COVID-19 Detection using Curvelet Transformation and Support Vector Machine
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Abstract: As the COVID-19 virus spreads over the globe, countries all over the world are going to great measures to combat the disease. To stop it from spreading, it's critical to have a high level of awareness and a well-thought-out COVID-19 recognition approach. By analyzing different methods and image-based detection using chest x-ray images, a method was proposed in this study which include preprocessing, texture feature analysis and support vector machines. X-ray image was augmented to make equal blocks and features were extracted using Curvelet. Finally, extracted features were fed into SVM for classification. Curvelet was based on rotational and slicing texture description which give most appropriate details for classification of COVID-19. Results in this experiment showed that method achieved 97.7 % of accuracy against other methods based on chest x-ray image.

Keywords: COVID-19, Image Processing, Machine Learning Approach, Curvelet Transformation, Support Vector Machines

I Introduction
The Corona Virus Disease of 2019 (COVID-19) has been wreaking havoc on the global well-being framework since December 2019. WHO has received reports of 493,392,853 confirmed COVID-19 cases, including 6,165,833 deaths (till April 7, 2022). The discovery of COVID-19 variations in late 2020 prompted the identification of explicit Variants of Concern and Variants of Interest, resulting in a surge in global research [1]. Because of the long hatching time and lack of obvious adverse effects, early appropriate treatment is sometimes ignored. Because of how quickly HPV spreads, early detection is critical. TR-PCR “Reverse Transcription Polymerase Chain Reaction” is a commonly used approach for detecting viral nucleic corrosive in COVID-19 sickness. In any event, because this method relies on nasopharyngeal and throat cloths, which can be limited by minimal public acceptance and examination difficulties, it may result in low precision [2]. According to reviews, the responsiveness pace of this test is between 60% and 70% [3].
Furthermore, the TR-high PCR's false negative rate [9], the size of the exam, and a scarcity of RT-PCR inspecting units may make it difficult to examine patients swiftly. As a result, a variety of methods, such as blood testing and clinical imaging, should be used to arrive at a precise conclusion. Clinical specialists may be able to get outstanding results by combining radiological imaging advancements with PC-assisted frameworks right now. Clinical imaging modalities such as CT (“computed tomography”) and X-beam imaging treatments are used to detect the condition early, track its progression, and treat it [4]. The lungs with COVID-19 contaminations can be imaged using CT (“computed tomography”) and chest X-beam (CXR) for diagnosis. In the initial stages of COVID-19, chest radiological imaging drugs such as X-beams and CT (“computed tomography”) filters are prescribed. These methods can be used to determine the severity of a patient's ailment [1]. To avoid the spread of illness, a strong determination strategy should be developed so that infectious preventive measures such as early quarantine, detection, and day-to-day follow-up may be implemented as soon as possible. Unlike the swab test, CT (“computed tomography”) and CXR show the potential pathology's spatial area. It also allows specialists to assess the severity of the ailment. Cloudy lung opacities that are reciprocally appropriated, as well as air space solidification, are signs of CXR [5]. Imaging has several advantages, including quick response, quick finishing time, and the ability to screen the severity of disease in the lungs. Imaging, on the other hand, has a limited specificity, making it complicated to distinguish between dissimilar types of lung contamination, particularly when the condition is severe [6].

Even though COVID-19 and exemplary pneumonia have a lot in common, the Artificial knowledge-based arrangement framework could be a huge step forward in reducing test time, precision, and cost efficiency [7]. AI and deep learning calculations were used to examine COVID-19-infected patients in numerous studies published in the writing. Coronavirus could be studied using CAD “Computer-Aided Diagnosis” frameworks that combine X-ray and, CT (“computed tomography”) image processing with artificial intelligence (AI) or deep learning computations [8].

The adverse effects of major execution crumbling due to the inadequate quality of carefully constructed highlights are a fundamental disservice to AI techniques. The hand-drawn highlights are a touch sloppy, and they take up a significant portion of the day to create. [9]. However, profound learning has recently piqued scholastics' interest. These arrangements not only eliminated the need for manual component extraction, but they also significantly improved order precision. Several profound learning-based arrangements have been developed to achieve the previously specified aims.

In a variety of PC vision tasks, including image splitting, gathering, object ID, and ordinary language handling, DL techniques have proven to be sufficient. The medical community has embraced the use of clinical images to diagnose and treat a variety of illnesses. Using DL models to manage clinical images, notwithstanding their value, is a particularly difficult task. When compared to vision-related datasets, such as ImageNet [10], huge, described datasets of clinical photographs are few. Similarly, inconsistencies in datasets and a lack of representation may make the problem much more difficult to solve.

This study presents an AI-based method for detecting COVID-19 from X-beam images. A curvelet modification was used to extract highlights. SVM was employed as an example order device to save time and enhance overall precision. The main goal of this research is to come up with a low-cost, high-precision solution for a variety of time modalities. The review's commitments to the writing will be discussed next.
Using AI and image processing technologies, create a choice emotionally supportive network that can aid clinical professionals in making decisions by allowing COVID-19 to be completed sooner.

A comparable strategy has produced positive results in both CT and X-beam imaging technologies.

One of the review's distinguishing features is that it covers a broad range of informational indexes. The generalizability of the review is demonstrated by the results obtained for three informative sets with varying properties. To put it another way, the informative index has no bearing on the proposed method.

Traditional learning procedures can produce as many successes as profound learning strategies, according to this review, and the presented strategy can also be used for a different type of informative index.

The following is how the rest of the article is organized. Section 2 illustrates the associated work. The nuances of the dataset used in this evaluation, as well as the recommended technique, are summarized in Section 3. Section 4 explains the trial setup and provides information, while Section 5 summarizes and analyses the results. With Section 6, the paper comes to a close.

II Literature Review

Because of the COVID-19 illness, which has been plaguing the planet since December 2019, scholastic examinations have swollen considerably. Several investigations, particularly in the area of COVID-19, have lately been conducted using PC-assisted frameworks. AI and deep learning are becoming increasingly visible in learning ways to study.

In numerous studies, AI approaches, deep learning, and half-breed models were used to organize CT and CXR images of the illness caused by the COVID-19 infection [11]. The proposed technique was tested using three public COVID-19 informational collections. The suggested model achieves exceptional degrees of COVID-19 identification accuracy, with COVID-19 recognition exactness of 89.41 percent, 99.02 percent, and 98.11 percent for CT-1-dataset, X-beam dataset-2, and CT-dataset-3, respectively. People with positive COVID-19, pessimistic COVID-19, and pneumonia had an accuracy of 85.96 percent in the X-bar enlightening file. Coronavirus may be linked to a high accomplishment rate in less than a second employing picture handling and old-style learning processes, according to the review. In this study, two-class and multi-class requests were used [12]. In available datasets, the researchers looked at four COVID-19 classes, bacterial pneumonia, non-COVID-19 viral pneumonia, and regular CXRs. The plants' surface and actual qualities were taken into account.

COVID-19 was recognized from a variety of situations using five directed AI calculations. Unpaired two followed tests with the unbalanced difference between bunches were used in the factual inquiry. The recipient working trademark (ROC) bend study was used to evaluate the presence of grouping models. The overall exactness and AUC for multi-class orders, respectively, were 79.52 percent and 0.87 percent. COVID-19 lung illness is accurately recognized in individuals in multi-class datasets using artificial intelligence grouping of textural and morphological aspects of convenient CXRs. Profound learning approaches for practical CXRs may be able to improve indicative accuracy and precision.

In [13] the updated COVID-19 plan shows remarkably profound learning-based join extraction mechanisms. To find the most dependable component, researchers used
ResNet, InceptionV3, InceptionResNetV2, MobileNet, DenseNet, Xception, VGGNet, and NASNet to examine a pool of significant convolutional mind associations. The acquired components were fed into a series of AI classifiers to determine if the images were COVID-19 cases or non-COVID-19 cases (DT, RF, XGBoost, AdaBoost, Bagging classifier, and LightGBM). To achieve greater thoroughness, our strategy avoided task-express data pre-dealing with techniques. A Coronavirus dataset involving chest X-beam and CT images was obtained from Github for leeway reasons. With a representation precision of nearly 100 percent, the DenseNet121 feature extractor with pressing tree classifier produced the greatest results. The second-smartest understudy was a blend of a ResNet50 incorporate extractor produced by LightGBM, which had an accuracy of 98 percent [14].

This work suggests a bi-specific crossbreed technique for identifying COVID-19 from chest CT images. The essential module used a Convolutional Neural Network (CNN) approach to destroy features from chest CT filters. In the next module, the significant features for expecting COVID-19 and non-COVID-19 cases were eliminated using a bi-stage incorporate assurance (FS) technique. Two-channel frameworks were used in the VA coordinated FS concept: Mutual Information (MI) and Relief-F. The Dragonfly estimation (DA) procedure was then used to narrow down the key components. Using the Support Vector Machine (SVM) classifier, the following capabilities were employed to organize COVID-19 and non-COVID-19 chest CT images. SARS-CoV-2 CT photos and COVID-CT pictures were used to test the proposed model, and both datasets had significant assumption rates of 98.39 percent and 90.0 percent, respectively [15].

The Worried Deep Neural Network (WDNN) model with move realization, which is a profound brain network-based independent order engineering, was presented by E. Samir et al. [8]. On various execution criteria, the suggested WDNN model outperforms three pre-preparing models, including InceptionV3, ResNet50, and VGG19. Due to the COVID-19 informational index's limited accessibility, information expansion was used to increase the number of photographs in the positive class, followed by normalization to verify that all photographs were the same size. The research is based on the COVID-19 dataset, which has 2623 distinct cases (1573 preparation, 524 approvals, 524 tests). Individually, the recommended model received scores of 99.046, 98.684, 99.119, and 98.90 for exactness, correctness, review, and F-score. Using a two-stage information expansion strategy, this study identifies six groups of photographs. To work on the insufficient dataset, a shallow picture increase strategy was used in the first stage. As a result, strategies for extracting highlights the hard way become more appropriate. The Synthetic minority over-sampling approach algorithm was used in the second data augmentation step. Finally, utilizing a stacked auto-encoder and principal component analysis methodologies, the feature vector is reduced in size by deleting correlated features. According to the obtained data, the proposed technique performs exceptionally well. As a result, methods for separating parts the hard way were appropriate. In the second information expansion stage, the Synthetic minority over-testing technique calculation was used. Finally, the component vector is reduced in size by eliminating related highlights using a stacked auto-encoder and head part analysis processes. According to the data collected, the proposed technique succeeds admirably, notably in terms of quickly and accurately identifying COVID-19.

In addition, deep learning calculations have been used to group chest x-beam photographs of the disease caused by the COVID-19 infection in distinct studies. Traditional exchange learning procedures were initially used in a study by Wang et al.
[16] from China, who used five pre-prepared profound learning models, one of which, the Xception model, produced an almost perfect outcome, with a determination exactness of 96.75 percent. An analytic technique that combines profound attributes and AI layout improves analysis precision significantly. It employs a comprehensive symptomatic model. The proposed strategy was tried on two datasets and performed splendidly on both. The model was first placed to the test on 1102 X-beam photos of the chest. As per the discoveries of the analyses, the blend of approaches has a finding exactness of 99.33%. When contrasted with the standard Xception model, finding exactness has worked on by 2.58 percent. The responsiveness, particularity, and AUC of this model were 99.27 percent, 99.38 percent, and 99.32 percent, individually. Utilizing a convolutional brain network plan, Azemin et al. [9] utilize the ResNet-101 classifier to distinguish COVID-19 in chest X-beam pictures. The consequences of this examination showed an exactness of over 71%, the explicitness of over 71%, and responsiveness of over 77%.

Profound learning and AI techniques were applied to a bunch of chest x-beam pictures for patients with COVID-19 in a review led by Ahammed et al. [17]. Numerous datasets were consolidated into a solitary dataset utilizing irregular examination. A few pre-prepared models were utilized in the profound learning method, as well as move learning, in this dataset. The proposed CNN model had the most elevated exactness of 94.03 percent, the most noteworthy AUC of 95.5 percent, the most noteworthy f-proportion of 94.03 percent, the most elevated awareness of 94.03 percent, the most noteworthy explicitness of 97.01 percent, as well as the least drop out of 4.48 percent and the most noteworthy miss pace of 2.98 percent, as well as the most reduced drop out of 4.48 percent and the most elevated miss pace of 2.98 percent.

Lansana et al. [18] suggest combining the convolution neural networks technique with three classifiers: InceptionV2, VGG-19, and decision tree to categorize a collection of CT scans and X-ray pictures. VGG-19, InceptionV2, and the decision tree model were shown to have 91 percent, 78 percent, and 60 percent accuracy, respectively, in the study.

Sekeroglu and Ozsahin [18] utilized AI and profound learning strategies to group chest x-beam pictures as sound, pneumonia, or COVID-19 in a review. The exploratory outcomes uncovered precision of more than 98%, awareness of more than 93%, and particularity of more than almost 100% utilizing a dataset of 6100 photographs.

III. Proposed Methodology
The proposed framework for Covid19 classification is shown in Figure 1. We have considered chest x-ray images available on Kaggle to predict covid19 patients. Firstly, we consider Curvelet as a feature extractor. Curvelet returns 12 features for the description of the image. As features are extracted for an image, these feature sets are passed to different classifiers to check the performance and efficiency of the feature set extracted using Curvelet. Different classifiers show different training and testing results are examined.
A. Preprocessing
Images are read from the directory then block division is implemented using non-overlapping block division. Each image is adjusted through padding so, it can be divided into blocks of size 256 x 256. After this process, an image is converted into multiple images of size as shown in Figure 2.

B. Feature Extraction
Each block of the image is passed to curvelet transform to get texture features of an image that will be used for differentiation and learning for normal and covid19 x-ray images.

1) Fast Discrete Curvelet Transform
According to the literature, the FFT (Fourier Transformation) is not suited for various image processing applications since it needs a huge number of terms to rebuild a gap with high precision. Wavelet transform has grown in favor of a solution to the Fourier transform challenge. Because of its localization and multiscale properties, researchers are interested in it. This transform performs well in 2D, i.e., it can handle point singularities; nevertheless, due to weak directional selectivity and isotropic scaling, it breaks to adequately depict
better dimensional singularities such as lines, curves, and so on. Curvelet transform has since gotten a lot more attention because it can successfully handle the challenges that traditional wavelets and their ilk have. Curvelet is a multiscale geometric analysis tool that efficiently handles image curve singularities. Curvelet transforms have better directional selectivity, multiresolution, localization, and anisotropy as their key characteristics. Furthermore, due to its parabolic scaling capabilities, it provides for a nearly optimal sparse symbol of objects with CS ("curve singularities"). The curve singularities, on the other hand, can be achieved by first dividing the picture into sub-images and then applying the RT ("ridgelet transform") to all of the sub-images obtained. CT (Curvelet transform) was the name for this block-based transform. However, the first-generation curvelets’ use in a variety of applications has been hampered by the ridgelet's imprecise geometry. Then, in [5,] a second-generation curvelet transform was offered as a solution to the difficulties with first-generation curvelets. We employ quick DCT (“discrete curvelet transform”) instead of wavelets and their derivatives to capture more directional data because the texture information of an X-Ray image, includes a mess of curves and lines. The following are the basic mathematical initiations of the CCT (“continuous curvelet transformation”) and DCT (“Discrete curvelet transforms”). The CV (“Curvelet transform”) can be defined as an inner product for a given signal f as

\[ C(j, l, k) = \langle f, \varphi_{j,l,k} \rangle \]

where the curvelet basis function is \( \varphi_{j,l,k} \) and parameters are j, l, and k, which are scale, direction, and position are j, l, and k, respectively.

The continuous curvelet transform is implemented in 2D i.e., (R2) and can be displayed in the frequency domain using x as the spatial variable and as the frequency domain variable. In the frequency domain, r and are the polar coordinates. Given a pair of smooth, non-negative, real-valued windows \( W(r) \) and \( V(t) \), referred to as radial and angular windows, respectively, with \( r \in [\frac{1}{2}, 2) \) and \( t \in [1, 1] \). W and V will always meet the following requirements:

\[ \sum_{j=-\infty}^{\infty} W^2(2^j r) = 1, \quad r \in \left(\frac{3}{4}, \frac{3}{2}\right) \]

\[ \sum_{l=-\infty}^{\infty} V^2(t - 1) = 1, \quad t \in \left(\frac{-1}{2}, \frac{1}{2}\right) \]

The frequency window \( U_j \) in the Fourier domain is then given for each \( j \geq j_0 \).

\[ U_j(r, \theta) = 2^{-3j/4} W(2^{-j/2} r)V \left(\frac{2\left\lfloor \frac{j}{2}\right\rfloor \theta}{2\pi}\right) \]

where \( \left\lfloor \frac{j}{2}\right\rfloor \) represents the integer portion of \( \frac{j}{2} \). As a result, the support of U_j is a polar wedge that is interpreted by the support of W and V, which are applied in each direction with scale-dependent window widths. To generate real-valued curvelets, consider the symmetric variant of \( U_j \) s, i.e. \( U_j (r + \theta) + U_j (r, \theta + \pi) \). Let us describe the waveform \( \varphi_j(x) \) using its Fourier transform \( \varphi_j(\omega) = U_j(\omega) \), where \( U_j(\omega_1, \omega_2) \) is the polar coordinate system window. In the sense that all curvelets at size 2-j are formed by rotations and translations of
\( \varphi_j \) it can be considered the mother curvelet. Curvelets can be generated at scale 2^-j, orientation \( \theta_l \), and position \( x_j^l \) using the function \( x = (x_1, x_2) \) by

\[
\varphi_{j,l,k}(x) = \varphi_j \left( R_{\theta_l} \left( x - x_j^l \right) \right)
\]

Where, \( k = (k_1, k_2) \in \mathbb{Z}^2 \) specifies the order in which the translation parameters are applied, \( \theta_l = 2\pi \cdot 2^{-\frac{|l|}{2}}, l, l = 0, 1, \ldots \) such that \( 0 \leq \theta_l < 2\pi \), and \( x_j^{l} = R_{\theta_l}^{-1} \left( k_1, 2^{-j}, k_2, 2^{-j} \right) \). \( R_{\theta} \) and \( R_{\theta}^{-1} \) denotes the rotation by \( \theta \) radians and its inverse respectively, and are defined as

\[
R_{\theta} = \begin{pmatrix}
\cos \theta & -\sin \theta \\
\sin \theta & \cos \theta
\end{pmatrix}, R_{\theta}^{-1} = R_{\theta}^T = R_{-\theta}
\]

The inner product of an element \( f \) and a curvelet is then the curvelet coefficients \( \varphi_{j,l,k} \) i.e.,

\[
C(j, l, k) = \langle f, \varphi_{j,l,k} \rangle = \int_{\mathbb{R}^2} f(x) \overline{\varphi_{j,l,k}} \, dx
\]

We can express the inner product as an integral over the frequency plane by expressing it as an integral over the frequency plane.

\[
C_{j,l,k} = \frac{1}{(2\pi)^2} \int \hat{f}(\omega) \overline{\hat{\varphi}_{j,l,k}(\omega)} \, d\omega = \frac{1}{(2\pi)^2} \int \hat{f}(\omega) \overline{U_j(\omega)} e^{i(x_j^{l} \omega)} d\omega
\]

The linear digital curvelet transform of an input Cartesian array \( f(t_1, t_2); 0 \leq t_1, t_2 < n \) is defined by a set of coefficients as

\[
C^D(j, l, k) = \sum_{0 \leq t_1, t_2 < n} f[t_1, t_2] \overline{\varphi^D_{j,l,k}[t_1, t_2]}
\]

**C. Classification**

Our focus of work is feature extraction rather than the design of the best classifier, we depend on the other existing works for the selection of the classification algorithm. The classification block's goal is to classify chest X-ray pictures based on the residual encoder block's extracted features. As the backbone of our classification system, we use the Support Vector Machine, which has a powerful feature representation ability and compares it with other machine learning algorithms. With its excellent resilience and classification ability, the SVM has shown to be a powerful tool in machine learning and data mining. In practice, the most important task is to detect COVID-19 cases with great sensitivity and efficiency. As a result, the labels were divided into two categories: COVID-19 infection cases and others. We focused on more practical work, such as identifying confirmed cases so that appropriate measures could be taken as soon as possible to prevent the epidemic from spreading. The pre-processed image was passed to feature extraction using Curvelet transformation. These features were used for the classification process using a non-linear SVM kernel.

**D. Chest X-Ray Dataset**

Datasets publicly available on public resources which have been used in most of the papers are being used for these experiments. We have used two of them. The first is named Chest x-ray (covid19 & pneumonia) [20] and includes 576 images for covid and 1577 images for normal patients. The second is named as Novel COVID-19 Chest x-ray Repository [21]
available on Kaggle includes 752 covid and 1639 x-rays for normal patients. These datasets are openly available on www.kaggle.com. Other details regarding these datasets are available in the meta information. Both datasets are labeled as Dataset-1 for the first and Dataset-2 for the second dataset. All the mentioned images were input to the proposed method for calculating the required features to classify normal and covid chest x-ray images.

Figure 3 (Left) Covid X-ray Image (Right) Normal X-ray Image

IV. Results and analysis
As discussed, we have used chest x-ray datasets. Different evaluation measures were used to evaluate the proposed method. The proposed method was checked using different training and testing environments. Details of these settings are under this section.

A. Experimental Environment
To create a simulated environment to verify the method discussed earlier we have used MATLAB R2021a with Intel Core I7-based processor having 8 GB DDR4 ram.

B. Data Processing
Different publicly published datasets were used for this experiment. Images were from different datasets, so they are of different dimensions and types. Details of datasets used to evaluate the proposed method are described in the following two sections. Two types of datasets are being used for this experimentation. The data set is divided into two parts 70% for the training set and 30% for the test set as shown in Table.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Training (70%)</th>
<th>Testing (30%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Covid</td>
<td>Normal</td>
</tr>
<tr>
<td>Dataset-1</td>
<td>404</td>
<td>1108</td>
</tr>
<tr>
<td>Dataset-2</td>
<td>526</td>
<td>1147</td>
</tr>
</tbody>
</table>

C. Evaluation Policy
A nonlinear SVM classifier is utilized for classification. A grid-search strategy is used to discover the optimal SVM kernel parameter values. We utilize 10-fold cross-validation to test the classifier's performance. Its accuracy is quantified in terms of average and standard deviation, True Positive Rate (TPR), False Negative Rate (FNR), and Area Under the Curve (AUC) of (ROC). These are the most commonly used measurements in picture forgery detection, and we utilized them to compare our work to
other current systems. The fraction of correctly identified samples to the total number of samples is known as accuracy.

\[ ACC = \frac{100(TP + TN)}{TP + TN + FN + FP} \]

True positive rate deals with the percent ratio of correctly classified samples and is calculated using

\[ TPR = \frac{TP}{TP + FN} \]

The false positive rate deals with the percent ratio of incorrectly classified samples and is calculated using

\[ FNR = \frac{FP}{FP + TN} \]

Here ‘TP’, ‘TN’, ‘FP’, and ‘FN’ are respectively the amount of true positive values, true negatives values, false positives values, and false negative values described in the previous section.

As it is noticed that the dataset available for this experiment is unbalanced so, we need to add more evaluation parameters. So, precision is to be calculated using the following formula.

\[ PPV = \frac{TP}{TP + FP} \]

D. Results and Discussion

1) Training Results Of The Proposed Method
To validate the proposed solution to a classification problem there is a need to conduct a classification experiment using a proposed classifier and discuss the results of the training process according to the evaluation policy mentioned in the previous section.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>ACC</th>
<th>TPR</th>
<th>FNR</th>
<th>PPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset-1</td>
<td>97.2</td>
<td>91.3</td>
<td>8.6</td>
<td>98.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>99.4</td>
<td>0.6</td>
<td>96.9</td>
</tr>
<tr>
<td>Dataset-2</td>
<td>95.5</td>
<td>89.5</td>
<td>10.5</td>
<td>96.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.3</td>
<td>1.7</td>
<td>95.3</td>
</tr>
</tbody>
</table>

In binary classification, the proposed method outperformed different available datasets. The area under the curve for this classification can be observed using Figure 4. Models were exported and tested using test data. Testing results were shown in the next section.
2) Testing Results
A trained model from support vector machines is tested using a test dataset. Results are shown in Table 3.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>ACC</th>
<th>TPR</th>
<th>FNR</th>
<th>PPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset-1</td>
<td>91.5</td>
<td>91.3</td>
<td>8.7</td>
<td>79.8</td>
</tr>
<tr>
<td>Dataset-2</td>
<td>94.3</td>
<td>99.4</td>
<td>0.6</td>
<td>92.8</td>
</tr>
</tbody>
</table>
3) Comparative Analysis with Recent Methods
For a comparative evaluation of the suggested method, some recent machine learning algorithms were chosen. The table compares the suggested method's efficiency to that of traditional machine learning and deep learning methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>ACC</th>
<th>TPR</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistical Features + PCA + SVM [22]</td>
<td>86.6</td>
<td>83.2</td>
<td>0.98</td>
</tr>
<tr>
<td>HOG + SVM [11]</td>
<td>83.2</td>
<td>80.8</td>
<td></td>
</tr>
<tr>
<td>LBP + SVM [11]</td>
<td>85.9</td>
<td>88.8</td>
<td></td>
</tr>
<tr>
<td>Color Features + SVM [17]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>97.2</td>
<td>99.4</td>
<td>0.97</td>
</tr>
</tbody>
</table>

V. Conclusion
Early detection and treatment of diseases that are difficult to resist, such as Coronavirus, are critical for overall health. As a result, automated detection frameworks are projected to aid in the speedy and exact analysis of the illness. We developed an AI-based framework that can detect X-ray images in this article. Nowadays, when the entrance to Corona information is severely limited, tests are conducted on a dataset with minimal information and with an imbalance between classes. The texture information of an image plays a vital role in producing features to fit SVM(“Support Vector Machine”) for the detection of COVID-19. Different openly existing datasets are used to calculate the proposed method and show the best results among different machine learning approaches. This study is so useful for the researcher to make use of Curvelet texture features in different areas of image-based research. In the future, A well-balanced dataset will be used to produce the best results, and also, CNN based model will be introduced to get higher performance using such types of datasets.

References


