Performance Analysis of Machine Learning Algorithms for COVID-19 Detection

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***Abstract*—The Novel Coronavirus Illness 2019 (COVID-19) was found in Wuhan, Hubei, China, in December 2019 and has since spread globally. When the patient's corona sickness worsened, his life was in danger. Coronavirus assaults the lungs. Diagnostic kits today only search for viral illnesses, which deceives doctors. All patients receiving the same treatment harm patients with less infection. This publication describes non-invasive treatment for infected people.**

Dissecting chest X-ray pictures to examine the coronavirus helps investigate and predict COVID-19 patients. We offer a hybrid method for detecting Covid. CNN and SVM identify Covid. Because X-ray pictures are inconsistent, CNN is used for feature extraction. To construct a training dataset before CNN, we used data augmentation. Data augmentation increases the training dataset's amount and quality. SVM is used for classification since it tolerates feature differences. The main goal is to help clinical doctors determine the severity of a chest infection so they can administer life-saving treatment. Deep learning and machine learning-based techniques will determine the degree of chest infection and lead to optimal medication, avoiding expensive treatment for all patients.

Keywords—Convolutional Neural Network, Covid-19, X-Rays, SVM, Artificial Intelligence

I. Introduction

The global spread of a novel coronavirus necessitated its early detection and effective treatment. The first wave's detection techniques have not changed, despite the frequent occurrence of pandemic waves. First, the patient is sent for an RT PCR test. depending on the lab's availability, the result takes more than 24 hours. Using this congenital test, you can only find out if COVID-19 is present. If affirmative, the patient is then treated. which wastes important treatment time. Therefore, various approaches to infection detection are offered. Here, we create AI-powered software for Covid-19 detection that is specifically built for front-line use to assist physicians in quickly and accurately identifying and monitoring the condition. Imaging characteristics common to patients with confirmed COVID-19 pneumonia can be useful in the early screening of highly suspect cases as well as in assessing the severity and breadth of the disease. Ground-glass opacities or mixed ground-glass opacities, consolidation, and vascular enlargement are present in the lesion in the majority of COVID-19 pneumonia patients. Lesions are more likely to be bilaterally involved, have a lower X-ray predominance, and have a peripheral distribution. The evaluation of the disease's severity and scope can be aided by the CT involvement score [1].

Bronchoalveolar lavage fluid specimens had the highest positive rates of 93 percent (n = 14) in a survey that examined the sensitivity of RT-PCR testing at different tissue locations [2]. This was followed by pharyngeal swabs at 32% (n = 126) sputum at 72% (n = 75), nasal swabs at 63% (n = 5), fibro bronchoscope brush biopsies at 46% (6/13), faeces at 29% (n = 44), and blood at 3% (n = 3). The authors of that study made the observation that using samples from various locations may increase sensitivity and decrease false-negative test findings. The letter looked at 1070 samples that were taken from 205 hospitalized patients in China who had COVID-19 verified.

Researchers observed that chest CT had better sensitivity for diagnosing COVID-19 than the initial RT-PCR from pharyngeal swab samples in a different study that was published in Radiology [4]. In Wuhan, China, 1014 hospitalized patients with suspected COVID-19 underwent serial RT-PCR testing as well as chest CTs for this retrospective analysis. The sensitivity, specificity, and accuracy of chest CT in diagnosing COVID-19 were 97% (n = 580), 25% (n = 105) and 68% (n = 685) accordingly using RT-PCR data as the reference standard.

These studies demonstrate the value of X-ray scans in identifying illness severity. X-ray pictures can be used to determine the exact infection level rather than RT-PCR testing, which has a limited degree of accuracy. Knowing the precise infection state will allow you to manage the number of patients being admitted. This will provide another benefit for social spending throughout the pandemic. Patients with serious infections may require expensive medication, but everyone else can be treated at home with common medicines. Our method is quick and takes potential errors in picture processing into account. The collected X-ray pictures need to be enhanced in order to correct their inconsistency. which handles image distortion after collection. The X-ray images need to have a lot of noise in them eliminated.

The accuracy of the automatic detection method will rise with such thorough adequate pre-processing of the X-ray images. After processing the uniform pictures for ground-glass opacities, patients who meet the required threshold will receive treatment for either pure or mixed ground-glass opacities. SVM technology is used to classify the images in order to determine the infection degree. Only patients who

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meet a certain criterion will receive treatment at a hospital to prevent infection.

II. Related Work

K. Garlapati and others in their paper [1], present an automatic detection system based on lung X-ray pictures as a possible method for a quicker diagnosis. Images' black patches reveal information regarding the severity of lung infection. In this study, 2000 X-ray pictures from publically accessible data sets are used to build a machine learning model. After the noise from the photos has been removed, areas in the photographs are properly segmented. The Sobel filter is utilized for accurate patch edge detection. Additionally, the picture augmentation photos are incorporated during training to strengthen the model. For the purpose of building the model, the pertinent features are taken from the photos. The X-ray images are susceptible to noise and spatial aliasing, making it difficult to determine the border, hence accurate boundary identification is required for image segmentation [18][19]. SVM kernel is used to categorize images into Covid and non-Covid classes. High precision and accuracy are provided by this SVM kernel. The correctness of the offered data images is seen to be over 99 percent.

N.Hany and others in their research [2], a brand-new approach based on ensembles with two stages of classification to find positive and negative cases is suggested. This will aid in the early detection of COVID-19 and allow for the right diagnosis and treatment of minor instances. Early diagnosis of COVID instances will aid the patient in preventing financial losses brought on by unnecessary treatment of minor cases. Their research is based on routine blood samples taken at labs. A little over 200 instances with known outcomes are used for training and testing. By using a hybrid approach [20], the performance of current classification techniques like Gradient Boosting and Random Forest can be enhanced.

The symptoms serve as classification criteria. Similarity distance is assessed following the application of the gradient boosting classifier. This ensemble's similarity index provides a more accurate classification of positive and negative cases for COVID-19. Both supervised learning and clustering [17] methods are applied. Two classes—one positive and the other negative—are formed using K-means clustering [17]. Classification models like Random Forest and Gradient Boosting are applied to each cluster. The two stages operate in a sequential manner to increase accuracy. The ensemble voting method is used to select the cross-validation model with the highest level of accuracy. Researchers discovered that random forest provides an accuracy of 87 percent. which is further increased by the ensemble method to 90 percent.

R. F. A. P. Oliveira and others [3], proposed a technique to classify the parameters of conventional laboratory tests in order to find positive cases. In order to classify patients and make an earlier decision about admission to the hospital, laboratory parameters are taken into account. Traditional clinical test analysis takes a long time, and during that time, the disease might spread throughout the patient's body and the community in which they live. The disease prediction model is based on techniques like Support Vector Machines Regression, Multi-Layer Perceptrons, and Random Forest. The duration of the clinical parameter analysis will be shortened. Based on the link between clinical indicators and Covid -19 detection, they have created a two-stage method.

It uses a machine learning algorithm to detect the presence of Covid-19 in the first stage and provides assistance for the hospitalization decision in the second. So limiting the duration of the treatment and the viral propagation.

C Koushik et al. [4], proposed a method in which machine learning techniques are also used to detect COVID-19 utilizing clinical tests. Blood test parameters like CBC, CRP, D-Dimer, S-ferritin, ALT, and LDH are taken into consideration for analysis in this paper. Early identification of COVID-19 may reduce mortality and improve treatment outcomes. Therefore, rather than using PCR parameters, the author employed blood parameters to find the covid-19. The collection of PCR parameters is challenging, and the analytical process takes longer. In the meanwhile, the patient's illness could get worse and necessitate hospitalization.

Blood tests aid in separating COVID-19 from other Pneumonia. The authors also touch on the methodology's financial benefits. The authors used a variety of classifiers, including Random Forest (RF), Support Vector Machine (SVM), and Naive Bayes, in their machine learning techniques. The authors determined that SVM classifier performance is satisfactory when compared to that of other classifiers after applying all three tests to the data set they had obtained. Correct findings are reported to be detected with an accuracy of over 88 percent.

A.Rahm et.al. in [5] have raised concerns about being hospitalized during the COVID-19 pandemic. Prioritizing the admission of patients to hospitals depending on their infection is important as the infrastructure's capacity was filling up due to a large number of patients. In this study, a unique system of decision-making is proposed to establish the patient's priority for the hospital admission. Based on chest X-ray pictures, the same technique can be used to identify covid and non-covid patents. Hospital management can be assisted in making an automated decision regarding patient admission by a decision-making system based on an AI algorithm.

The images of the lungs are provided by X-ray machines for automation rather than by RTPCR clinical testing. The normal turnaround time for RT-PCR laboratory results is more than 24 hours before positive and negative results are announced. The classification of the photos in covid and non-covid patients uses the VGG-16 network. The machine learning algorithms are trained using the X-ray pictures that were gathered. The degree of infection is detected using machine learning from the pictures gathered by X-rays. This degree of seriousness will aid the automated procedure used by the decision-making system to choose the patient for the hospital admission. One particular sort of convolution neural network, the VGG-16, is utilized mostly for classification.

The results are categorized and then sent to various criteria and sub-criteria to aid in the decision-making process. Decision support systems employ the Analytic Hierarchy Process (AHP) paradigm to make decisions. The consistency index will determine the admission outcome after considering the predetermined criteria and sub-criteria. In their trials using several datasets like squeezenet, densenet, inception, and resnet, the recall and precision were determined to be 96 percent for the correct judgment.

Md. Badrul Alam Miah and his co-author reported CT-based research [6] on lung cancer. Their research employed a neural network-based method for the early diagnosis of lung cancer infection. Covid-19 also causes lung infections. This study can be applied to identify Covid-19 instances from lung pictures by using a similar technique. To distinguish between cases of cancer and non-cancer, photos are first rendered bland, and then a threshold is applied. Prior to the neural network classifier, pre-processing, banalization, and thresholding steps are completed. By segmenting the left and right lungs from the original pictures, features are extracted. The classifier has a detection rate of about 96%. The method's processing time for the neural network classifier is a drawback.

A.A.Reshi et al. [7] developed a deep learning technique for classifying X-ray images of Covid and non-Covid patients. The approach of picture augmentation has been used to improve CNN training with a small sample of images. The data augmentation approach is a useful method for expanding the quantity and quality of data in a database. To improve the quality of the photographs, data pre-processing incorporates expert judgment and data set balancing. The clarity of X-ray images varies, making it challenging to train CNN on them. This issue is solved by image augmentation, which also provides CNN with the effective training it needs [9]. For each stage of pre-processing, picture augmentation, and classification, writers have proposed a new technique to address the shortcomings of each approach.

The CNN training is carried out iteratively using various datasets. This aids in achieving the highest levels of performance and precision. In incremental training, each layer is added after each iteration dependent on the performance matrix. This keeps happening until a stable performance is reached. The basic dataset's small size and class distribution imbalance problems have an impact on how well CNN models function [10]. This problem was solved through image augmentation, which improved classification performance by 98 percent.

A. loddo et al. [11] Deep neural networks for Covid -19 detection research that has compared publicly accessible data sets. Two of publicly accessible datasets are chosen for the experiment. A research and performance comparison of ten well-known convolution neural networks is conducted [12]. According to the authors, VGG19 is the best choice for using the COVID classification. The cross-dataset experiment revealed that the deep learning network's real-time performance for Covid patient classification was only 75% [15][16]. Observations indicate that it performs poorly for sources of heterogeneous images.

III. Proposed Method and Algorithm

A. System Architecture

Our intelligent hybrid [21] system's goal is to create a tool that enables hospitals to quickly identify COVID patients and gauge the severity of infection before making an admissions decision. For that, we can make use of the covid detecting system's input of X-ray images of the chest. The technology will identify positive patients and the severity of the infection based on the photographs. This will cut down on patient testing in two stages. the course of diagnostic as usual. Prior to receiving the results of the RT PCR test, the patient is moved on. It doesn't indicate the severity of the infection, so more X-ray scans are required.

The severity of infection is determined by the study of these photos, and the patient is then categorized as having a severe or mild infection. Our system's goal is to shorten this wait time and ease hospital admittance lines for everyone.

We are feeding X-ray images into our system as input for this reason. The examination of X-ray pictures has two purposes: finding positive cases and figuring out how bad the illness is. Only patients with greater infection levels are isolated and given medical treatment. During the pre-processing stage, the aspect ratio and intensity of X-ray pictures are standardized. Because the images are not consistent, the augmentation step is included.

All images are standardized during this step of the augmentation so that characteristics can be extracted. The Sobel edge detection algorithm is used to highlight the black patches in the photos. Such an image is run through the CNN step, allowing for the extraction of features as numerical values. These photos are then sent to an SVM classifier in the last step to identify positive and negative cases. This procedure is dependable and quick because it simply requires X-ray images of the patient's chest. Additionally, it provides an infection level, which causes dangerous patients to be admitted to the hospital right away. The death rate of covid-19 can be decreased with the aid of these quick detection and isolation procedures.

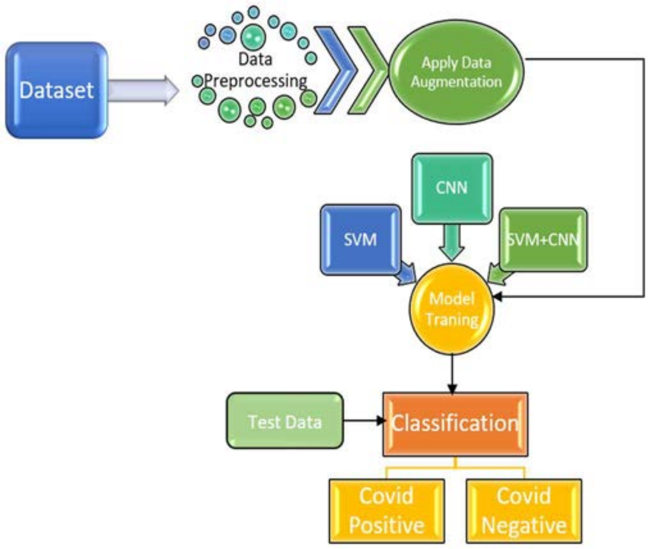

Fig. 1. Block Diagram of Hybrid Approach

B. Dataset

We used a Github picture collection for our experimental work [8]. The medical staff under supervision chooses the photographs. Only 135 of the 700 photos in the data set with confirm COVID-19 were chosen. The final 45 photos are chosen using non-Covid cases. Covid and non-covid samples can be found in the CXR images. Image augmentation is used since there are fewer exact Covid-19 positive cases in the data sets. This supports development in two different ways. Both the quantity and quality of photos rise as a result. This data collection is utilized to train and test our algorithm and the integrated system that has been suggested.

C. Pre-processing

It is required to normalize the photos at the pre-processing stage. The dataset's photos are transformed into grayscale. This will simply provide image illumination data. The size of the photos also decreases, which aids in accelerating the pre-processing stage and subsequent phases of image processing.

Regardless of their original size, all photographs are reduced to 150x140 pixels during the normalization stage. Noise reduction is accomplished by using a filter like the median filter. Machine learning algorithms receive incorrect training from more noisy images.

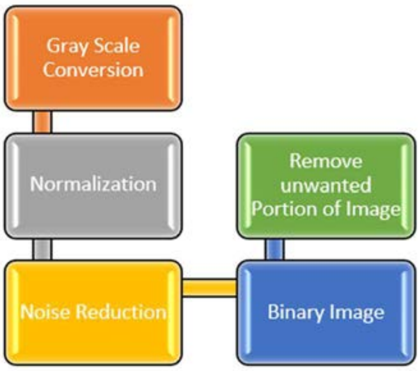

Fig. 2. Pre-processing of Images

D. Data Augmentation

The data augmentation approach is used to enhance the number of data instances from the available data. [9]. The more instances, the more effectively the model will be trained. Basic image operations can be used to conduct data augmentation for our image data set. Flipping, rotating, cropping, and padding are examples of these procedures. These actions create a new dataset that helps to expand the training samples and make the CNN module more efficient. In our study, data augmentation is employed to train CNN in order to get over the dataset size restriction.

Additionally, this is used to give the model more features. We solely used the flip and rotation strategies for our data augmentation. X-ray pictures are first rotated to provide an additional set of images. To obtain the third data set, the original image is rotated by 900 degrees in the second stage. For the fourth data set, the original image is rotated 1800 times in the third stage.

To obtain the fifth data set, the original image is rotated by 2700 in the final stage. By capturing photographs from various angles, data augmentation is able to solve the issue of image variance. Additionally, it aids in the classification process, when class differences are accentuated.

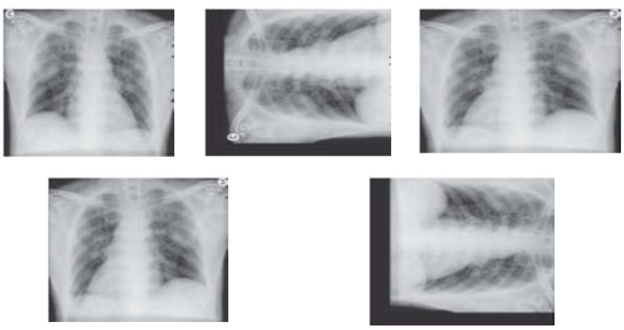

Fig. 3. *Flip and Rotate Operation on CXR Images*

Table 1 enumerate the image manipulations made during the augmentation. The different operations produced a number of images. The size of the image database grows as a result. Additionally, the quality of the photos used by CNN for training purposes has improved.

TABLE I. IMAGE MANIPULATIONS DURING AUGMENTATION

Operation	***Image Count***
Original	180
Original flipped	180
Original with a 90^0 rotation	180
Original with 180^0 rotation	180
Original with 270^0 rotation	180
Total data set after augmentation	**900**

E. Convolutional Neural Network

Convolution neural network (CNN) works as the human brain [13]. CNN is used in image processing because its processing can be equal to human viewing systems. CNN is consequently utilized in image processing, analysis, and classification. The convolution layer, maximum pooling, and nonlinear activation layer make up CNN. Given that images are inherently nonlinear, ReLU is employed as an activation function to augment the nonlinearity in the input layer. ReLU makes CNN implementation simpler and quicker. As data augmentation is carried out, the dataset's quantity and quality are improved. Such a dataset is required for a better deep learning model to be encapsulated. enumerate the image manipulations made during the augmentation. The different operations produced a number of images. The size of the image database grows as a result. Additionally, the quality of the photos used by CNN for training purposes has improved Performance Evaluation of the Algorithms on the Dataset.

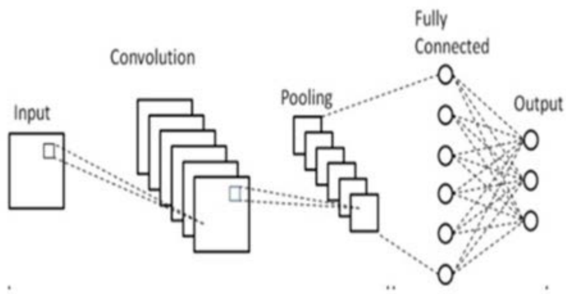

Fig. 4. CNN-Block Diagram

F. SVM Classifier

SVM was employed for classification. SVM uses data from the CNN stage, which isolates an image's features. It is required to categorize them as covid and non-covid cases based on the attributes chosen.

The course of treatment will be determined by the patient's severity. Because SVM is a supervised classifier, it can be trained more quickly than random forest or NN [14]. The elements can be properly classified by obtaining the maximum marginal hyperplane. The hyperplane is iterated to discover the most distinct classes.

IV. RESULTS AND ANALYSIS

The Covid-19 X-ray database is used for data pre-processing and data augmentation, as was previously stated in the suggested section. It is utilized as a primary programming language alongside Python. The HP Elite Book with a Core i5 processor is used for the experiment.

A. Experimental Results

We used augmented photos from the original dataset for the classification of images for covid and non-covid. 550 photos make up the entire dataset utilized for categorization. Of that, 80% is utilized for training, and the remaining 20% is used for testing.

The data set's profile is displayed in Table II. It displays the complete profile of the used images/photos. Counting the number of images/photos utilized, as well.

The experimentation results of proposed work are given in Table III, Table IV and Table V. The feature extraction results are given in Table III. Here the features are extracted using GLCM and CNN algorithms. It is observed that for the image size 64*64, the accurate features are extracted.

TABLE II. DATASET PROFILE

Type of data	***Covid***	***Non-covid***
Original data	135	45
Augmented data	675	225
Total images	900	
Training images	720	
Testing images	180	

TABLE III. FEATURE EXTRACTION RESULTS

Input Images (Size)	***Candidate Model Accuracy (CNN)***
28 x 28	95.99
32 x 32	96.13
64 x 64	**96.14**
128 x 128	95.97
256 x 256	96.04

TABLE IV. COVID-19 IDENTIFICATION USING CNN AND ML ALGORITHMS

Candidate Models	***Accuracy (Train)***	***Accuracy (Test)***
CNN + Naive Bayes	85.28	82.89
CNN + Decision Tree	82.49	80.92
CNN + Random Forest	89.51	79.27
CNN + K-Nearest Neighbor	83.22	81.56
CNN + SVM	**96.23**	**95.23**

Confusion matrix of the experiment.

(0,0) = TP, (0,1) = TN, (1,0) = FN, (1,1) = FP

TABLE V. TEST RESULTS

0	131	4
1	3	42
	0	**1**

B. Analysis

The accuracy, precision, and recall numbers produced from the experiments are used to evaluate the model's performance. The confusion matrix in figure 6 is used to assess the model. The confusion matrix's conclusion on the test data set is self-explanatory. True positives provide a classification confusion matrix for two classes. (TP/0), false positives (FP/1), false negatives (FN/0), and true negatives (TN/1).

The accuracy is calculated by using the following formula,

$$accuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (1)$$

Accuracy of the model comes out 96%

The precision is calculated by the following formula,

$$precisin = \frac{TP}{TP+FP} \quad (2)$$

Precision of model comes out 97%

The recall is calculated by the following formula,

$$recall = \frac{TP}{TP+FN} \quad (3)$$

Precision of model comes out 97.7%

All performance measures of the model are listed in Table VI.

TABLE VI. RESULTS

Accuracy	**0.9611**
Precision	**0.9703**
Recall	**0.9776**
F1-Score	**0.9620**

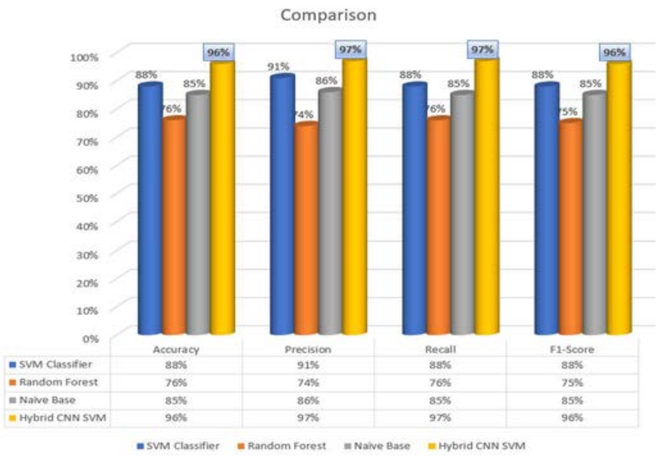

Fig. 5. Comparative Analysis

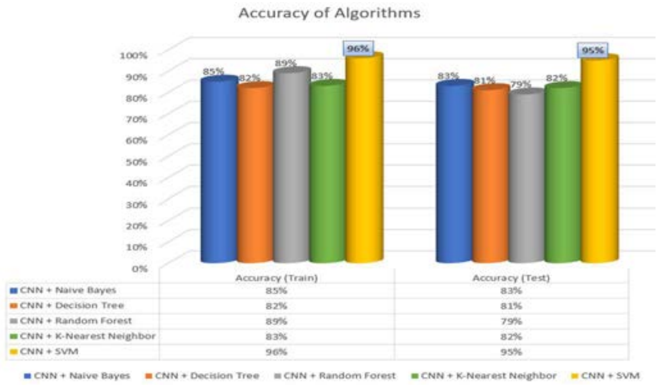

Fig. 6. Comparison of accuracy of different algorithms

CONCLUSION

The primary focus of the study is to develop a rapid method for distinguishing covid from non-covid situations. Traditional diagnostic procedures, such as RT-PCR and X-rays, take too much time, delaying treatment for critically ill patients. In our study, we can tell who the patient is and how much covid-19 he or she has just from looking at their X-rays. Only a subset of the photographs in the original dataset were used for the training. We employed the picture augmentation method to expand the scope of our data set and enhance its overall quality. As a result of training on such a huge dataset, the model's performance is enhanced. Incorporating a cascade of CNN and SVM stages helped the suggested model achieve greater speed and accuracy. The hybrid model is superior to either the SVM or deep learning alone due to the SVM's ability to perform flexible hyperplane classification. This hybrid method is faster and more precise than any previous computerised technology. To reduce the mortality rate caused by COVID-19, our hybrid model approach will aid clinicians in treating patients as soon as possible. The fully integrated method may help doctors in hospitals make more informed diagnoses and expedite patient care.

REFERENCES

[1] K. Garlapati, N. Kota, Y. S. Mondreti, P. Gutha and A. K. Nair, "Detection of COVID-19 Using X-ray Image Classification," 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI), 2021, pp. 745-750, doi: 10.1109/ICOEI51242.2021.9452745.

[2] N. Hany, N. Atef, N. Mostafa, S. Mohamed, M. ElSahhar and A. AbdelRaouf, "Detection COVID-19 using Machine Learning from Blood Tests," 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), 2021, pp. 229-234, doi: 10.1109/MIUCC52538.2021.9447639.

[3] R. F. Albuquerque Paiva de Oliveira, C. J. A. Bastos Filho, A. C. A. M. V. F. de Medeiros, P. J. Buarque Lins dos Santos and D. Lopes Freire, "Machine learning applied in SARS-CoV-2 COVID 19 screening using clinical analysis parameters," in IEEE Latin America Transactions, vol. 19, no. 6, pp. 978-985, June 2021, doi: 10.1109/TLA.2021.9451243.

[4] C. Koushik, R. Bhattacharjee and C. S. Hemalatha, "Symptoms based Early Clinical Diagnosis of COVID-19 Cases using Hybrid and Ensemble Machine Learning Techniques," 2021 5th International Conference on Computer, Communication and Signal Processing (ICCCSP), 2021, pp. 1-6, doi: 10.1109/ICCCSP52374.2021.9465494.

[5] A. Rahim, M. Kurniawan and Kusrini, "Machine Learning Based Decision Support System for Determining the Priority of Covid–19 Patients," 2020 3rd International Conference on Information and Communications Technology (ICOIACT), 2020, pp. 319-324, doi: 10.1109/ICOIACT50329.2020.9332000.

[6] M. B. A. Miah and M. A. Yousuf, "Detection of lung cancer from CT image using image processing and neural network," 2015 International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), 2015, pp. 1-6, doi: 10.1109/ICEEICT.2015.7307530.

[7] Aijaz Ahmad Reshi, Furqan Rustam, Arif Mehmood, Abdulaziz Alhossan, Ziyad Alrabiah, Ajaz Ahmad, Hessa Alsuwailem, Gyu Sang Choi, "An Efficient CNN Model for COVID-19 Disease Detection Based on X-Ray Image Classification," Complexity, vol. 2021, Article ID 6621607, 12 pages, 2021. https://doi.org/10.1155/2021/6621607.

[8] J. P. Cohen, "Github Covid19 X-ray dataset", 2020, https://github.com/ieee8023/covid-chestxray-dataset, 2020. Online.

[9] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," Journal of Big Data, vol. 6,p. 60, (2019). https://doi.org/10.1186/s40537-019-0197-0.

[10] D. Dong et al., "The Role of Imaging in the Detection and Management of COVID-19: A Review," in IEEE Reviews in Biomedical Engineering, vol. 14, pp. 16-29, 2021, doi: 10.1109/RBME.2020.2990959.

[11] A. Loddo, F. Pili, and C. Di Ruberto, "Deep Learning for COVID-19 Diagnosis from CT Images", Applied Sciences, vol. 11, no. 17, p. 8227, Sep. 2021, doi: 10.3390/app11178227. [Online]. Available: http://dx.doi.org/10.3390/app11178227.

[12] Roberts, M., Driggs, D., Thorpe, M. et al. "Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans," Nat Mach Intell 3, 199–217 (2021). https://doi.org/10.1038/s42256-021-00307-0.

[13] Anisha Isaac, H. Khanna Nehemiah, Anubha Isaac, A. Kannan, "Computer-Aided Diagnosis system for diagnosis of pulmonary emphysema using bio-inspired algorithms," Computers in Biology and Medicine, Volume 124, 2020, 103940, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2020.103940.

[14] Adel Oulefki, Sos Agaian, Thaweesak Trongtirakul, Azzeddine Kassah Laouar, "Automatic COVID-19 lung infected region segmentation and measurement using CT-scans images," Pattern Recognition, Volume 114, 2021, 107747, ISSN 0031-3203, https://doi.org/10.1016/j.patcog.2020.107747.

[15] Murat Canayaz, "C+EffxNet: A novel hybrid approach for COVID-19 diagnosis on CT images based on CBAM and EfficientNet," Chaos, Solitons & Fractals, Volume 151, 2021, 111310, ISSN 0960-0779, https://doi.org/10.1016/j.chaos.2021.111310.

[16] Yildirim, M., Cinar, A. (2020). "A deep learning based hybrid approach for COVID-19 disease detections," Traitement du Signal, Vol. 37, No. 3, pp. 461-468. https://doi.org/10.18280/ts.370313.

[17] C. A. Dhote, A. D. Thakare and S. M. Chaudhari, "Data clustering using particle swarm optimization and bee algorithm," 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), 2013, pp. 1-5, doi: 10.1109/ICCCNT.2013.6726828.

[18] Sakshi Kaul, Ruchita Sharma, Sakshi Sitoot, Shruti Chaudhari, "A Survey on MR Brain Image Segmentation using Hybrid PSO and AFSA," International Journal of Innovative Research in Science, Engineering and Technology, Vol. 7, Issue 10, October 2018, ISSN(Online): 2319-8753, DOI:10.15680/IJIRSET.2018.0710051.

[19] Hrishikesh Kamble, Sanket Rane, Prince Raj, Yogesh Pawar, Shruti Choudhari, "Survey on Image Segmentation using Improved DBSCAN Algorithm and Edge Detection," International Journal of Innovative Research in Science, Engineering and Technology, Vol. 7, Issue 12, December 2018, ISSN(Online): 2319-8753, DOI:10.15680/IJIRSET.2018.0712059.

[20] Prof. Anuradha D. Thakare, Mrs. Shruti M. Chaudhari, "Introducing a Hybrid Swarm Intelligence Based Technique for Document Clustering," International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 2, Issue 6, November- December 2012, pp.1455-1459.

[21] C. A. Dhote, A. D. Thakare and S. M. Chaudhari, "Intelligent hybrid approach for data clustering," Fifth International Conference on Advances in Recent Technologies in Communication and Computing (ARTCom 2013) DOI: 10.1049/cp.2013.2210 ISBN: 978-1-84919-842-4.