling healthcare professionals worldwide to leverage its capabilities. This aligns with the goal of creating a globally accessible tool for combating the pandemic.

5. CONCLUSION

Deep learning as a concept approach to the augmented data-set for COVID-19 detection is presented in this research. The active experimentation is the effective implementation of the system, evaluation parameters, and Django execution. It is seen that larger batch sizes yield similar accuracy, irrespective of the number of epochs. Here, not makes use of hyper-parameter tuning, but a performance was good when the learning rate was 0.01. Wrongly categorized classified Covid-19 samples may have to be reduced before field deployment. Performance of CNN's can be improved by applying a Min-Max objective layer below the output layer COVID-19 was detected utilizing chest CT Scan pictures using a diagnostic algorithm based on VGG16. With the use of an augmented data-set, the model was able to detect COVID-19 quickly and reliably, with an F1 score of 0.94. While this platform showcases promise, and acknowledge its limitations. The model's performance may be influenced by variations in X-ray quality and patient demographics. The novelty of this research can use advance deep learning algorithm such as GAN, RNN, Deep Reinforcement Learning, Convolutional Neural Networks, vgg19. These algorithms can improve the model and get more accurate results. And, by using many images to train the model can helps to get accurate results and also improve the web page, so the user can use it and understand properly.

Future Enhancement: Future refinements may include a more diverse dataset to enhance the model's robustness across different populations. Looking ahead, further research could explore the integration of additional imaging modalities and the incorporation of AI-driven insights for more comprehensive diagnostics. Additionally, collaboration with healthcare practitioners and organizations can facilitate the refinement and validation of the platform.

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