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Covid-19 Detection by Machine Learning Using Chest Radiographs

Umar Alqasemi

Associate Professor, Biomedical Engineering, King Abdul-Aziz University, KSA

Abdullah Al Baiti

Bachelor Degree, Biomedical Engineering, King Abdul-Aziz University, KSA

ahusseinalbaiti@stu.kau.edu.sa

Abstract

The recent pandemic caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) has highlighted the importance of early detection of infections, especially when RT-PCR testing equipment is scarce. This study introduces a machine learning algorithm using CT scan imaging for rapid COVID-19 identification. The algorithm, designed as a computer-aided detection model, analyzed 536 CT images (32x32 pixels) categorized into COVID-19 infected and non-infected groups. The model preprocesses images using the Prewitt filter and discrete cosine transform, then extracts features through various statistical methods and the histogram of oriented gradients (HOG). Out of 32 analyzed features, 29 showed high significance (p-value < 0.05), effectively distinguishing normal and abnormal cases. These features were classified using support vector machine (SVM) and k-nearest neighbor (KNN) methods. Performance metrics like sensitivity, specificity, and accuracy were used to evaluate the classifiers. The results of metrics showed that the classifiers of KNN-1, KNN-3, KNN-5, and SVM-Linear could distinguish between normal and abnormal images perfectly (100%) when it was applied to the proposed model on the tested ROIs images. Also, the SVM-RBF had less performance than other classifiers with 98.38% of accuracy but was still at a

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high-performance level. These results indicate that physicians can utilize the proposed model as an assisted tool for detecting COVID-19.

Keywords: COVID-19, MRI images, SARS-CoV-2, RT-PCR, machine learning-based techniques, CAD.

1- Introduction

In December 2019, The COVID-19 pandemic which was caused by the novel coronavirus SARS-CoV-2 has had a profound impact on the world. [1]. This virus, causing a respiratory illness, has since spread globally, with a significant 2% death rate, prompting the WHO to declare it a pandemic [2]. The real time polymerase chain reaction (RT-PCR) examination has long served as the gold norm for COVID-19 diagnosis. However, RT-PCR has limitations, including being time-consuming, expensive, and having a variable specificity between 30% and 60%, which has led to concerns about accuracy and false negatives [3] [4]. Due to these challenges, especially during disasters and epidemics when lab kits are scarce, alternative diagnostic methods like chest radiography (CXR) and chest computed tomography (CT) are being explored [5] [6]. Chest CT and X-rays are handy for earlier detecting and monitoring the progression of COVID-19 [7], where they show typical signs such as ground glass opacities and other abnormal patterns in the lungs. However, interpreting their images is time-consuming, subjective, and requires expertise [8]. These challenges can be addressed by utilized the Machine learning (ML) to create a Computer-Aided Detection (CADe) system for automatic COVID-19 recognition. This approach can reduce the need for extensive RT-PCR testing. ML algorithms extract unique features from COVID-19 CT or X-ray images and classify them as normal or abnormal, aiding in faster and more efficient diagnosis [9]. In CADe models, feature extraction from medical images is crucial for accurate categorization and diagnosis. Histogram of Oriented Gradients (HOG) for identifying local patterns, Local Binary Patterns (LBP) for local color patterns, and the Gray Level Co-

Occurrence Matrix (GLCM) are commonly used manual feature techniques that improve the accuracy of classification models [10] [11] [12]. Classification models such as Random Forest (RF), Support Vector Machines (SVMs), and k-closest Neighbors (k-NN) are reliable models for differentiating COVID-19 from other viruses. SVMs use an optimal hyperplane to minimize misclassification, RF aggregates multiple decision trees to manage noise and irrelevant data, and k-NN classifies data according to the majority class of the neighbors nearest it [13] [14] [15]. The effectiveness of these classification models is evaluated by using various metrics involves sensitivity, precision, specificity, accuracy, as well as the Area Under the Curve (AUC), i.e. the Receiver Operator Characteristic (ROC) curve, providing a comprehensive assessment of the model performance.

2- Literature Review

Many studies have provided Computer-Aided Detection (CADe) systems for detecting or diagnosing COVID-19. These studies vary in their approaches to preprocessing, segmentation, feature extraction, and classification, yielding different results. This summary outlines the key findings and methodologies of these studies. Barstuan et al. [16] utilized ML to detect COVID-19 in its early stages using CT scan segments and various feature extraction methods. They achieved a 99.68% success rate in classification by using the GLSZM feature extraction method and 10-fold cross-validation.

Emtiaz et al. [17] developed the CoroDet CNN model for proposed an automated COVID-19 detection by using chest CT and X-ray images. The model showed high accuracy across different class categorizations, achieving 99.1% in two-class, 94.2 % in three class, and 91.2% in four class classifications. Dimeglio et al. [18] utilized deep-learning and machine-learning for improved the detection of COVID-19. With a dataset of 15,000 images, the system achieved a 97% detection rate using Random Forest and 99% with deep-learning methods. Abraham et al. [19] created a CAD system for X-ray chest images, feature extraction from pre-trained networks, and a Sparse Autoencoder. The combined use of Xception “extreme inception” and Inception-ResnetV2 models resulted in an accuracy of 95.78% and an AUC of 98.21%. Bakheet and Al-Hamadi [20] presented an automated system to identify COVID-19 from chest images obtained by X-ray using textural properties. The system achieved an average of 95.88% for recall, accuracy, F1- score, and precision. N. Hasoon et al. [21] proposed a COVID-19 classification and early detection model. The LBP-KNN model achieved sensitivity, high accuracy, specificity, and precision with 97.76%, 98.66%,100%, and 100% respectively. Ardakani et al. [22] suggested a clinical CAD tool using CT features for differentiating COVID-19 pneumonia with high sensitivity (0.96), precision (93.54%), and accuracy (90.3%), also the COVID ensemble predictor had a 91.94% accuracy rate. Nabizadeh et al. [23] provided a COVID-19 classifier using a Bag of Features technique involving image preparation, vocabulary development, and classification. This method achieved accuracies of 96.1%, 99.84%, and 98% across three datasets. Shakarami et al. [24] presented COV-CAD, a diagnostic system for COVID-19 incorporating a modified CNN AlexNet for extracting feature and a classifying the dataset. The system also includes a content-based photo retrieval platform. COV-CAD successfully identified 93.20% of COVID-19 cases of CT images and 99.38% using X-ray images.

In summary, these studies demonstrate the potential of CADe systems in the early detection and accurate classification of COVID-19. They highlight the effectiveness of various models and techniques in differentiating between the images of COVID-19 that were taken from CT scans and X-rays. The high accuracy rates achieved by these systems indicate their potential utility in clinical settings, offering promising tools for healthcare professionals in managing the pandemic.

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3- Methodology

In this chapter, we delve into the creation of a Computer-Aided detection system aimed at detecting COVID-19 through chest CT images. The purpose is to develop a highly efficient system that can facilitate early detection and management of COVID-19. The procedure involves a series of steps, as depicted in figure (1), which includes gathering, preprocessing, and postprocessing datasets, followed by feature extraction then classification using SVM and K-NN classifiers. Subsequently, performance matrices were utilized to assess the effectiveness of the proposed system.

3-1 Data Gathering

The data was sourced from Kaggle, focusing on 536 images of infected and non-infected with COVID-19 obtained via chest CT scans such as in figure (2). These images are evenly divided into 268 normal and 268 abnormal cases which were cropped into 32x32 size, as exemplified in figures (3,4) [25] [26].

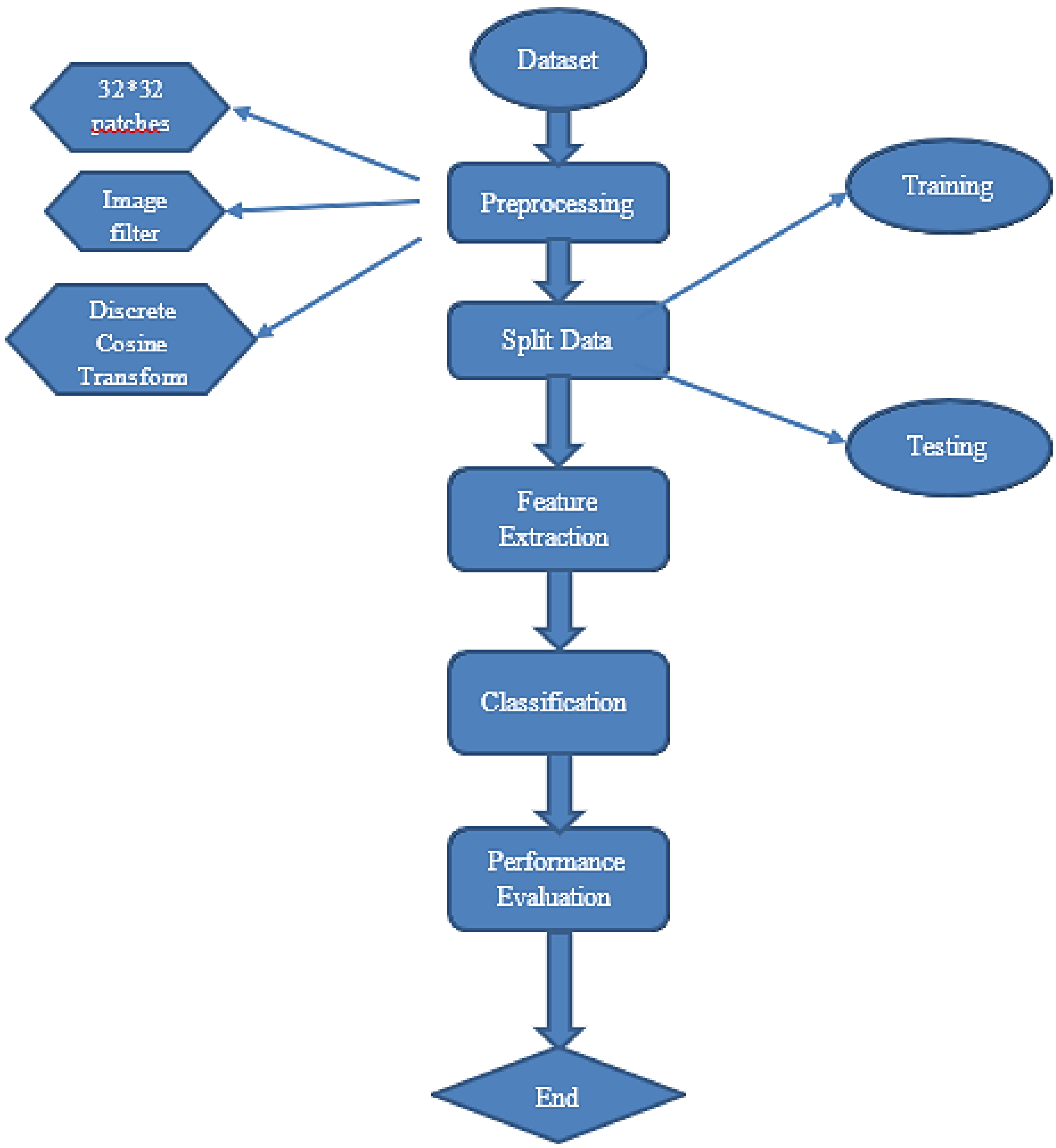

Figure (1): Proposed CADe flowchart

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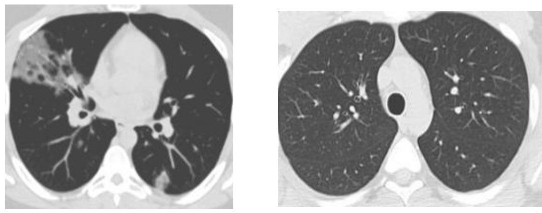

Figure (2): (Left to right) CT scans of abnormal case, and normal case

Figure (3): Dimension 32X32 for COVID abnormal case

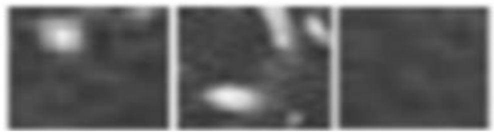

Figure (4): Dimension 32X32 for COVID normal case

The dataset was partitioned into two subsets, with 70% of the data allocated to the training set and the remaining 30% assigned to the testing set, as per Table 1.

Table (1): Number of training and testing Datasets

No. of	Normal Images	Abnormal Images	Percentage
Training	188	188	70
Testing	80	80	30
Total	268	268	100

3-2 Preprocessing

The preprocessing phase in the study involved preparing the dataset for analysis by enhancing image quality, reducing noise, and ensuring uniformity in format. This included converting the Region of Interests (ROIs) in COVID CT scans into grayscale 2D images with 8-bit unsigned integers, scaling and normalizing pixel values between 0 and 256 to standardize intensity ranges. Additionally, a Prewitt filter was applied to remove noise, define edges, and enhance resolution and contrast of the ROIs.

3-3 Postprocessing

Regions of Interest (ROIs) in images were transformed using the Discrete Cosine Transform (DCT), which converts pixel grayscale values into different frequencies. This process adds features while retaining essential data. DCT segments the image into areas of varying importance, represented as waveforms of different magnitudes and frequencies. It translates each pixel into DCT coefficients, mirroring the original size but distributing values non-uniformly: areas with low pixel variation appear at low frequencies, and those with high variation at high frequencies [27].

$$C(u) = \alpha(u) \sum_{x=0}^{N-1} \cos\left[\frac{\pi(2x+1)u}{2N}\right] \dots\dots..(1)$$

N is the length 1-D sequence, $u = 0,1,2,\ldots,N-1$, and $\alpha(u)$ gives by equation (2),

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}}, & u = 0 \\ \sqrt{\frac{2}{N}}, & u \neq 0 \end{cases} \dots\dots\dots\dots\dots\dots.(2)$$

When (u = 0), a direct current (DC) waveform is produced, while (u ≠ 0) results in alternating current (AC) waveforms with frequencies increasing proportionally with N, known as "cosine basis functions" [28]. For image processing, the Discrete Cosine Transform (DCT) is applied by dividing the image into 8x8 blocks and applying the DCT equation to each block. DCT is advantageous due to its speed, ease of computation, real-valued frequency production, and its ability to concentrate most image information in low-frequency components.

3-4 Features Extraction

The process of feature extraction from CT scan images focuses on quantifying the attributes of a Region-of-Interest (ROI) based on the spatial and spectral distribution of pixel gray levels. This is achieved by preprocessing ROIs and converting them into numerical features, enabling machine learning algorithms to use them as input. These features are crucial for classifiers to effectively differentiate between infected and uninfected cases. Extracting features was performed on the following steps:

a. Calculate the statistical features which represent the image attributes based on pixel value, where the pixel values reflect the gray level distribution in the image. These statistical features are: variance, percentiles, mode, geometric, kurtosis, trimmean, moment, skewness, range, standard deviation, mad, median Root mean of square data (RMS), quantile, mean, Interquartile range of data set, maximum, and minimum.

b. Then calculate the histogram of gradient (HOG) is a feature descriptor used in object detection, emphasizing the structure or shape of an object by creating histograms based on gradient magnitudes and orientations at each pixel in an image.

3-5 Classification

Classification in image processing involves predicting labels for regions of interest (ROIs), using feature vectors to correlate the features with their classes. The classifier classifies ROIs as normal or abnormal, depending on the quality and quantity of features [30]. This approach uses two types of classifiers; Support Vector Machine and the K-nearest neighbor algorithm. SVM uses a hyperplane to maximize separation margin in a high-dimensional space. SVMs can handle both linear and nonlinear tasks thanks to various kernel functions [31] [32]. In the proposed CADe system, both linear and nonlinear SVMs are employed such as in figures (5,6). KNN calculates distances from input data during classification without a training phase.

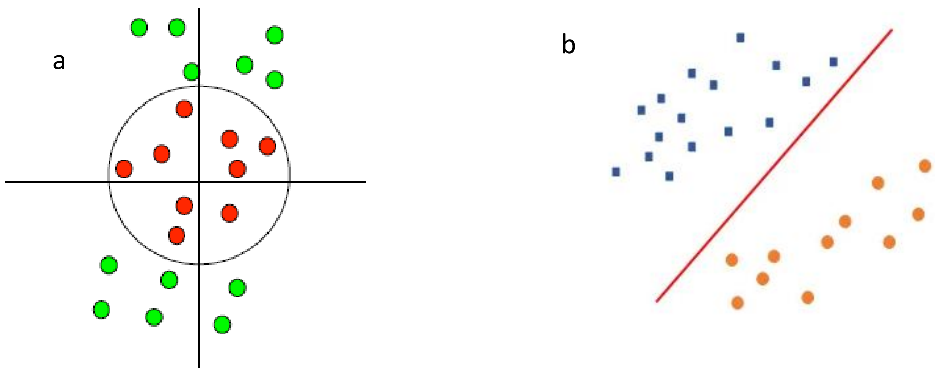

Figure (5): a) Nonlinearly separatable data, b) Linearly separatable data.

The choice of distance function affects its performance [33], figure (7) shows an example where k=4 in k-nearest neighbors.

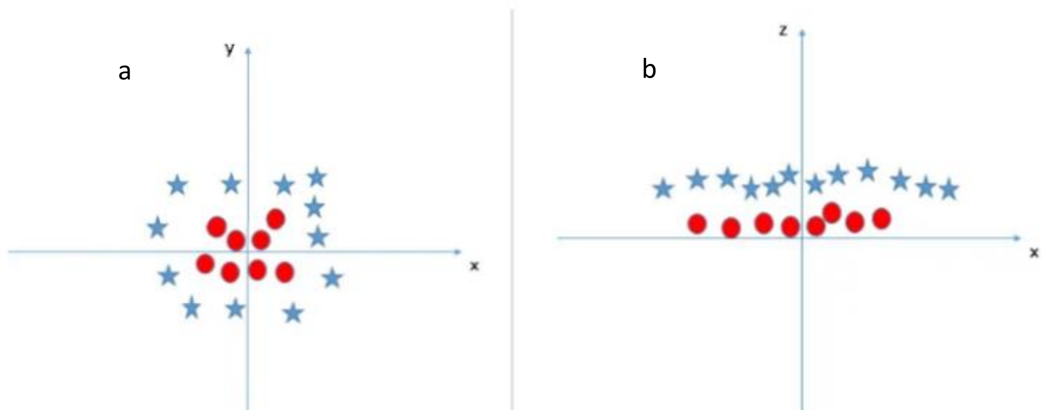

Figure (6): Polynomial kernel separate nonlinear data a into linear data b

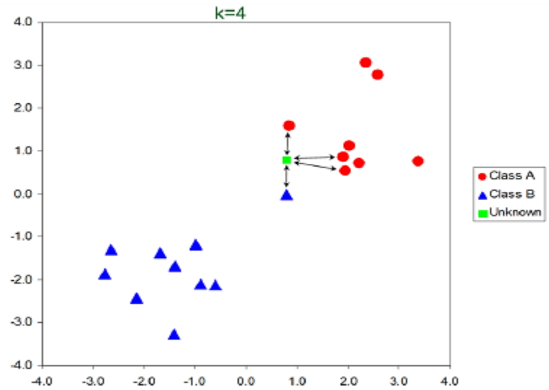

Figure (7): an example of 4-nearest neighbors

3-7 Performance Metrics

The quality of the CADe model's classification is crucially assessed by its performance, which is determined by the results in the confusion matrix presented in Table (3). This involves counting of actual classes and predicted classes.

Table (2): Confusion Matrix for binary Classification

	Predicted Positive Class	**Predicted Negative Class**
Actual Positive Class	True Positive (TP)	False Negative (FN)
Actual Negative Class	False Positive (FP)	True Negative (TN)

The model was evaluated using five metrics: sensitivity (SEN), specificity (SPE), accuracy (ACC), precision (PPV), and Negative Predictive Values (NPV) (Equations 3-7).

Sensitivity: used to calculate the percentage of correctly classified positive cases.

$$SEN = TP / (TP + FN) \;\ldots\ldots..(3)$$

Specificity: used to calculate the percentage of correctly classified negative cases.

$$SPE = TN / (TN + FP) \;\ldots\ldots..(4)$$

Accuracy: used to compute the percentage of correct predictions to the overall number of cases assessed.

$$ACC = (TP + TN) / (TP + TN + FN + FP) \dots\dots..(5)$$

Precision or Positive Predictive Value: used to calculate the percentage of correctly classified positive cases from the total cases in the positive class.

$$PPV = TP / (TP + FP) \dots\dots..(6)$$

Negative Predictive Values: used to calculate the percentage of correctly classified negative cases from the total cases in the negative class.

$$NPV = TN / (TN + FN) \dots\dots..(7)$$

4- Results and Discussion

4-1 Feature Extraction Results

Various feature extraction techniques were applied to CT scan images to transform them into numerical data for classification. These methods extracted essential information like variance, mean, standard deviation, maximum, minimum, skewness, kurtosis, and percentiles, forming a unique feature vector for each image. These features, particularly intensity levels, are crucial for identifying potential COVID-19 infections, with higher intensity levels indicating a greater likelihood of infection. Figure (8): The differences and similarities in the distribution of some features between two normal and abnormal ROI images. Insights into additional statistical measurements, data ranges, and image-based qualities that may aid in COVID-19 case categorization are provided by these features.

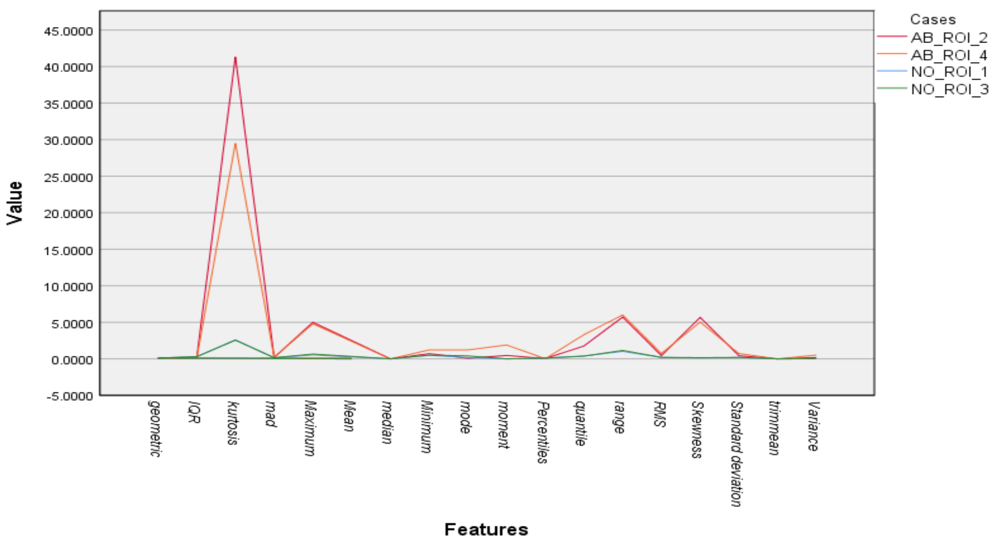

Figure (8): The comparison of features between normal and abnormal ROIs

The red line in figure (8) represents the features of two abnormal ROI images, while the green line represents the features of two normal ROI images. The feature extraction results prove that the abnormal images had greater variability and probable departures from normal patterns. This increased dispersion in abnormal instances is indicative of underlying problems caused by COVID-19 transmission. These results provide valuable information about the distribution of the data and help distinguish between normal and abnormal cases.

4-2 Features Selection Results

Features were extracted and P-values were then used to select the significant ones. Only features with a P-value less than 0.05 were passed on for classification. In this proposed approach; 29 out of 32 analyzed features were found to be highly significant (p-value < 0.05) and can act as potential biomarkers as depicted in figure (9). These significant features assisted in the diagnosis of COVID-19 and can lead to the development of more accurate diagnostic tools.

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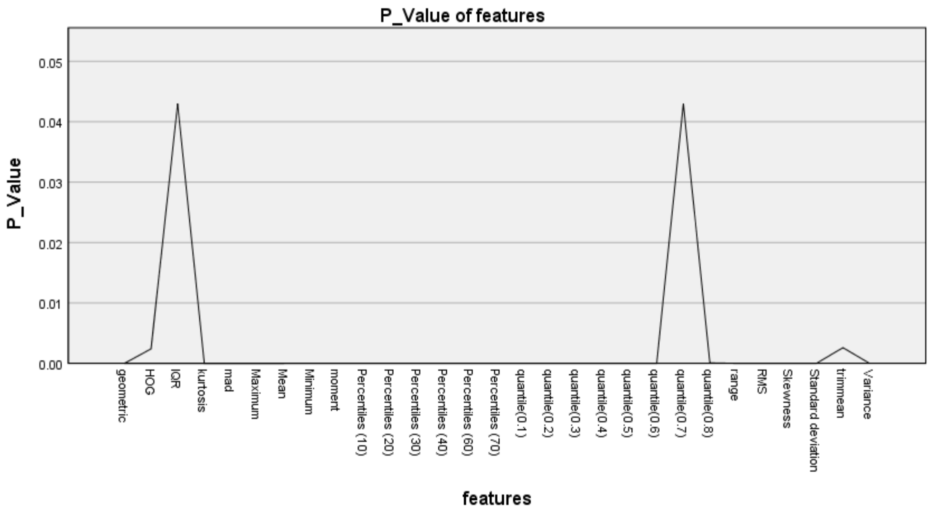

Figure (9): Highly significant features with a p-value of less than 0.05.

4-3 Classification Results

SVM classifiers of linear and Radial Basis Function (RBF) kernels and KNN classifiers of 1,3,5 neighbors were used to categorize the tested images as normal or abnormal. The metrics in table (2) were used to evaluate the performance of the classifiers. These metrics collectively determine classifier effectiveness in accurate case differentiation.

Table (3): Assessment Performances Metrics Results for Classifiers

Metrics / Classifier	SEN (%)	SPE (%)	ACC (%)	PPV (%)	NPV (%)
KNN-1	100	100	100	100	100
KNN-3	100	100	100	100	100
KNN-5	100	100	100	100	100
SVM-Linear	100	100	100	100	100
SVM-RBF	100	98.77	99.38	98.75	100

In table (3), sensitivity reflects the percentage of positive (abnormal) cases successfully recognized by the classifiers. Sensitivity results showed that all classifiers used in this model were highly sensitive (100%) to detect COVID-19 in patients, even at early stages. This signifies that all abnormal images have been detected and correctly labeled as abnormal. The extremely high sensitivity of classifiers is critical to avoiding errors that result from classifying abnormal cases as normal. According to the specificity results, four classifiers can accurately detect normal cases with 100% accuracy. The SVM with RBF kernel can detect normal cases with an acceptable accuracy of 98.77%. The specificity results of classifiers can help prevent errors in classifying normal cases as abnormal cases infected with COVID-19. The classification models' high sensitivity and specificity, demonstrate their ability to correctly identify both positive and negative COVID-19 instances. This is essential for reducing the possibility of unintended positive and negative results in patient care and public health actions.

After detecting positive (abnormal) and negative (normal) cases in tested ROI images, precision (PPV) and NPV matrices are used to determine whether the images selected by the model as positive/negative were truly positive/negative. The model demonstrated that the five classifiers: KNN with nearest neighbors 1, 3, and 5, and SVM with linear and RBF kernels achieved perfect percentage with 100% in the NPV metric assessment. This indicates that all classifiers were able to categorize all normal cases as normal while not categorizing any abnormal cases as normal. In the PPV metric assessment, all classifiers except SVM-RBF obtain 100% which refers to the ability of these classifiers to detect only the abnormal cases without incorrectly classifying any normal case as abnormal. The SVM-RBF classifier achieved a 98.75% in the PPV assessment, indicating that it categorized some typical cases as abnormal. Although this little error has little impact on SVM-RBF performance, it is still acceptable and can be used to detect COVID-19.

The overall assessment of classifiers is represented by the accuracy in the table (3). Through accuracy, the model achieved a perfect score of correctness in predicting

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the ROIs class in all classifiers except for the SVM-RBF. This indicates that out of the total number of tested cases, these classifiers accurately predicted all abnormal and all normal cases. The accuracy of the SVM-RBF classifier was 98.38% and was influenced by selectivity and PPV results.

The area under the curve (AUC) for each classifier was plotted as shown in figure (10) and gave the same result of metrics.

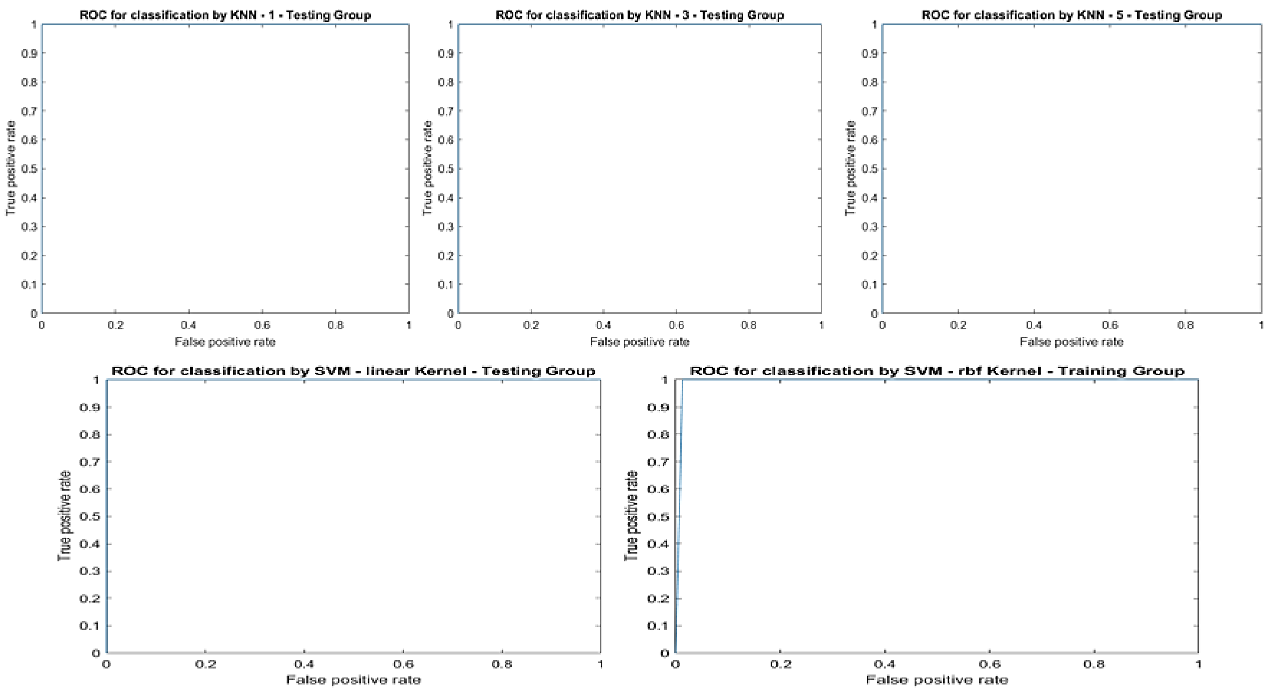

Figure (10): The AUC for SVMs and KNN classifiers

In conclusion, the results of the assessment performances metrics for classifiers of this research tress the value of classification algorithms for improving COVID-19 diagnosis and treatment. These results highlight the promise of machine learning approaches for the detection and discrimination of COVID-19 cases. The findings of this research contribute significantly to our knowledge of COVID-19 diagnosis and treatment. The proposed model did an excellent job of correctly categorizing COVID-19 cases. These results showed it can be used by physicians as an assisted tool for diagnosing COVID-19. However, this performance of the model depends on the type and size of the dataset and may be compromised under certain situations.

5- Conclusion and Future Work

This approach presented a MATLAB-based CADe system for analyzing CT COVID-19 chest images with size 32x32. The approach used the Prewitt operator for edge detection and the Discrete Cosine Transformation (DCT) function for efficient feature extraction. Statistical features were derived for understanding pixel intensity and spatial distributions. The system identified 29 significant features for distinguishing infected images and classified the ROI images as infected or not.

The sensitivity, specificity, accuracy, PPV, and NPV metrics were used to evaluate classifiers' performance. These metrics were applied to the classifiers; SVM of linear and Radial Basis Function (RBF) kernels and KNN classifiers of 1,3,5 neighbors. The accuracy of the proposed model obtained that all classifiers except the SVM-RBF classifier achieved the perfect score of 100% scores, while the SVM-RBF classifier achieved 99.38%. These results indicate that the suggested model could serve as a valuable diagnostic tool for COVID-19.

This study's key achievement is the use of the discrete cosine transform (DCT) to segment ROI images into areas of varying significance, enhancing feature extraction and aiding in classification, leading to positive results. However, the model has limitations, including a small image dataset due to hardware constraints and its testing limited to CT scans, though it's also applicable to X-ray chest images. Results might vary with different databases, and the model's efficiency could be improved with a larger, more diverse database. Future enhancements include adapting the model for a broader range of data and incorporating more sophisticated imaging methods like CT 3D, CT abdomens, X-ray chests, and blood tests. This would deepen understanding of COVID-19 and foster innovative machine-learning approaches for accurate diagnosis and treatment.

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