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ARTIFICIAL IMMUNE ALGORITHM BASED CHEST IMAGE DIAGNOSIS FOR COVID DETECTION

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Abstract— In many areas of human life, technology has increased efficiency. To understand more about the patient's condition, the medical field has also used the equipment. Many academics are focused on medical image diagnosis in order to advance the health sector. The AISCD (Artificial Immune System Based COVID Detection) model is presented in this study. The histogram feature from the image has been extracted by AISCD, and to speed up model learning, the image training set has been blocked. By virtue of its cluster centre, each block is represented. Therefore, those affecting cluster centres are found by artificial immune genetic algorithm. In the training phase, an error back propagation model was used. Images from datasets with and without COVID infections were used in the experiment. Results and current detection were compared. Results were contrasted with already available detection models, and it was discovered that AISCD had enhanced work performance on a number of evaluating factors.

Index Terms— Image Data analysis, image processing, Genetic Algorithm, visual processing.

I. INTRODUCTION

The sickness known as COVID-19 is brought on by the SARS-CoV-2 coronavirus. According to figures from the World Health Organization as of June 2021, global spread makes it more harmful, since the discovery of the first case, killing almost 4 million individuals among the over 180 million confirmed cases.

Patients are screened in hospitals or primary care clinics as the initial step in the therapy of COVID-19. Although transcription-polymerase chain reaction are still the primary method for making the final diagnosis, in hospitals today, the election protocol is based on medical imaging because it is quick and easy to use, which enables doctors to diagnose illnesses and their effects more quickly. According to this approach, patients who are thought to have COVID-19 first undergo an X-ray but, if more information is required, a CT-scan session. This methodology has led to a significant increase in the use of computed tomography (CT) scans and X-ray pictures in the clinic as various treatment methods for identifying COVID-19 and determining the consequences of the virus.

Doctors use X-ray or CT scan images of the lungs to diagnose the condition and look for COVID deformation symptoms. The high COVID transmission rate has caused a rapid increase in the number of patients entering hospitals, creating a heavy pressure on imaging doctors and frequently leading to a scarcity of doctors in the fight against COVID. Deep learning techniques can be used to solve this issue. These techniques have made significant advancements recently, primarily as a result of rising computing power, an increase in the amount of data available, and ongoing development of deep neural networks and their algorithms, as seen in challenge competitions that set records. The goal of deep learning is to develop a machine learning model with multiple hidden layers that is trained on a vast quantity of sample data in order to eventually improve the precision of classification or prediction.

Each neural network that has been trained learns information relevant to the task at hand. Recognition system in artificial neural systems is used to utilise the stored knowledge of one job for another activity that is related, despite the fact that the basic idea of synthetic neural networks is to replicate human behaviour and intellect. Millions of images may be learned using machine learning for machine vision applications, and several enormous models have been trained using various architectures. To enable all researchers to utilise the knowledge that has been preserved, these learned models have been made available to the public. It is crucial for both patients and physicians to find COVID-19 in chest X-ray images in order to accelerate diagnosis and cut expenditures. Deep learning and artificial intelligence are able to identify images. Deep learning and artificial intelligence are able to recognise image class. ConvNets were used in this study's studies to detect COVID-19 with great accuracy in chest X-ray pictures. For the classification, three groups—COVID-19/Normal, taken into account. Utilizing images and statistical data, various image dimensions, network designs, state-of-the-art pre-trained models, and models of machine learning were applied and assessed.

II. Related Work

The Edge detection algorithm sobel were used in the pre-processing stage of Demir12's [7] research to present an LSTM network-based strategy. Although the model performance was greatly enhanced by the author, training both the CNN and LSTM techniques resulted in a significantly greater computational cost.

Oh et al.[8] used a patch-based classification approach in addition to a CNN model-based base classifier to address the issues brought on by a small training sample. Prior to producing random patch to train the CNNs with the ResNet-18 model, they first employed deep CNNs to segregate the images. They were capable of training the CNN as a result. As an outcome, they only needed a few training examples to build the CNN model. They just needed a small number of training datasets to successfully train the CNN model. The technique also somewhat decreased the cost of training. In the aforementioned study, the basis classifiers' fuzzy measurements were the normalised validation accuracies; however, this approach might not be applicable to other datasets. In order to filter COVID-19 instances from chest X-ray images, Ouchicha et al. [9] created a CNN model with inter-network skip links. The authors used two concurrent CNN models to connect each layer of networks using multi and intra-network backpropagation in order to tackle the vanishing gradient problem.

In order to effectively detect COVID-19 using the VGG-19 model, Das et al. [10] used chest X-ray pictures. A feature extraction method should be used in place of the DL-based model's direct prediction of the class. In order to accurately predict whether the person is COVID-positive or healthy, extracted VGG-19 model properties are fed into commonly used machine learning models (regression). It had a 99.26% accuracy rate.

A public dataset of CT scans gathered from studies in this area was made accessible by Yang et al. [11]. Additionally, they achieved an accuracy of 84.7% when separating COVID-19 true positives from negatives using DenseNet.

pneumonia-deep learning According to Zech et al.18, classifiers trained on two separate hospital systems predicted outcomes by identifying the origin of those institutions rather than critical characteristics that cause pneumonia. To solve this problem, Janizek et al. [12] developed an adversarial training-based approach. The prevalence of pneumonia was found to be two times higher in posterior-anterior (PA) chest X-rays than in anterior-posterior (AP) images.

In order to detect pneumonia, Dong et al. [13] showed a network configuration that produced high classification accuracy. They used an improved quantum neural network to train their model on the Kaggle chest X-ray data set, which included 5232 training images. With 624 different photos used for evaluation, this model has an accuracy of 96.07%. Considering the fact that the authors' research does not involve feature analysis, it is improbable that a quantum neural net could learn features that were inaccurate or unnecessary and still achieve such high accuracy. The University of California, San Diego made the data collection that these authors used public. Both the specificity and sensitivity were 0.9756 and 0.9460, respectively.

III. Proposed Methodology

The AISCD (Artificial Immune System Based COVID Detection) model is briefly discussed in this section. The block diagram of the covid-19 predictive steps is shown in Fig. 1. The part with all of the equations also included a description of each block to aid in better comprehension of the AISCD.

X-Ray input pre-processing

Before feature extraction, input X-Ray XI images were processed in a preliminary manner. Resetting the input image dimension to match the working environment is necessary. The image was then converted to grayscale. The transformation into a particular matrix was carried out by eq. 1, where

$$PCI \leftarrow \text{Pre-Processing}(CI)$$

The cost of calculation is decreased by using the grayscale format to extract histogram features from the image. As a result, work has converted RGB format to grey scale.

Generate Antibodies

According to the cluster centre, the image is divided into c numbers. So, an artificial immunological genetic algorithm was employed to obtain the sample cluster pixel values. As a result, population A is a collection of antibodies.

$$\mathbf{A \leftarrow Generate\_Antibody(m)}$$

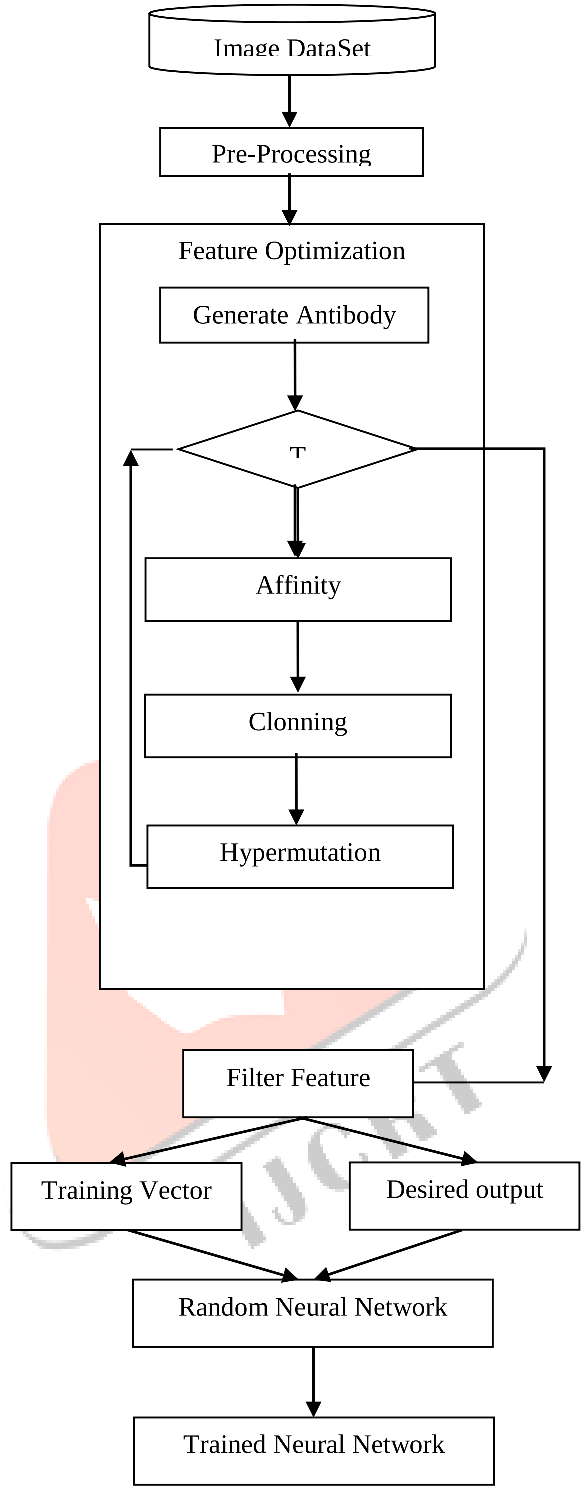


Fig. 1 Block diagram of AIFCMSD.

Affinity

By calculating the smallest difference between one image and other images, affinity of antibodies that are found in the population was estimated. The chromosome's affinity is therefore defined as the difference between the total of each antibodies in a population. The minimal image pixels difference from cluster centres was added together to assess each chromosome's fitness.

$$BFV \leftarrow SUM(min(B, XIP))$$

Cloning

The optimal solution Ab is obtained according to the affinity values of each antibody in the population. In accordance with the best antibody Ab, pixel values were randomly changed. by current feature status change.

$$A \leftarrow Cloning(A_b, A)$$

Hypermutation

The clones are then put through a hyper mutation process, where they undergo mutations inversely correlated to their affinities, with the finest antibody's clones undergoing the least mutation and the worst antibody's clones undergoing the most. The best N antibody are then picked for the subsequent iteration after a comparison between the clones and their parent antibodies. The algorithm's hyper mutation step's output is given by equation (Eq.).

$$A \leftarrow Hypermutation(A)$$

Max Iteration

Verify the maximum number of iterations. The final cluster centres of the image are the best current antibody of the maximum iteration if the maximum iteration is not reached before moving on to the fitness function phase.

Blocked Image

The pixels in the image are assigned c numbers of values by the genetic cluster centre. The entire image was now divided into bxb blocks. Blocks were shifted from top to bottom and from left to right. The blocked image's cluster values were converted into a single-dimensional vector and combined with a histogram feature to create the training feature.

$$GC \leftarrow Block(HIP, B, b)$$

$$TF \leftarrow [\ GC\ HF]$$

Training of Neural Network

• A three-layered neural network is assumed to have layers.

• I was used to identify input layer neurons, and j was used to identify hidden layer neurons. Neuron in the output layer is designated by k.

• Wij, where I and j are the layers of the neuron, represents the weights between neurons.

• Eq. 11 depicts the neuron's output based on weight and biassing value bj:

$$X_j = \sum x_i \,.\, w_{ij}\, b_j$$

where, $1\leq\ i \leq n$; n is the node j's input count, and bj is the node j's biassing. As a result, the network will discover the weights between the layers. The output weights of each layer must be changed in order to fix this problem.

Proposed AISCD Algorithm

Input: CI //X-Ray Images

Output: CTNN// Covid Trained Neural Network

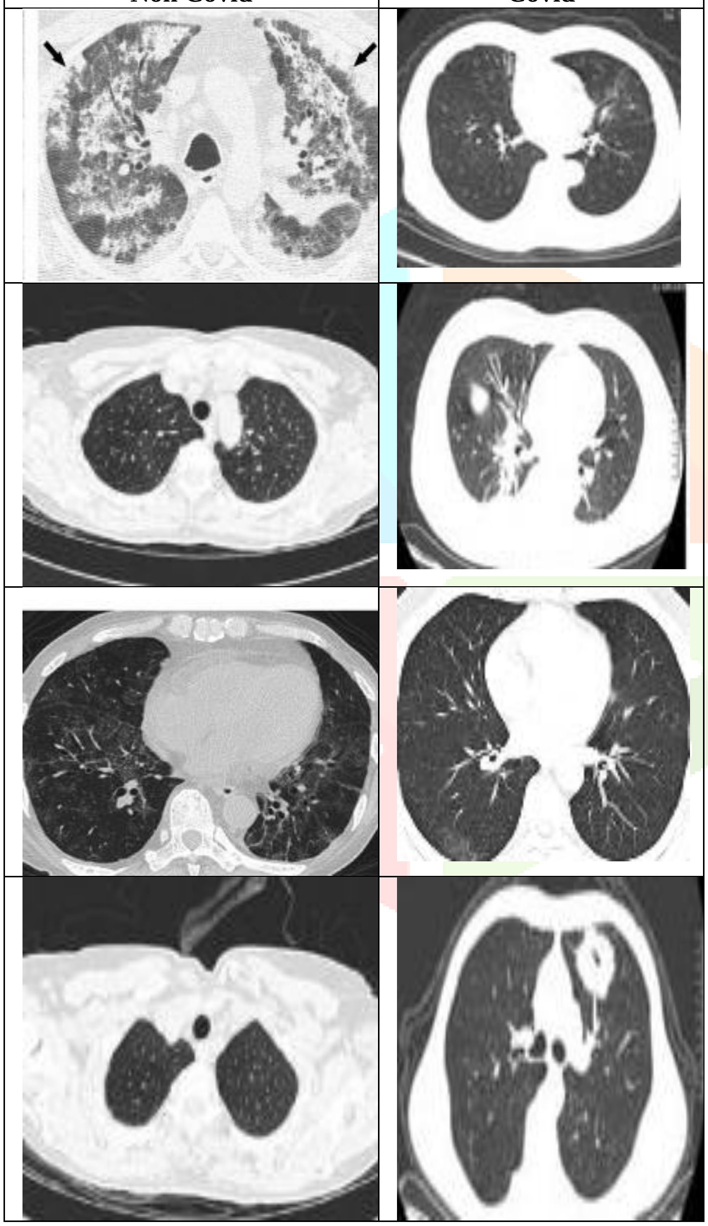
1. PCI←Pre-processing(CI)
2. CHF←Histogram-Feature(PCI, bins)
3. CC←Genetic_Cluster(PCI,c) // CC: Cluster Center
4. GC←Block(PCI, CC, b) //b: size of block
5. Loop 1:nb // Number of Blocks
6. CTF←[GC CHF] //CTF: Covid Training Features
7. Endloop
8. CTNN ←Initialize(TF)
9. Loop 1: epochs
10. CTNN ←Train(CTNN, CTF, Desired_Class)
11. EndLoop

IV. Experiment and Results

MATLAB was used to implement the classification of X-ray chest pictures. I3 CPU from the sixth generation and 4GB of RAM are configurations of the experimental system. Dataset for the experiment was acquired from [16]. Table 2 provides a detailed overview of the dataset.

COVID teach plentyTable 3 Dataset images.

Non Covid	Covid



Evaluation parameters

Prediction of image class models were evaluate on following parameters.

$$Precision = \frac{True\_Positive}{True\_Positive + False\_Positive}$$

$$Recall = \frac{True\_Positive}{True\_Positive + False\_Negative}$$

$$F\_Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

$$Accuracy = \frac{Correct\_Classification}{Correct\_Classification + Incorrect\_Classification}$$

Results

Table 1

Chest image classification models precision values.

Testing Images	AISCD	LFA-RNN
50	1	0.9105
100	1	0.9297
150	1	0.9094
200	1	0.8678
250	1	0.8455

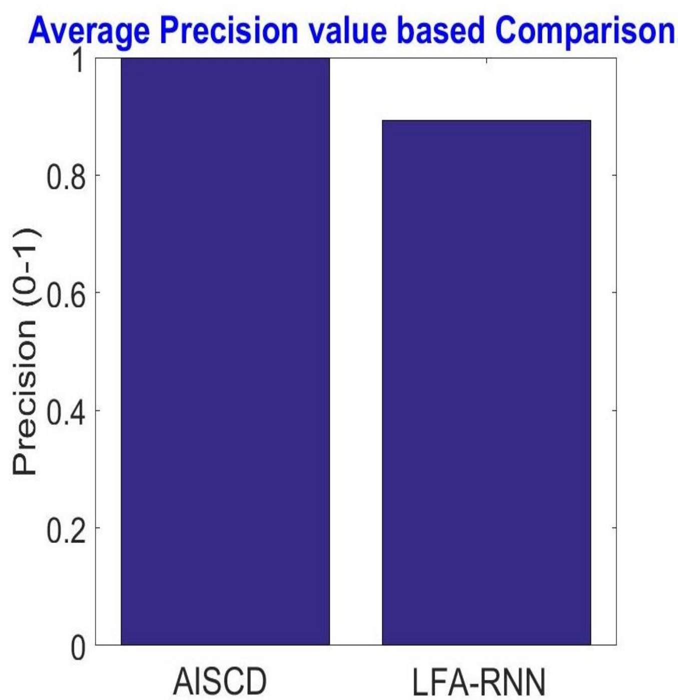


Fig. 2 Average precision value based comparison.

On the basis of the precision values displayed in table 1, COVID recognition by diagnostic X-ray image algorithms was compared. The value has increased by 10.742% as a result of using artificial neural networks to learn optimum attributes, according to a table. The work is enhanced by the incorporation of a genetic algorithm for feature extraction.

Table 2 Recall value based image comparison.

Testing Images	AISCD	LFA-RNN
50	1	0.9116
100	0.9994	0.9302
150	0.9993	0.9097
200	0.9989	0.8768
250	0.9978	0.8389

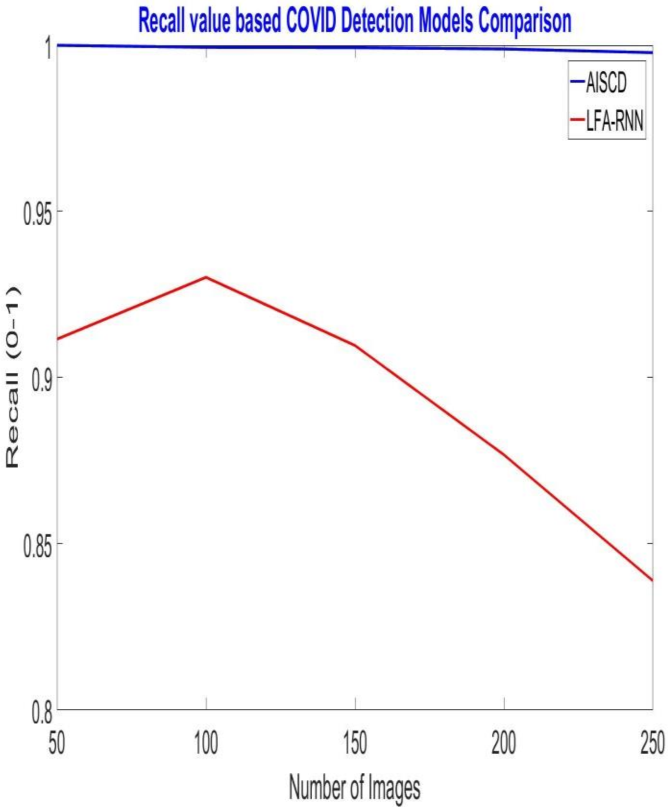


Fig. 3 Recall value based comparison.

Table 2 displayed the recall values for the COVID detection technique. It was demonstrated that the parameter values were improved by using the suggested Artificial Immune genetic algorithm.

Table 3 F-measure value based image comparison.

Testing Images	AISCD	LFA-RNN
50	1	0.9111
100	0.9997	0.93
150	0.9996	0.9095
200	0.9995	0.8723
250	0.9989	0.8422

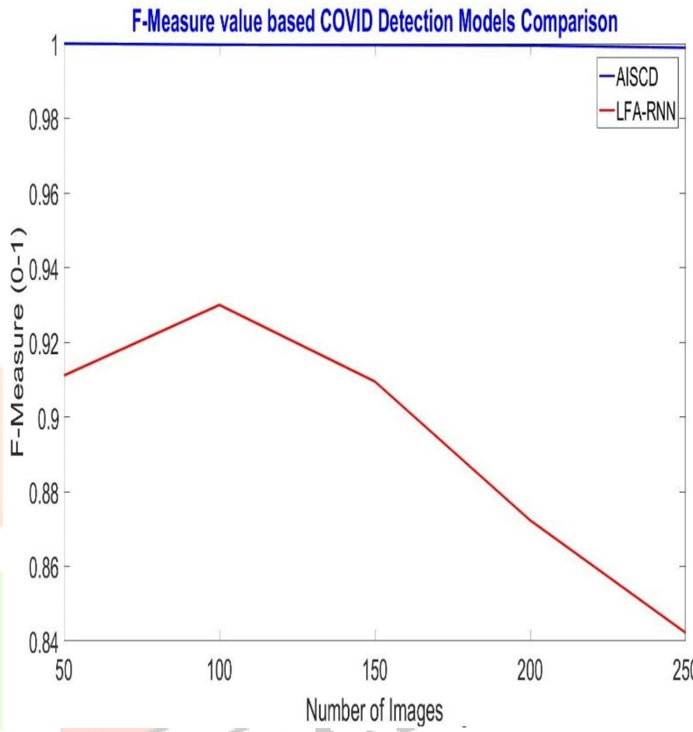


Fig. 4 F-measure value based comparison.

COVID detection by medical X-ray image diagnosis algorithm was compared on the basis of precision values shown in table 1. It was obtained from table that use of artificial neural network for the learning of optimized features has increase the value by 10.65%. This enhancement was achieved by use of histogram feature and genetic algorithm for the feature extraction also improves the work.

Table 4 Accuracy value based image comparison.

Testing Images	AISCD	LFA-RNN
50	**100**	**95.521**
100	**99.9688**	**96.4819**
150	**99.9625**	**95.4669**
200	**99.9493**	**93.3546**
250	**99.8906**	**92.3067**

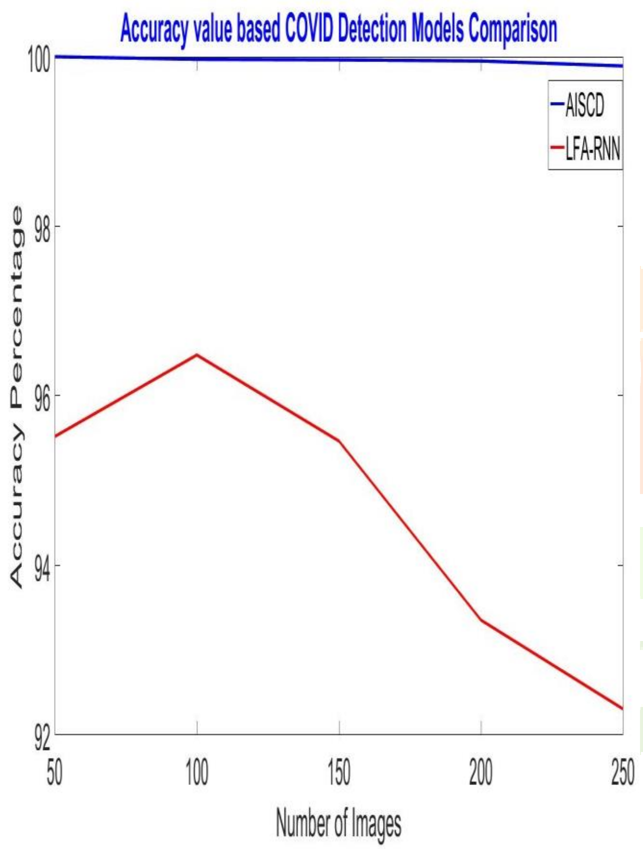


Fig. 5 Accuracy value based comparison.

Genetic algorithm based feature and histogram feature values were used in the model for the training of neural network. It was found from table 4 that accuracy of correct class prediction of proposed AISCD model was improved by 5.33%.

V. Conclusions

COVID imparts several lessons to people, and in that scenario, every sector not only becomes affected but also gets upgraded. The technology lessened the workload for medical professionals. A trained COVID detection model based on X-rays is suggested in this paper. The employment of artificial neural networks for the learning of optimum characteristics has increased performance metrics, according to the results. The usage of the histogram feature and the evolutionary method for feature extraction allowed for this improvement. The experiment used an actual dataset of X-ray images. Results reveal that when compared to the existing model, the suggested AISCD model has an increase in accuracy of 5.33% and a precision value of 10.742%. In the future, researchers can improve the model using different kinds of image, including as Diacom.

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