Diagnosing COVID-19 Lung Inflammation Using Machine Learning Algorithms: A Comparative Study

Abbas M. Ali, Kayhan Zrar Ghafoor, Halgurd S. Maghdid, and Aos Mulahuwaish

Abstract In this paper, we performed a comparative analysis using machine learning algorithms named support vector machine (SVM), decision tree (DT), k-nearest neighbor (kNN), and convolution neural network (CNN) to classify pneumonia level (mild, progressive, and severe stage) of the COVID-19 confirmed patients. More precisely, the proposed model consists of two phases: first, the model computes the volume and density of lesions and opacities of the CT images using morphological approaches. In the second phase, we use machine learning algorithms to classify the pneumonia level of the confirmed COVID-19 patient. Extensive experiments have been carried out and the results show the accuracy of 91.304%, 91.4%, 87.5%, 95.622% for kNN, SVM, DT, and CNN, respectively.

Keywords Pneumonia · COVID-19 · Machine learning algorithms · Level of COVID-19 severity

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1 Related Work

In this section, we review the existing methods that are used for the diagnosis of novel COVID-19. There are many methods that are utilized to distinguish viral pneumonia in dubious cases.

Today, the coronaviruses is impacting over hundreds of countries around the globe. The first confirmed coronavirus case is found in Wuhan city, Huanan Seafood, which is large comprehensive market, includes frozen seafood. In December 30, 2019, Wuhan health commission issued a notice on the continues occurrence of pneumonia cases due to COVID-19 at Huanan Seafood Market. This notice received public attention about the epidemic. On January 26, 2020, the institute of virology of China announced that 33 out of 585 cases were found to contain novel the coronavirus nucleic acid. Thus, health officials concluded that Huanan Seafood Market being the suspected source of the epidemic [1, 2].

The fast transmission of COVID-19 and the increase in demand for diagnosis has encouraged researchers to evolve more intelligent, highly sensitive, and effective diagnostic methods to help stem the spread of coronavirus disease 19. The diagnosis method which is managed by the radiologists is the manual measure of the lung infection quantity. Furthermore, Al-based automated pneumonia diagnosis is used to distinguish the density, size, and opacities of the lesions in COVID-19 confirmed cases. These algorithms are capable to analyze CT scan images outcome in a little while comparing to other available ways [2].

Because of the new existence of COVID-19, there is a scarcity of existing literature in this field. In an effort, the researchers used deep learning based on an Al engine to identify COVID-19 by using high resolution CT images [2]. However, their suggested model exclusively depends on CT images. In reliance on the latest research [3], the detection of COVID-19 is more credible when multiple methods are used together. In another attempt, a smart reading system for CT image, developed by Ping An Insurance Company of China Ltd [4, 5] which can read and examine in a short period of time.

There was an important arguement in [2], related to the importance of CT scan images in the detection of COVID-19 cases, which can be deemed a lot faster way in comparison with the traditional method utilizing the nucleic acid detection. Besides its effectiveness in diagnosing the disease, it can assess the severity level of pneumonia [6, 9]. With all 140 laboratory-confirmed COVID-19 cases, CT results were reported positive. Moreover, CT scan was capable to identify these positive cases even within their early stage, which shows its effectiveness in detecting symptoms of pneumonia level [7, 8]. Thus, developing a diagnosis tool of COVID-19, lung inflammation level is a pressing need in order to detect the severity stage of the pneumonia.

In this chapter, we performed a comparative analysis using machine learning algorithms named support vector machine (SVM), decision tree (DT), k-nearest neighbor (kNN), and convolution neural network (CNN) to classify pneumonia level (mild, progressive, and severe stage) of the COVID-19 confirmed patients. More precisely, the proposed model consists of two phases: first, the model computes the volume and density of lesions and opacities of the CT images using morphological approaches. In the second phase, we use machine learning algorithms to classify the pneumonia level of the confirmed COVID-19 patient. Extensive experiments have been carried out and the results show the accuracy of 91.304%, 91.4%, 87.5%, 95.622% for kNN, SVM, DT, and CNN, respectively.

2 The Proposed Approach

The proposed approach comprises three main parts; in first part, the weight for CT images has been computed for confirmed COVID-19 patient utilizing morphological methodology, and the second subsequent technique classifies the pneumonia level of the confirmed COVID-19 patient and internal representation for the CT images. To accomplish the exact classification of lung inflammation, a modified CNN has been utilized and some other traditional classifications. The following sections are showing the three phases.

2.1 Preprocessing of CT Images

This phase related to pre-handling and clustering of the salient features for the phases of COVID-19 infection virus CT image to be determined and feed to the CNN and other traditional machine learning algorithms. This procedure was to fragment the lesions in the lung using segmentation process, and afterward to improve the image concentration on this area. Then, extracting significant features for the lungs containing lesion areas. These features simply were joining together to improve the feature depiction of the tainted lung. The proposed algorithm steps for extracting important features vectors for the images are outlined in Fig. 2. The procedure will apply for the all images that expected to train the framework on the COVID-19 cases. This is to recognize different cases, which depends on the trained images. Preprocessing of the images is significant and makes the morphological operation to remember many features for CT scan images as early, progressive and sever together with noncovid case. This process depends on weight pixels looked in the two sides of lung. Figure 1 shows the training machine learning algorithms on the CT images COVID-19 stages

The greater parts of morphological operations have done to make the sores places in the lungs to be clearer; this will impact on the abstraction of the feature vectors. The implementation of morphological procedure on the original images and the outcome it will adjust the lesion areas produced by COVID-19 to be white pixels inside a black lung quarters, this let determining of the affected areas by the virus infection become extremely basic. Figure 3 illustrates the resulted image after applying the steps which are mentioned in Fig. 2. The two calculations HOG and EOH are extracted the

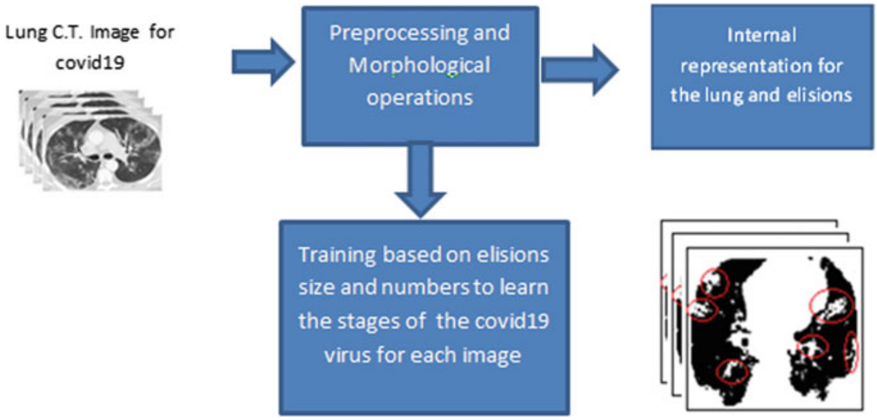

Fig. 1 Training machine on COVID-19 patient and internal representation

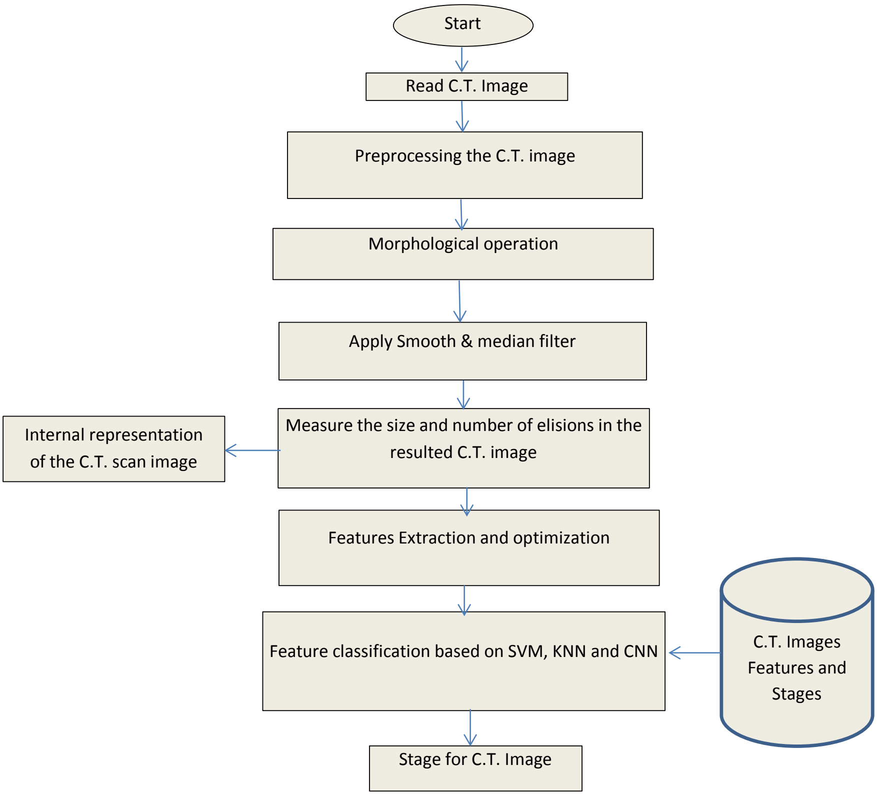

Fig. 2 CT scan image classification

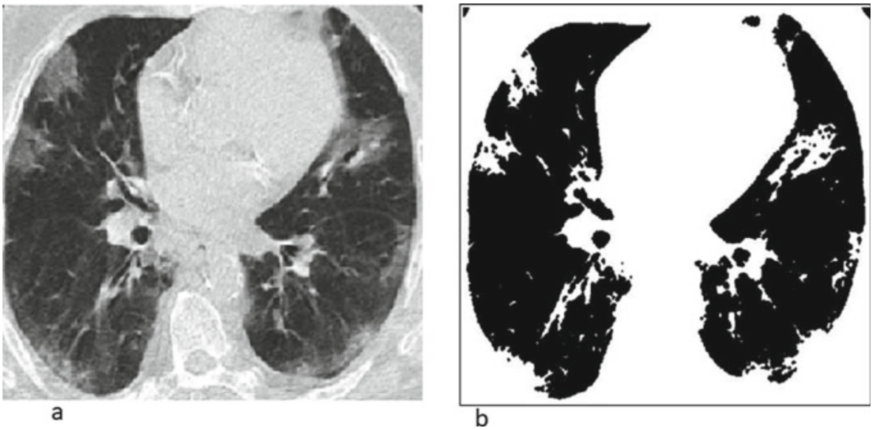

Fig. 3 CT scan images after morphological operation a: before processing, b: after processing

important features to be taken care of to the CNN and other learning algorithms. The portion of the elisions inside the different sides of lung will be relative to the phases of the COVID-19 infection inside the patient body. For instance, the lung image containing small areas in size, a number will point to beginning stage of the virus. While the large lesion areas inside the lung show to sever stage for the patient.

(a) Histogram of Gradient (HOG) [10]

The CT scan images are partitioning into windows of images (cells), these windows state to small windows or districts (cells) spatially related, the histograms for every region will produce a local histogram of these segment gradient directions which will be gathered together. The combined histograms of these districts independently will shape the entire image representation. The normalization for these neighborhood histograms could be built up or applying some valuation on these local histograms to separate the local reactions for the CT images considered.

This leads to more prominent spatial district that can be abused for standardized significant descriptors like histogram of oriented gradient. The procedure has been utilized by [1, 2]. The promising results and acknowledgment of these descriptors drove the authors to utilize it in such analyzing of these kinds of images and joining it naively with EOH includes after some morphological tasks to extract more powerful descriptor for elisions areas inside the lung. Figure 4 shows the distribution of features creation for the image. The CT image will be partitioned into cells inside small zones and these zones are associated with one another. Every cell containing pixels throwing channel direction dependent on came about estimation of slope calculation. From 0 to 180 degrees, the channels of the histogram are spreading similarly. At that point, the assortment of these histograms of gradient directions produces the image's features vector.

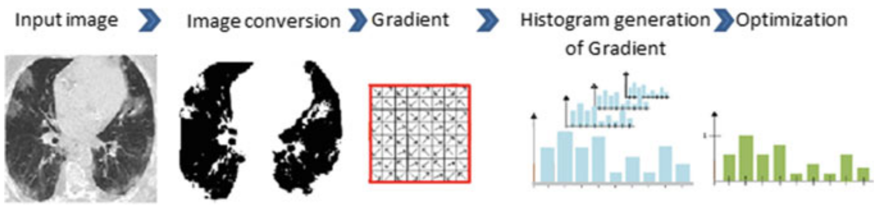

Fig. 4 HOG descriptor

(b) Edge of Histogram (EOH) for the CT images

The orders of edges inside the CT scan images provide a significant features where it can show some additional elisions inside the lung and this originating from local direction of edges inside CT image which can consider it as descriptors. Edge direction histograms (EOH) is utilized in this work to promote features for representing the sides of the lung. The histograms are assembled by starting with ascertaining the direction of the edges inside the image. This will be achieved by filtering process for the edge in the image. This filtering utilizes two kernels: [− 1 0 1] and [− 1 0 1] to get filtered CT images is coordinated by dx and dy individually. Two parameters will be thought of, the magnitude (M) and the direction α and for the edge's pixels inside the image. These are registered by Eqs. 1 and 2 separately.

$$\alpha = \arctan(\mathrm{d}y/\mathrm{d}x) \tag{1}$$

$$M = \mathrm{SQRT}\left(d_x^2 + d_y^2\right) \tag{2}$$

The bins identified with edge direction inside the histogram are equally scattered through orientation of the edge. The quantity of histogram bins relies upon the edge magnitude; at that point, the computation of the histogram will be identified with the weighted vote [3]. Figure 5 illustrates the effect of implementing edge detection on the lung images for the normal and COVID-19 virus infection.

Naively combining HOG and EOH features learning for visual elision recognition is building more distinct features for the lung as stated in Eq. 3:

$$(x, f1 : nm) = Hg(1 : n), Eh(1 : m) \tag{3}$$

where x is the CT image handled morphologically, Hg is the features for histogram of oriented gradient, and Eh is the features for edge histogram.

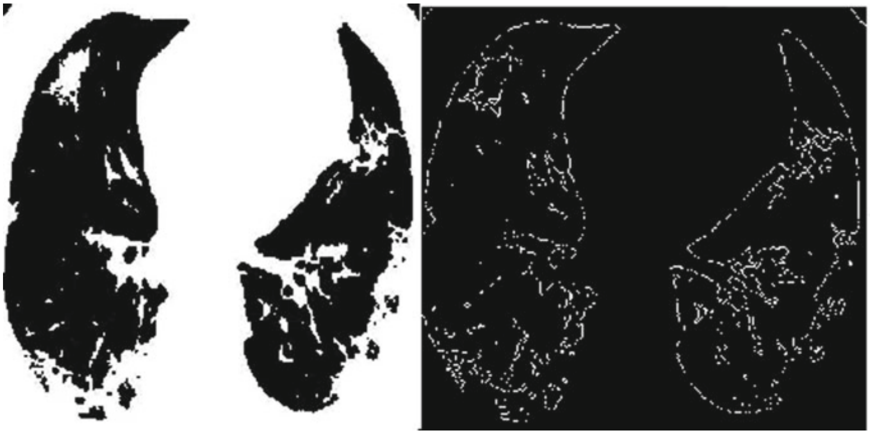

Fig. 5 Edge descriptions for CT scan image

3 Classification of COVID-19 Pneumonia Level

This phase is to classify the CT images based on the features extracted from the CT image, in this work, the classification for these features has done based on CNN, KNN, SVM, and decision tree. The following sections some explaining for these algorithms which are used:

(a) **Convolutional Neural Network (CNN)**

The second phase of the proposed work is that the constructed element vectors (NV) which are computed are rearranged to a square grid then entered to the CNN for training based on these kinds of feature vectors. For CNN testing, the CT test image will be handled as same procedure in Fig. 2, the achieved features from morphological stage rearranged to be entered into the CNN. In the training phase, 15 layers CNN from scratch have been utilized. These layers involve, 1 layer used for input, 3 layers used as convolution filtered by 3 × 3 size, 2 layers used for max pooling, 3 layers used for bunch standardization, 3 layers used for rectified linear unit, and 3 layers used for (completely associated, softmax, and classification). Coming up next are some descriptions of the layers:

1. **Input layer**: Pass features for CT images after resizing them to feed it into the next layers [11]
2. **Convolution layers**: These are known as filter values. In each layer, convolutions and kernels are there in addition to a stable stride is running on the CT complete image. Here, the features inside the images will be recognized and passed to the pooling layer [12]. The convolution operation is expressed in Eq. (4):

$$y^j = \max\left(0, b^j + \sum_i k^{ij} * x^i\right) \tag{4}$$

k^{ij} is the kernel for convolution between ith output of map and input x map, while the * sign points to convolution operation.

3. **Max Pooling Layer**: In this layer, the big sized CT images are shrinking down with keeping most important information in them. In each window, greatest value will be reserved; finally, the finest fits will be reserved of each element in the window [12]. The maximum pooling process is outlined in Eq. (5) [5].

$$\begin{matrix} i \\ yj, k \end{matrix} = \max_{0 \le m,n \le r}\left(x^i_{jxr+m,kxr+n}\right) \tag{5}$$

4. **Rectified Linear Units Layers (ReLU)**: The result of negative numbers from the pooling layer will be noticed as zeros. This layer provides the CNN steady mathematically [12]. It is expressed by Eq. (6) underneath:

$$F(x) = \max(0, x) \tag{6}$$

5. **Batch normalization layer**: The setting of this layer can be placed in the model, for example, fully connected layer. It applies the results from the previous layer as input feed-forwarding to calculate gradients with respect to the parameters.
6. **Softmax layer**: It is a function to provide the property of deep learning to give an answer for classification issue. This layer identifies the discrete likelihood P allocation for K classes. This can be demonstrated by $\sum_{k=1}^{k} pk$. Assume x is the activation, and θ indicate to weight parameters at the softmax layer, at that point, o is considered as input to the softmax layer,

$$F(x) = \sum_i^{n-1} \theta i x i \tag{7}$$

Then,

$$pk = \frac{\exp(o_k)}{\sum_{k=0}^{n=1} \exp(o_k)} \tag{8}$$

Thus, the calculation of the class would be $\hat{y}$

$$\hat{y} = \underset{i \in 1 \ldots N}{\arg\max} \quad pi \tag{9}$$

4 Traditional Classification Methods

In this section, some traditional classifications which have been used in this work to check the performance accuracy for recognizing the COVID-19 stages from the CT images

(a) **K-Nearest Neighbors Classifier (kNN)**

It is simple and common method to categorize the natural scene objects whose supervised learning algorithm. The process is built on one notion that the similarity between observations and groups which are relating to each other [13]. The algorithm has two phases in its working, which are training and testing. The process of training phase is building the training dataset by means of a set of cases holding training pattern with its related class.

In the process of testing phase, the query begins with a given unlabeled point and the algorithm generates a set of k closest or nearest (results) scores corresponding to the trained input patterns. The similarity results of two feature vectors are estimated by using distance measure such as Euclidian or Manhattan. Finally, the classification or decision is established by tagging the class of a tested pattern based on the majority voting method.

(b) **Support Vector Machine (SVM)**

One of the supervised learning algorithms for classification is the support vector machine which was introduced by AT&T Bell Laboratories members Vapnik and others [14]. Since an excellent performance results with the researchers today's SVM is used widely with the efficient way in implementation of classification problems.

The binary SVM classification was extended to take multi-class problems. SVM finds the optimal separating hyper-plane and separates the classes negative (-1) from the positive (+1) ones. The classification is done by maximizing the biggest margin between the classes. The main idea is shown in Fig. 6. The optimal hyper-plane separation is in the middle of the margin.

(c) **Decision tree classification (DT)**

A decision tree is a device for classification support that utilizes a tree-like model of results and their possible values, comprising chance event results, resource costs, and utility. It is one way to show an algorithm that only covers conditional control statements.

Decision trees are widely used in operations research and machine learning, especially in decision analysis, to help reaching the goal. It helps determine expected, best, and worst values for unlike scenarios.

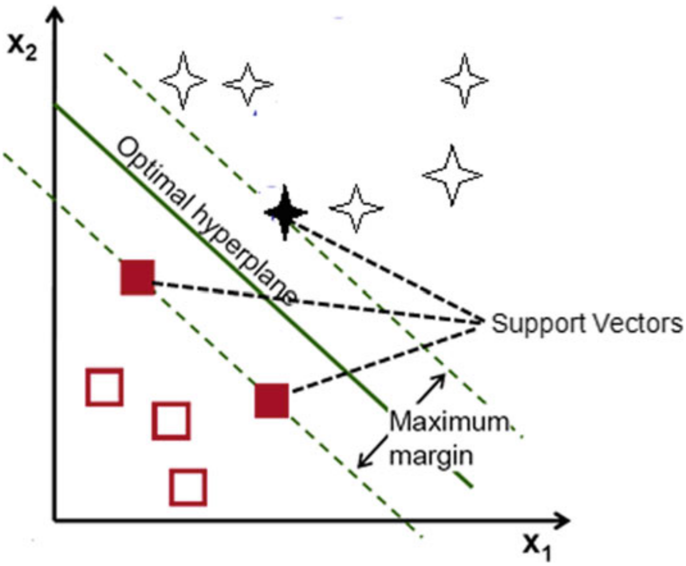

Fig. 6 SVM classification

5 Infected Lung Severity Level

Since Coronavirus Disease 2019 (COVID-19) quickly spread worldwide specially in early 2020, causing the researchers of the world to think of detection and representation of lung infections from CT images in many different ways. Since a huge of CT images transferred and stored for the COVID-19 stages; which in turn leads to consuming more time for processing like transmitting the image and more space needing to store in memory. Furthermore, CT image faces some challenges, containing high disparity in infection appearances, and low contrast intensities between infection areas and normal tissues in the lung.

The authors proposed an internal representation for the segmented image using morphological operations. The CT scan image for lung segmented into two parts the first part boundary is that containing holes and the second part without holes. Figure 7 shows the two parts in two colors red and green.

It is clear that the green region of the CT image is boundary which containing holes.

Representing these features as a text instead of image is better to store. Thus, representing the CT image is aggregating of partial representations of the regions features and generates a global representation for the whole CT lung. This gives an implicit representation for the explicit illusion-attention is exploited to shape the boundaries and enhance the representations. The function can be expressed in

$$\mathrm{IR} = \mathrm{bwboundaries(holes)} + \mathrm{bwboundaries(no\,holes)} \tag{10}$$

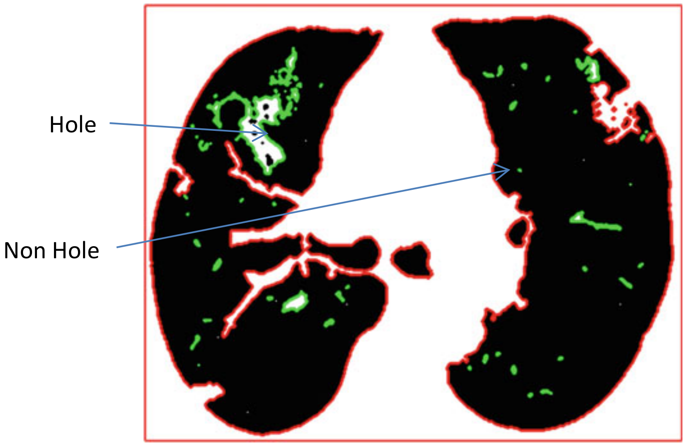

Fig. 7 Two parts boundaries

6 Experimental Setup

The feature vectors are developed naively to be 89 features (81 HOG and 8 EOH). In this work, the practical experimental has been conducted in two ways. CT scan images dataset has been used that is accessible in a GitHub store [15]. It was built by a group in [15] on a number of confirmed COVID-19 patients. The COVID-19 dataset contains 186 CT scan images of pneumonia lungs. Specifically, the images are clearly show the variety of lung inflammation over the span of COVID-19 patient between 1–21 days. The scanned images size is 346 × 442 × 3 uint8. Obviously, we currently do not have a lot of COVID-19 images openly accessible to the research community to lead extreme investigation and there is a need to gather more radiology images which can be available by the research community.

COVID-19 severity classification, the experiment has done based on some traditional machine learning algorithms like k-nearest neighbor (KNN), SVM, and decision tree. The results of the experiment are done by testing arbitrary CT images. These images are not trained by the chosen algorithms. In Fig. 8, the result distances of tested CT scan image's feature vectors based on Euclidean's distance with the other CT image's feature vectors. These distances sorted in ascending order, from small to large value, the smallest distance value is more similar to the tested CT image. The results of testing the query image and based on the KNN algorithm implemented on the dataset. The precision (p) of the N retrieved CT images for the query (Q) CT image is expressed in Eq. 10

$$p(Q, N) = \frac{|Ir|\text{Rank}(Q, Ir) \leq N \text{ such that Ir} \in g\,(Q)\}||}{N} \tag{11}$$

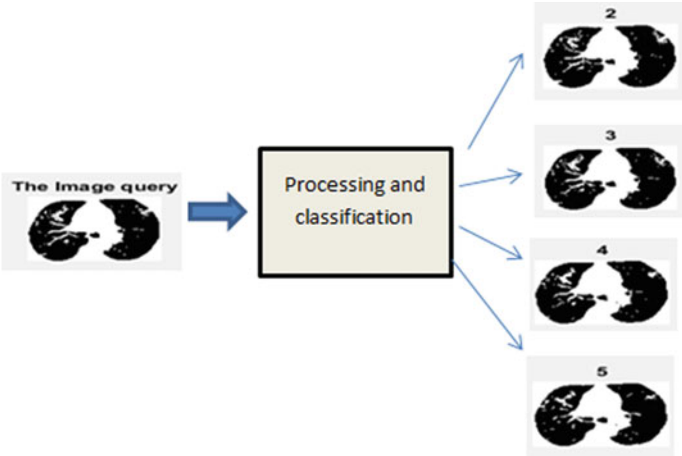

Fig. 8 Distances between query image and CT images answer

Table 1 COVID-19 confirmed patient pneumonia stage accuracy diagnosing

Classification	Results
kNN	91.304
SVM	91.3
DT	87.5
CNN	95.622

where $g(Q)$ denotes to the virus's group stage for the query image and Ir is the retrieved CT image. The results for all constructed distance feature values are arranged in ascending order; at that point, the best matching virus stage is the minimum value.

The results of performance accuracy based on Weka software results implemented to all algorithms listed in Table 1.

BSTI dataset comprises CT images is isolated into two categories to check the proposed strategy. For this reason, a multilayer perceptron's Weka implemented deep learning Rj has been utilized for checking the accuracy of the proposed procedure. Table 1 shows the consequence of the accuracy performance to find the virus stages. Further, Fig. 9 shows the proposed method result of the perceived stages of the question image fed into the program. The number over the CT image demonstrates to zone size of the elision inside both sides lung.

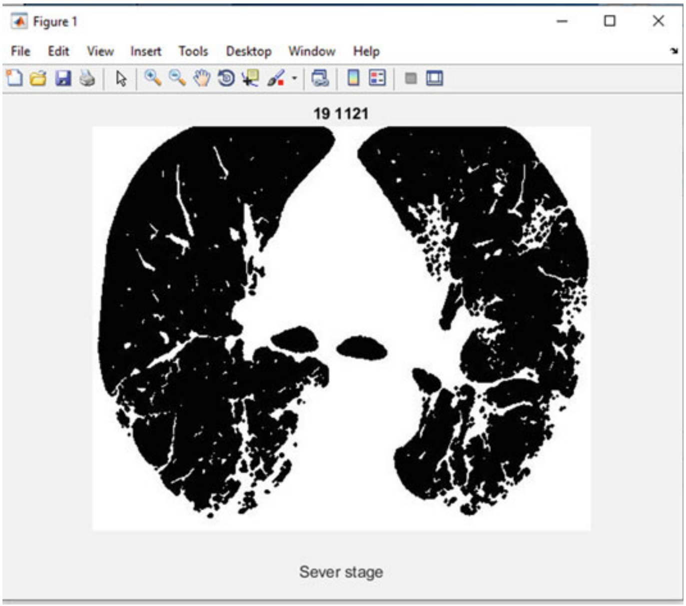

Fig. 9 Patient's stage of COVID-19 recognition

7 Results and Discussion

In this work, the accuracy performance of pneumonia stage detection during a course of confirmed COVID-19 patient has been computed. For this purpose and to attain this goal, morphological operations and deep learning with traditional learning algorithms are applied on the extracted feature vectors by using HOG and EOH. GitHub dataset repository is exploited to extract feature vectors. GitHub COVID-19 dataset includes a set of CT scan images for confirmed COVID-19 patients, whereby the whole images containing two sides lungs for the patients, the dataset consists of several stages (early stage, progressive, and sever) collected from different patients. The dataset composed of 186 CT images of size 372 × 556 × 3 uint8. Morphological operations are applied to convert the dataset to logical images. In this operation, noises within the images are filtered out to make the lesions and opacities on the infected lungs appear more clearly. The feature vector is constructed from HOG and EOH to get higher invariant features for classification. When CNN is used to the severity stage of the lung infection, we obtained the accuracy of 95.6%. Furthermore, the results for KNN and SVM were 91.3, while DT was 87.5 when CNN applied on HOG features without EOH, we achieved 82.608%, which is lower accuracy while EOH achieved less than the others, which is 34.782%. Table 1 presents the detection accuracy of different features used for classification. The results assure the improvement of detection accuracy through changing the features and classification methods. As shown in Table 1, CNN outperforms the other classification algorithms using HOG with EOH.

8 Conclusion

In this paper, CNN and other traditional machine learning algorithms like KNN, SVM, and DT have been used to recognize the stage of pneumonia in the lung by using CT scan images. This work is adopted to improve the accuracy of diagnosing lung in inflammation severity in confirmed COVID-19 patient. We build a complete pre-processed dataset of CT scan images which are taken from GitHub repository. After extensive experiments, the results show that the proposed CNN with combined HOG and EOH significantly outperforms the other approaches. Furthermore, when morphological operation based on EOH is used, the result is not promising. This indicates that multi-scale features for medical image recognition are better than a single scale features. The morphological operation is more useful to filter out noises and unnecessary features in the classification, which results in high accuracy of lung in inflammation detection.

Submission Guidelines: Prospective contributors are invited to submit chapter proposal to *cchakrabarty@bitmesra.ac.in* with the subject "IoMTSH-2020"

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