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An Enhanced MSVM Covid-19 Detection with Firefly Optimized Feature Extraction Technique

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ABSTRACT: COVID-19 affects the lives of a huge number of people every day, making it a deadly disease. The disease (CORONA) has shown to be a deadly illness that has harmed the human body on a global scale and is rapidly progressing. It's tough to tell the difference between COVID-19-infected and healthy people. Image processing plays an essential role in the medical field. Image processing and machine learning provide various algorithms in the medical field for the detection of diseases. This work is based on machine learning and image processing methods. The different types of classification and feature extraction methods have studied and compared. In this work, optimized HOG feature extraction and selection techniques have implemented in the CXR dataset. The research methodology is divided into different phases like; first phase is the pre-processing phase in which the median filter is used for the noise removal purpose. The OSTU method will be implemented for the segmentation of the CXR images. The essential features will be extracted by HoG in the third phase. Then, the features will be optimized by the FF (firefly) optimization technique. The multi-class support vector machine technique will be applied for classification and detection systems. For the covid-19 detection through CXR images, an enhanced MSVM machine learning method is implemented. The FF (firefly optimization) algorithm is used for feature selection. Comparison analysis of several previous methods is also calculated in this work. The research work has attained accuracy 97.81 %, spec of 97.6 %, and 98.4 % of sens. The research work is compared with previous methods and attained better performance and the compared with squeezeNet, googleNet, and detract models.

KEYWORDS: Covid-19, Chest X-ray Images, OSTU method, Firefly Optimization, MSVM (multi-support vector machine).

I. INTRODUCTION

The number of respiratory cases in China increased dramatically in December 2019. At first, the specific causes of this epidemic remained a mystery. But nevertheless, those were all soon connected to the wet commodity retail market pharmacologically. On 31 of December, China notified the Department Of Health regarding unusual bacterial infections in Wuhan, Hubei Province, several of the most populated cities [1, 2]. Among the most widely being used available approaches for direct measurement of lung disorders is chest-X-ray radiation therapy [1]. Physicians almost have direct access to chest-X- ray artefacts for study. Since CXR imaging was readily available mostly during latest COVID-19 disease outbreak, it became one of the first treatment technologies for use. Due to the increasing and emerging developments in computerised medical image visualisation, research techniques, and computer-aided diagnosis, it has expanded from one of the most significant facets throughout risk assessment methodology, for example, a critical important in the early identification, detection, and prevention of illness [3]. The term "medical imaging processing" relates to something like a computer to manipulate objects. Image acquiring, processing, interpretation, and coordination are only a few of the strategies and activities included in this manufacturing. The image is a feature that represents a measurement of a perceived sight's features including such brightness or shade [4]. Several medical image processing applications are X-ray imaging system, CT-Scan, Ultrasound, and Nuclear Medicine. COVID-19 is a highly contagious strain that communicates primarily by contact with the infected person's droplets in the air. Breathing or absorption of these particles may allow them to enter the living organism [5]. Fig 1. defines an example of non-infected

CXR (chest x-ray), an infected one with covid-19, and an infected one with the SARS (Severe Acute Respiratory Syndrome).

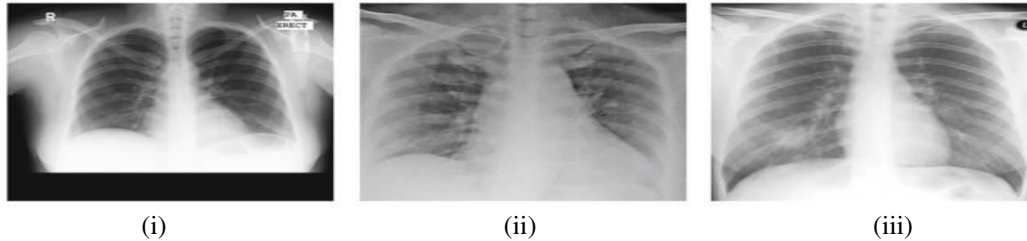


Fig 1. Illustration: (i) Non-infected or normal (ii) Covid-19 Infection, and (iii) SARS CXR images.

Whenever an individual seems to have a minor infection and displays minor side effects such as a cold or the flu, they are said to be in the early stages. Infection is widely consumed throughout the body of an infected person in certain time. Physicians recommend the 'Palliative care plasma therapy,' in which fluid from patients who have already stabilized is transmitted to survivors to minimize viral infection and thus recover more quickly [5]. The various signs and symptoms of COVID-19 are mentioned in Table I.

Table I. various signs and symptoms of COVID-19

| Sr. No. | Type of Signs | Symptoms |
|---------|--------------------|---|
| 1. | Common Signs | <ul style="list-style-type: none"> • Dry cough • High fever • Exhaustion |
| 2. | Less common Signs | <ul style="list-style-type: none"> • Sore throat • Headache • Skin rashes • Body pain • Diarrhoea • Loss of taste and smell |
| 3. | Highly risky Signs | <ul style="list-style-type: none"> • Chest pain • Breath shortness • Loss of movement |

A chest X-ray is a medical imaging procedure that involves introducing the chest to exposure for a slight specified period of time to obtain an image of the chest and its major organs. An X-ray material is formed against by the individual just on reverse side of the lens, which emits a quite low beam of medication [6]. The chest x-ray image is shown in fig.2.



Fig 2. Chest X-ray image [6]

In existing work, introduced CNN (convolutional neural network) framework depends on class de-composition, that in terms of de-compose, transfer, and compose mode (DeTrac) method, to enhance the performance of pre-trained models on the detection or recognition infected (covid-19) cases from CXR images. Adding a class de-composition layer objective to partition individual categories within the medical image database into various sub-categories is treated. For the classification evaluation, they used medical images of CXR collected from various UCI sites. The database gives difficult CV (computer vision) challenges issues due to intensity inhomogeneity in the medical images and irregulars in the data division.

The proposed work, analyse several classification and feature extraction techniques used to detect the disease in CXR images. It develops and implements optimized HoG (histogram-of-gradient) feature extraction methods to



extract the main component of the chest x-ray images. It develops and implements enhanced MSVM with optimized feature extraction to classify the infected X-Ray samples. It evaluates the system performance metrics such as accuracy rate, specificity, sensitivity, error rates, and compared them with the existing methods.

II. RELATED WORK

Arevalo-Rodriguez, et al. [7] had monitor and evaluate data on the incidence of RT-PCR falsified during preliminary COVID-19 analysis. The authors had used electronic databases, LILACS, EMBASE, and database of COVID-19 such as the Centre living EPPI structured graph of details regarding COVID-19 as well as the Coronavirus Identified Needs System living documentation repository to conduct proposed system examination. Authors individually reviewed and categorized studies were based on the entry requirements, and information from studies that were included in the gathered data. The QUADAS-2 (Quality Assessment of Diagnostic Accuracy Studies) method was used to determine the margin of error. A multidimensional matrix was made by mixing correlation coefficient scale and was used to estimate the probability of false-negative test effects. The GRADE approach for tests and methods was used to evaluate the reliability of the proof regarding cases of false-negative. The information collected had some flaws, such as the possibility of discrimination, widespread diffusion, and questions about its potential application. The proposed system results highlight the importance of multiple assessments in individuals with presumption infection with 54 percent of accuracy. **Xiao, A. T., et al. [8]** generated a report on negative results of false RT-PCR test. The conversion of COVID-19 nucleic acid was analyzed on different patients. The main attributes of nucleic acid of patients were extracted and used to generate the false relations. A deep convolutional neural network was developed and implemented for identifying Chest Infections. Deep networks, Pooling layer, ReLU Activations, and fully linked layer model was proposed. The 15 transfer function made the final densely integrated plate. The findings revealed that 21.4% of respondents had a satisfactory RT-PCR positive test after 2 sequential negative consequences. These are some of the greatest obstacles in this epidemic is rapidly identifying and tracking COVID-19 victims in order to make prompt care, tracking, and operational works. **Sharma, A., et al. [9]** worked on to create approaches that would be consuming small amount of time process to substitute or complement RTPCR test based approaches. The main objective of proposed research was to develop effective deep CNN (neural network) for qualitative identification of COVID-19 victims using x-ray chest input dataset. In the advancement of advance learning AI based identification frameworks for CORONA as well as other significant contagious diseases. The authors were utilized publicly accessible X-ray chest scans of adolescent CORONA victims. The authors were implemented 25 multiple kinds of enhancements mostly on actual pictures to maximize the dataset size and create generalized models. In addition, for the training and validation of the classification techniques, the authors used the deep learning approach. For mild fever, pneumonia, CORONA, tuberculosis, and non-CORONA were the mixture of multiple strongest systems and had the greatest predictive performance. **Gao, T., et al. [10]** introduced a new diagnostic framework using deep neural networks to support healthcare professionals through detection by separating COVID-19. The different patient's datasets from hospital patients on X-ray chest images were collected. The differentiation and examination of speeding up the identification of COVID-19 disease deep CNN mechanism was used. Such a tool could save time and improve reliability when evaluating chest X-rays, enhancing our clinical potential towards treatment and classification. The concept seems to be a collection of medical images of X-ray lung (COVID-19 infected, regular, and, infected by bacteria) were used to train the model CNN that really could differentiate amongst disturbance and valuable details, and then used that experience to analyse new images by identifying behavior and predict disorders like COVID disease inside the patient. The ML (machine learning) based supervised approach was implied because the learning method from the training sample could be compared to having a doctor overseeing the method. **Khuzani et al. [11]** found the correlation in characteristics of COVID-19 CXR artefacts and pneumonia affected by several other diseases makes health providers' clinical manifestations difficult. The authors hypothesized that automated learning-based classification algorithms would be able to consistently differentiate COVID-19 patients' CXR images from several other infections such as pneumonia. To develop an appropriate machine learning classification algorithm which could differentiate COVID-19 instances against non-COVID-19 patients with a high specificity and consistency, the authors had used a dimension reduction technique to create a collection of feature selection of CXR images. The authors were successful in implementing classification model that used an extremely smaller dataset containing CXR images through using spatial information of chest x-ray images dataset. The authors recommended that the proposed COVID-Classifer be included in combination with some other measures to ensure the most efficient use of healthcare resources by remove unwanted cases to be quickly triaged. **Goldstein et al. [12]** developed and test a predictive model for COVID-19 evaluation, as well as to provide such a method for scanning for patients with specific samples of XRAY. The identification of CORONA inside prefrontal CXR images, the classification method was developed by implementing a pre-trained based RENET 50 deep convolutional neural network and improved its dimensionality reduction and respiratory fragmentation. Depends on the network performance, a KNN algorithm was introduced, which determines the artefacts

and were most identical to an input dataset. The precision, responsiveness, and AUC (Area under the curve), precision-recall (PR) curve ROC (receiver operating characteristic) curve were used to evaluate the model. The database used for the analysis contains 2362 CXRs including 1384 patients, matched through CORONA positive and CORONA negative. On a testing image containing 15% of the original results, the proposed model had achieved accuracy of 89.7 percent and sensitivity of 87.1 percent in COVID-19 identification, with 0.95 AUC-ROC and 0.94 PR curve. **Pereira, R. M., et al. [13]** suggested an evaluation method that takes into account the important components: the first component was multi-class division; the second component was systemic categorization, although pneumonia was a patriarchal disease. The authors suggested using random sampling methods in the specification to re-balance the group's allocation due to the inherent measurement errors in classification of COVID-19 field. The identification paradigm extracts the features utilizing a few well variations of parameters as well as a Convolutional Neural Network pre-trained model, as texture was essential of the key characteristics images of chest XRAY. In the proposed framework, the authors were also looked at early and late fusion strategies in order to take advantage of the strengths of numerous segmentation techniques and foundation classification methods at the same time. A deep neural network was developed and implemented by **Chaudhary, A., et al. [14]** for the identification of chest Infections. Deep networks, Pooling layer, ReLU Activations, and fully linked layer were used in proposed model. The fifteen transfer function made the final densely integrated plate. Each of the fifteen diseases would be predicted by each destination network. To train the proposed model, researchers used an accessible to the public Chest X-Ray dataset that contains 15 groups of images titled Atelectasis, Emphysema, Infiltration, Cardiomegaly, Mass, Effusion, Pleural Thickening Nodule, Pneumothorax, Pneumonia, Edema, Consolidation, Hernia, Fibrosis, and No finding. Interestingly, in classification tasks, the proposed model had provided efficient performance. The identification of infectious illnesses had an overall accuracy of 89.77 percent. The validity of the proposed design was shown by the comparative evaluation. The proposed method was best for categorizing multiclass clinical data for various thoracic illnesses. The existing techniques of COVID-19 detection are compared in Table II with research gaps, datasets, and implemented tools. The comparison methods, parameters, and further enhancement are depicted in Table III.

Table II. Existing techniques of COVID-19 detection System

| Author Name | Techniques | Problem/Gaps | Dataset | Tool |
|-------------------------------|---|-------------------------------------|--|--------------------|
| Arevalo-Rodriguez, et al. [7] | Logistic regression based covid detection technique | Heterogeneity is high | Repositories of EMBASE, MEDLINE, LILACS, and, COVID-19 | - |
| Xiao, A. T., et al. [8] | RTPCR test | - | - | RTPCR kit |
| Sharma, A., et al. [9] | Artificial Intelligence and transfer learning-based model | Data argumentation issues | External validation dataset 2 | Python environment |
| Gao, T., et al. [10] | Deep convolutional neural network | Limited dataset | NHI patients | |
| Khuzani et al. [11] | Multi-layer neural network-based methodology | Small dataset | Data collected from the online repository | Python environment |
| Goldstein et al. [12] | ResNet-50 CNN model | Data annotation issues | Collected samples | - |
| Pereira, R. M., et al. [13] | Hierarchical classification based technique | Data imbalance issues | RYDLS-20 dataset | - |
| Chaudhary, A., et al. [14] | Deep convolutional neural network | In complex cases inaccurate results | Chest x-ray 14 | - |

Table III: Comparison methods of existing frameworks

| Author Name | Comparison Methods | Parameters | Enhancement |
|-------------------------------|---|---|---|
| Arevalo-Rodriguez, et al. [7] | - | Heterogeneity | The test will be conducted on more cases |
| Xiao, A. T., et al. [8] | - | - | Need to improve less false detection |
| Sharma, A., et al. [9] | | Number of iterations Batch size | The enhanced Transfer learning approach will be implemented for efficient results of classification |
| Gao, T., et al. [10] | Vgg-19 CNN | Accuracy | Need to extract more radionics features for more accurate results |
| Khuzani et al. [11] | VGG-16 GoogleNet-V1 ResNet-50 | Sensitivity Precision AUC Accuracy | Need to explore other classifiers for more efficient results of classification |
| Goldstein et al. [12] | Deep learning models | Precision Recall Accuracy Sensitivity AUC | More data will be used for the high reliability of the model |
| Pereira, R. M., et al. [13] | KNN MPL Random forest SVM Decision tree | F1 score | More performance evaluation parameters will be used |
| Chaudhary, A., et al. [14] | LeNet Alexnet | Precision Recall Accuracy F1 measures | The classifier will be enhanced for better results |

III. RESEARCH METHODOLOGY

In this section, the main objective of the proposed method is to improve the process of detection of disease (Covid-19). For this, an enhanced MSVM Covid-19 Detection with Firefly Optimized approach is used to improve the accuracy rate, spec, sens, and error rates. Normally, we will be using enhanced MSVM machine learning (ML) methods which have to follow two steps and shown in fig 3;

- (i) Knowledge Domain and
- (ii) Testing Domain

The brief description phases are discussed as follow:

- (i) Chest X-ray Image Acquisition
- (ii) Chest X-ray Image Pre-processing
- (iii) Chest X-ray Image Feature Extraction
- (iv) Selection of the component with MSVM
- (v) Evaluation of the performance metrics and comparison.

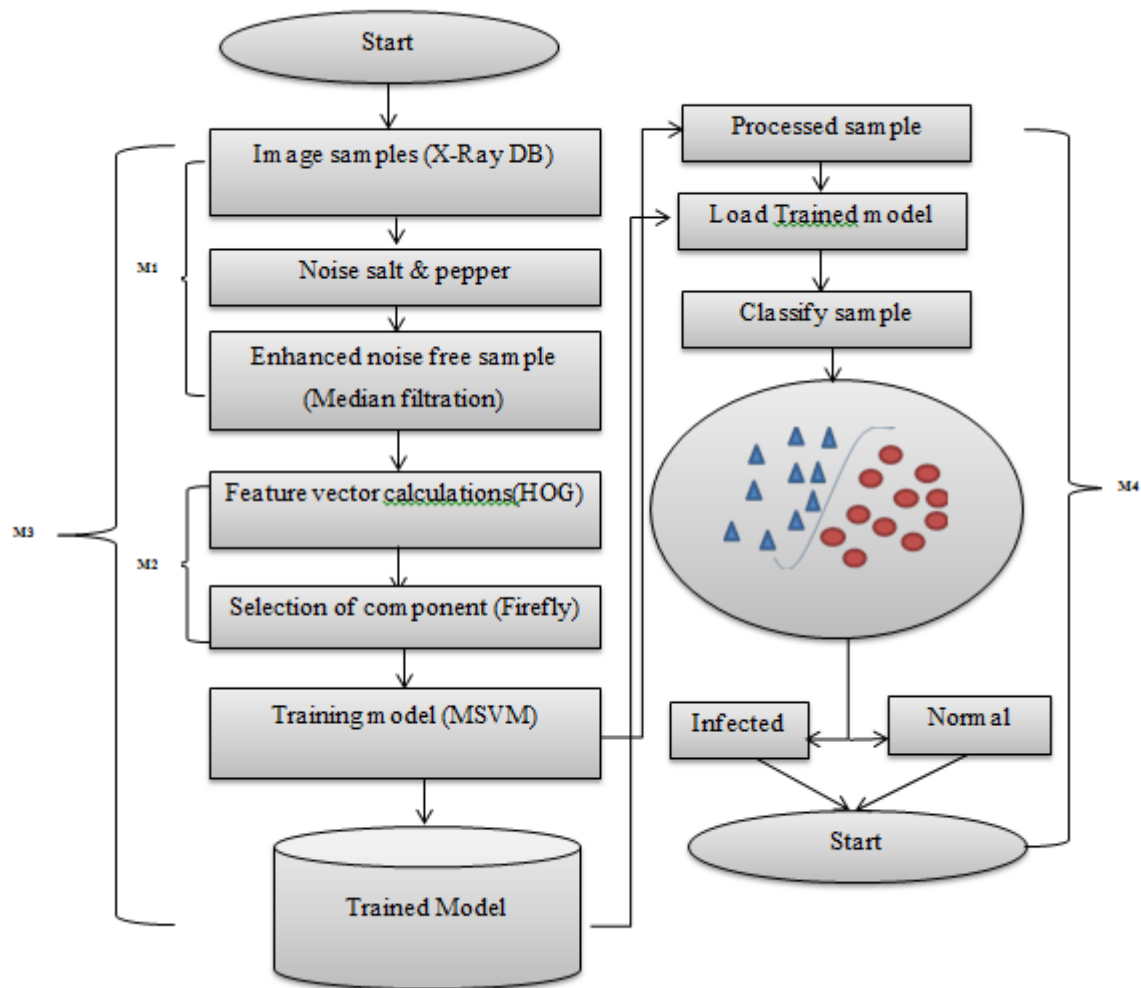


Fig 3. Research Methodology

Step I: CXR Image Acquisition and Pre-processing: This research work, find the database from the JSRT and MC covid-19 radiography database [15]. The database is a collection of CXR medical images. These databases are of various categories like infected covid-19, non-infected chest x-ray images (Normal), and Virus (Pneumonia). Firstly, upload the input images and re-size the CXR image 256*256 range set. It reduced the dimensional size of the CXR input image. It identifies the unwanted noise in the converted image. The pre-processing step is introduced 2D MF (median filter) transformation approach to remove the artificial noises in the CXR image. After that, the 2D transformation filtration procedure detects the segmented edges using ostu threshold approach. In OTSU thresholding, the pixels of the image are divided into two classes. The first class is the foreground class of pixels and the second class is the background pixels. The foreground and background pixels of the image are collaborating in such a way that forms minimal variance.

Step II: CXR Image Feature Extraction: This step introduced the HoG (Histogram-of-Gradients) approach for feature extraction. A feature extractor is a way to find the essential information from the image. The HoG is the abbreviation of Histogram of Gradients which is used as a feature extractor and describes the necessary features of the image. The main focus of the HoG descriptor is to find the shapes of the objects inside the image. The directions of edges are also provided by the HoG extractor.

Step III: Selection of the component with MSVM: This proposed method will implement the firefly algorithm and its implementations are an interesting topic in image processing. The Firefly algorithm is one of several evolutionary algorithms with multiple purposes. It's convenient and straightforward measures, as well as its efficacy, inspection and analysis throughout multiple disciplines. Several experiments have been conducted to improve the standardized firefly

algorithm's efficiency and adapt it to the nature of the problem. This FF optimized FV (feature vector) will pass the MSVM classification to predict the Covid-19 Disease. MSVM is a machine learning algorithm based on supervised learning. It helps in classification as well as regression. The main objective of SVM is to provide a hyperplane and generate the different class clusters [13]. The MSVM is used to generate discrimination between two or more classes. After that, the extracting features, the enhanced classification is calculated by using enhanced MSVM Covid-19 Detection with Firefly Optimized approach. The dataset for validation set and training sets consists of 2 parts like the train feature vector that are used to train the classification model and test feature vectors are used to detect the accuracy rate (%) of the train MSVM model.

Step IV: Evaluation Process: Finally, the covid-19 disease type with accurate value is calculated the proposed system performance parameters like acc, spec, sens, error rate and compared with the existing models.

IV. RESULT ANALYSIS

In this section, the evaluation performance of the research model is examined on The JSRT and MC covid-19 chest x-ray images. The database is divided into three categories such as normal or non-infected, infected covid-19, and pneumonia virus chest x-ray images. The proposed systems performance metrics are used for the examination of the proposed model are acc, spec, sens, error rate.

4.1 Database

The proposed methodology will be examined on two types of datasets. The datasets with number of images are shown in Table IV.

Table IV. Images used in work

| Sr. No. | Reference | Types of Images | Number of images |
|---------|-----------|--------------------|------------------|
| 1. | [16] | Chest X-RAY images | 200 images |
| 2. | [17] | Chest X-RAY images | 200 images |

4.2 Performance Metrics

For the proposed performance calculation, we adopted accuracy arte, spec (Specificity), sens. (Sensitivity), and MSE (mean Square Error) Rate. They are explained as:

$$\text{Acc} = \frac{tp+tn}{n} \quad (\text{i})$$

$$\text{Sens} = \frac{tp}{tp+fn} \quad (\text{ii})$$

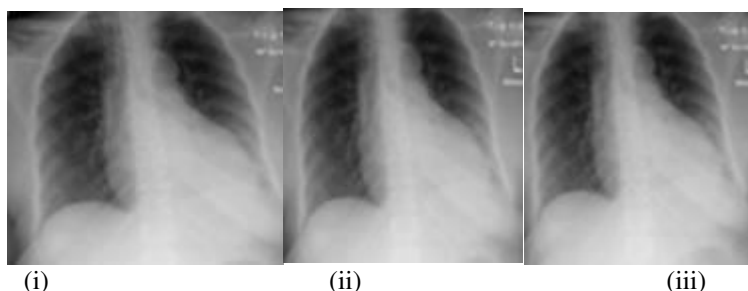
$$\text{Spec} = \frac{tn}{tn+fp} \quad (\text{iii})$$

$$\text{MSE} = 1/m \sum_{k=0}^n (x_i - x_i^{\wedge})^2 \quad (\text{iv})$$

Here, tp = true positive in case of infected case (Covid-19), and tn = true negative in case of non-infected (normal) case or other disease, while fp and fn are the in-correct model detection of covid-19 and other cases. **m**- Number of total data points, x_i – Expected values, x_i^{\wedge} - Actual values.

4.3 Simulation Result Analysis

The research work is performed in the MATLAB tool used, and graphical user interface has designed a desktop app. The total of 200*3 images have been utilized in these experiment result analysis including infected (covid-19), non-infected (normal), and covid-19 pneumonia CXR images are defined. It almost 200*3 CXR images have been utilized for knowledge domain. Testing stage has used 120 images for disease detection. The testing stage defines the research model enhanced MSVM Covid-19 Detection with Firefly Optimized approach.

**Fig 5** (i) Input Image (ii) resize image and (iii) conversion image.

Above fig 5 (i) shows the infected covid-19 disease type in CXR input image is uploaded, and (ii) shows the re-size the test input image 256*256 ranges. (iii) It converts the three-dim into two-dim CXR resize image and evaluates the gray-scale image. It optimizes the dimensional of the resize image.

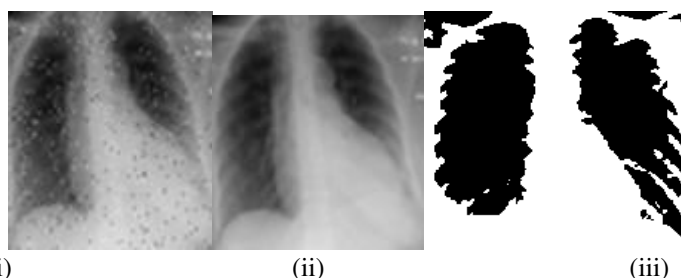
**Fig 6.**(i) Artificial Noise Attack (ii) Filtered Image and (iii) Segmented Image

Fig 6 (i) represents the artificial noise attack in the uploaded test input image.(ii) It applied the filtration method using median filter to calculate the smooth image and remove the artificial noise data in the infected image. (iii) The segmentation using Otsu method is applied to evaluate the regions of the filtered chest x-ray image. In OTSU thresholding, the pixels of the image are divided into two classes. The first class is the foreground class of pixels and the second class is background pixels. The foreground and background pixels of the image are collaborating in such a way that forms minimal variance.

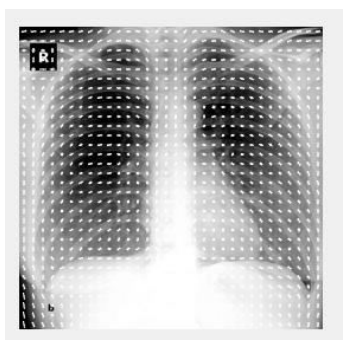
**Fig 7.**HoG Description Feature Extraction

Fig 7 defines the main focus of the HoG descriptor is to find the shapes of the objects inside the image. The directions of edges are also provided by the HoG extractor. Pre-processing information is a valuable part of any computer vision work, as well as dealing with imagery is no exception. The file must be pre-processed to reduce the dimension to height (1:2) ratio. The graphic must ideally be 64×128 pixels in dimension. It is because the attributes will be extracted by segmenting the process into 8×8 as well as 16×16 portions. The gradient for each image pixel must then be calculated. Gradients are minor changes in x and y coordinates.



| Epochs | Accuracy Rate (%) |
|--------|-------------------|
| 0 | 1 |
| 2 | 2.5 |
| 4 | 4 |
| 6 | 6 |
| 8 | 8 |
| 10 | 10 |
| 20 | 18 |
| 30 | 28 |
| 40 | 38 |
| 50 | 48 |
| 60 | 58 |
| 70 | 68 |
| 80 | 78 |
| 90 | 88 |
| 100 | 95 |

| Model | acc (%) |
|--------------------------------|---------|
| Enhanced MRBM with EE approach | 98 |
| DeTao | 97 |
| Graphlet | 90 |
| Graphlet with Private Windows | 83 |

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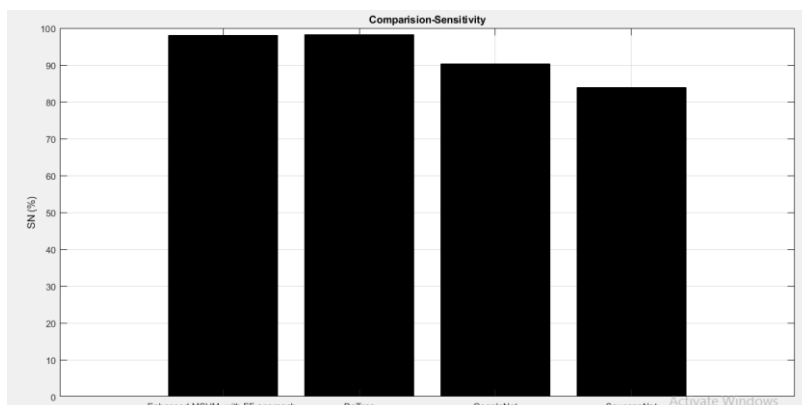


Fig 11. Comparison Analysis – Sensitivity Rate (%)

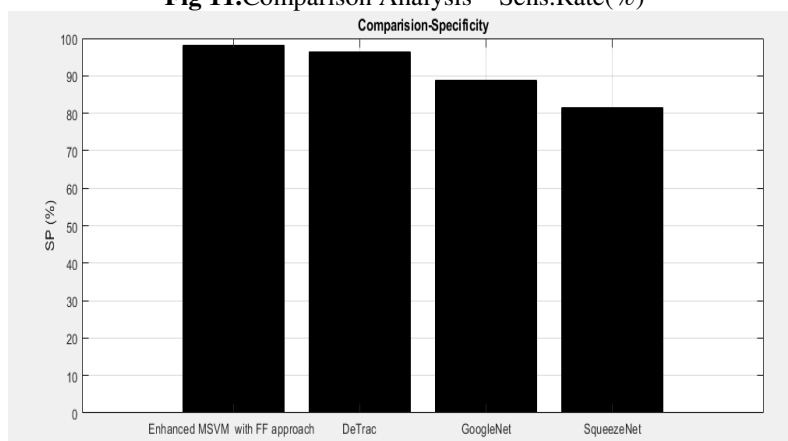


Fig 12. Comparison Analysis – Specificity Rate (%)

Fig 10, 11 and 12 shows the comparison analysis with proposed and existing methods using googleNet, SqueezeNet, and DeTrac method. This proposed method has improved the accuracy rate, SP (Specificity), and SN (Sensitivity).

Table V: Comparison Performance

| Parameters | Proposed Enhanced MSVM with Firefly Optimization Approach | DeTrac | GoogleNet | SqueezeNet |
|------------|---|--------|-----------|------------|
| Acc (%) | 97.9 | 97.30 | 89.60 | 82.70 |
| SP (%) | 97.9 | 98.20 | 90.30 | 83.80 |
| SN (%) | 98 | 96.30 | 88.80 | 81.40 |

Table 5 shows the comparison between Enhanced MSVM with Firefly Optimization Approach and existing methods using Enhanced MSVM with Firefly Optimization Approach, DeTrac, GoogleNet, and SqueezeNet classifiers. The proposed system performance value of accuracy is 97.9 with Enhanced MSVM with Firefly Optimization Approach; accuracy value is 97.9 %, GoogleNet value is 89.60 %, and SqueezeNet value is 82.70 %. The existing DeTrac approach SP performance value is 98.20 %, GoogleNet is 90.30% and SqueezeNet classifier value is 83.80 %. The existing DeTrac approach SN performance value is 96.30 %, GoogleNet is 88.80 % and SqueezeNet classifier value is 81.40 %. The proposed work performance with parameters such as Acc. value is 97.9%, SP value is 97.9, SN value is 98, and MSE value is 0.0053.



V. CONCLUSION AND FUTURE SCOPE

Detection of Covid-19 is normally connected with the sign and symptoms of PNEUMONIA, which can be shown by image tests. Medical Image test can give a speed detection of covid-19 and consequently contribute to manage the world wide spread of the disease. Chest X-ray and CT are the imaging methods that play a significant role in the detection of disease (Covid-19). Enhanced MSVM Covid-19 Detection with Firefly Optimized approach has been used for the disease detection of infection covid-19. MIP (medical image processing) that is described in this proposed work. ML (machine learning) and computational intelligence optimization methods are used for effective outcomes. The Enhanced MSVM Covid-19 Detection with Firefly Optimized approach is used for classification of CXR images. The JSRT and MC datasets are used for the knowledge domain and testing stage of the network. There are around 200*3 CXR images exist in the database. The database is divided into 4 sub sections that are infected covid-19, non-infected or normal, and pneumonia cases. The research model is compared with the previous systems and attained better performance and the compared with squeezeNet, googleNet, and detract. The proposed system performance is analyzed with 4 different which are acc, spec, sens, error rate. The further work will implement an effective pre-trained feature extractor and selection approach. It will implement a deep learning with computational intelligence approach to detect the disease and improve the system performance in the form performance metrics such as time consumption, and expensive.

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