Comparison of Machine Learning Performance for Covid-19 X-ray Image Classification Based on Texture Features

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***Abstract*— The most prevalent method for early detection of Covid-19 is polymerase chain reaction (PCR). Unfortunately, the quantity of accessible test kits restricts the use of PCR. The development of automatic detection is limited due to the absence of the digital output of PCR data, resulting in an extremely low sensitivity level. Another possibility for Covid-19 detection is based on medical imaging diagnostic. Using digital images offers the opportunity to develop a computer-based system. Image processing mixed with machine learning is the purpose of this study. The comparison of machine learning performance aimed to determine the best classification model. The methods developed for the Covid-19 detection system applied 2-D Haar Wavelet Transform feature extraction and classification methods of Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (DT). Quadratic SVM achieved the best classification results with an accuracy of 86.96%, precision of 94.64%, recall of 86.89%, specificity of 90.00%, and F-score of 89.83%. This study succeeded in comparing three machine learning methods with texture features.**

Keywords*— *Covid-19, 2-D Haar Wavelet Transform, Support Vector Machine, K-Nearest Neighbor, Decision Tree.

I. INTRODUCTION

As of May 2022, Covid-19 has been reported to infect more than 500 million people and cause more than six million deaths [1]. With so many instances and such rapid transmission, medical personnel are overburdened. Handling and diagnosing Covid-19 is time-consuming, not only because the number of patients is rising daily but also due to a shortage of medical professionals and suitable diagnostic instruments [2].

Polymerase chain reaction (PCR) is currently the most familiar method for early Covid-19 diagnosis. Unfortunately, the quantity of accessible test kits confines the use of PCR. Subsequently, this test's sensitivity only falls between 60% and 70%. Thus, if 100 people undergo the PCR test, only 60 will receive a proper diagnosis [3][4][5]. Additional methods should complement the Covid-19 test to obtain a genuinely accurate diagnosis. Medical imagery of chest X-ray images is one of which [6] [7].

Covid-19 can also be diagnosed using medical X-ray imagery combined with computational (artificially intelligent) methods. Machine learning (ML) using artificial intelligence is a standard method for understanding medical images. Several other research [8][9][10] utilized ML to diagnose Covid-19 using chest X-ray images. The results unveiled that ML delivered a relatively high level of accuracy and demonstrated potential as a tool for the early detection of Covid-19.

Feature extraction is one of the ML phases. In [11][12][13], wavelet transform was applied as a method of feature extraction for Covid-19 detection. This method yielded an accuracy ranging from 80% to 95%. Histogram of Oriented Gradients (HOG) [14] and Gray Level Co-occurrence Matrix (GLCM) are other methods commonly utilized to identify Covid-19. Feature extraction using HOG [15] produced an accuracy of 98.5%, whereas extraction with GLCM [16] generated an accuracy of 99.68%.

Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (DT) are a few of the classification methods in ML. Several investigations have applied classification methods to detect Covid-19. Previous studies [16] [17] [18] discovered that the SVM, KNN, and DT methods worked appropriately in detecting Covid-19.

Wavelet transform performs adequately in classifying Covid-19 images. With few references to Covid-19 detection using wavelet feature extraction methods, this study aims to establish an autonomous computer-based method for detecting Covid-19 using 2-D Haar Wavelet Transform feature extraction combined with SVM, KNN, and DT classification methods.

II. METHODS

A. System Design

Figure 1 displays the whole process of the system design in this study. Preprocessing was the step after acquiring chest X-ray image data, followed by feature extraction using 2-D Haar Wavelet Transform feature extraction. Three distinct methods were applied in the classification phase: Quadratic SVM, Weighted KNN, and Fine Tree DT. The classification results were analysed using a performance matrix.

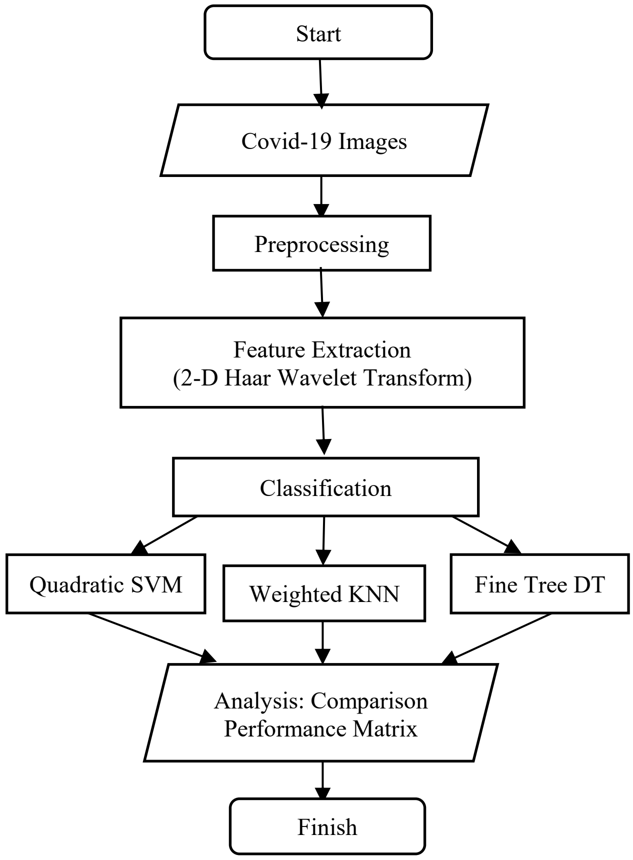


Fig. 1. System Design Flowchart.

TABLE I. COMPUTER SPECIFICATION

Hardware	Specification
Processor	Intel® Core i5 9400f
RAM Memory	16GB
GPU	Nvidia RTX 2060 6GB

In this study, the computer was the primary device for the whole process throughout training and testing. Table 1 describes the computer specification. This study also employed the MATLAB program version R2020a as the software

B. Data Collection

This research utilized chest X-ray images comprising three distinct classes: Covid-19 images (class 1), pneumonia images (class 2), and standard chest images (class 3). These images were taken ethically from the open-source website Kaggle. The chest X-ray images totaled 1,065. Two datasets were derived from the total images: training and testing. The training dataset comprised 90% of the overall images (959 images), whereas the testing dataset numbered 10% of the total images (106 images).

C. Preprocessing

Preprocessing involved separating image data into training and testing datasets. This preprocessing aimed to recreate the images and transform them to be extracted and classified. The preprocessing procedure covered a vertical flip, an RGB-to-grayscale conversion, and a high stability engine control (HISTEC) conversion aiming to equalize the contrast of the whole image.

D. Feature Extraction

The chest X-ray images were extracted using 2-D Haar Wavelet Transform, a system to compress images. In classification using the Haar Wavelet Transform, the output was a four-piece coefficient obtained by energy and standard deviation. This feature extraction was performed on both datasets (training and testing) and yielded seven feature extractions for every X-ray image in the entire dataset.

E. Classification

This classification step, commonly referred to as the training stage, utilized three distinct methods: Quadratic SVM, Weighted KNN, and Fine Tree DT.

The SVM algorithm is a supervised machine learning algorithm for classification and regression challenges. However, it is primarily used in classification problems. In the SVM algorithm, each data item was plotted as a point in n-dimensional space (n is several features owned); each feature became the value of a particular coordinate. Then, classification was performed by finding the hyper-plane that differentiated the two classes properly.

K-NN algorithm assumes the similarity between the new case/data and available cases and puts the new case into the category most similar to the available categories. K-NN algorithm stores all the available data and classifies a new data point based on the similarity. Accordingly, new data can be easily classified into a well-suited category.

DT is a supervised learning technique beneficial for classification and regression problems. However, it is mainly preferred for solving classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules, and each leaf node represents the outcome.

After the feature extraction procedure had been acquired, the classification step was carried out. The dataset used during classification was the training one. The test (running) was administered ten times. The acquired classification data consisted of training accuracy and time.

F. Analysis

The analysis phase is often referred to as the testing phase. The dataset used was testing, which resulted from the feature extraction. The study compared the performance matrix values, encompassing accuracy, precision, recall, specificity, and F-score.

III. Results and Discussions

A. Feature Extraction Results

2-D Haar Wavelet Transform was applied to extract the features from images. In this step, the training and testing datasets were utilized. Six feature extractions were the outcome for each image (features). Table 2 illustrates the average feature results for every class.

TABLE II. FEATURE EXTRACTION RESULT

Feature of 2-D Haar Wavelet Transform	Covid-19 Image Classes		
	Class 1	*Class 2*	*Class 3*
Horizontal Energy	0.129 ± 0.045	0.167 ± 0.038	0.093 ± 0.055
Vertical Energy	0.143 ± 0.065	0.340 ± 0.089	0.214 ± 0.086
Diagonal Energy	0.024 ± 0.010	0.046 ± 0.013	0.026 ±0.017
Horizontal Standard Deviation	13.337 ± 4.757	13.155 ± 8.374	10.694 ±5.262
Vertical Standard Deviation	18.191 ± 9.744	20.437 ± 12.788	9.015 ± 10.497
Diagonal Standard Deviation	20.883 ± 17.337	24.884 ± 10.804	10.172 ± 9.442

B. Classification Results

The classification step, also known as the training stage, utilized a feature-extracted training dataset. The classification deployed the Quadratic SVM, Weighted KNN, and Fine Tree DT methods. At this point, each method's classification test was conducted ten times. The outcomes acquired after classification were the training's accuracy and time, as described in Table 3. Figure 2 displays the training's visual results in a Receiver Operating Characteristic (ROC) graph.

The results of the training classification provided in Table 3 indicate that the best accuracy value for Quadratic SVM was achieved in the tenth running, with a time of 6.6892 seconds and an accuracy of 81.10%. In the ninth running, Weighted KNN achieved the maximum level of accuracy of 80.90% and the quickest time of 0.68924 seconds. Fine Tree DT obtained the maximum accuracy of 76.40% and the quickest training time of 0.7047 seconds in the sixth running. In other words, Quadratic SVM obtained the highest training accuracy, and Weighted KNN had the fastest training time.

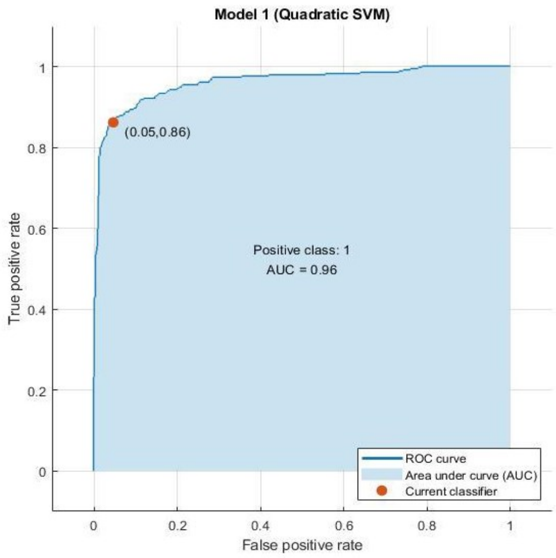
C. Analysis Results

In this research, the analysis process employed the testing dataset, also known as the testing phase. The testing dataset being evaluated was derived from feature extraction. Testing was conducted using the best training results from each method (Quadratic SVM, Weighted KNN, and Fine Tree DT). The test results were analyzed and compared using a performance matrix to determine which of the three classification methods performed the best. The performance matrix assessed included accuracy, precision, recall, specificity, and F-score. Figure 1 shows the model's optimal confusion matrix results. Table 4 displays the results of the performance matrix for the three methods.

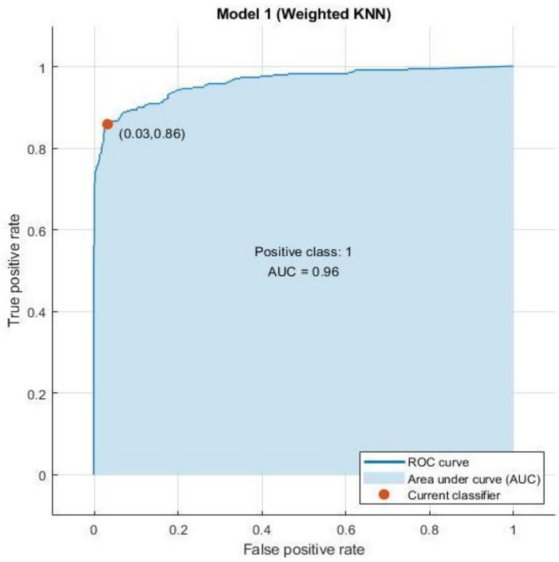
Quadratic SVM testing acquired the best performance matrix value compared to Weighted KNN and Fine Tree DT. The performance matrix accuracy values for classes 1, 2, and 3 Quadratic SVM were 86.96%, 80%, and 80%. The precision values for classes 1, 2, and 3 were 94.64%, 81.54%, and 82.81%. The recall performance ratings were 85.48%, 86.89%, and 85.48% for classes 1, 2, and 3. The specificity results for classes 1, 2, and 3 were 90%, 69.23%, and 71.05%. The relative F-scores for classes 1, 2, and 3 were 89.83%, 84.13%, and 84.13%.

TABLE III. TRAINING RESULTS OF THREE MODELS OF MACHINE LEARNING

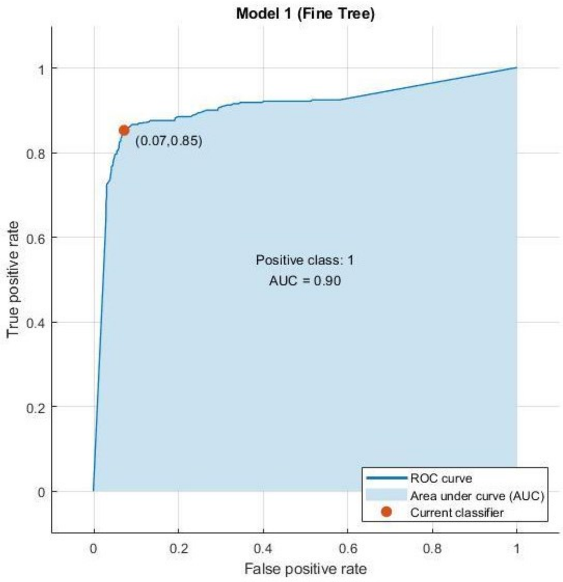
Run	Quadratic SVM		Weighted KNN		Fine Tree DT	
	Accuracy (%)	*Time (s)*	*Accuracy (%)*	*Time (s)*	*Accuracy (%)*	*Time (s)*
1	80.40%	**6.689**	80.20%	0.713	75.50%	0.722
2	81.00%	11.223	79.60%	0.699	76.30%	**0.705**
3	80.70%	9.154	79.80%	0.707	74.60%	0.712
4	79.80%	8.136	79.10%	0.703	74.30%	0.725
5	80.00%	9.612	80.90%	0.690	74.70%	0.706
6	80.20%	7.635	79.40%	0.716	**76.40%**	0.729
7	80.60%	11.144	79.50%	0.708	75.40%	0.717
8	80.00%	8.645	80.50%	0.731	75.60%	0.758
9	81.00%	9.155	**80.90%**	**0.690**	74.90%	0.705
10	**81.10%**	10.658	80.20%	0.702	75.00%	0.745
Average	80.48% ± 0.45%	9.205 ± 1.43	80.01% ± 0.60%	0.706 ± 0.012	75.27% ± 0.67%	0.722 ± 0.017



(a)



(b)

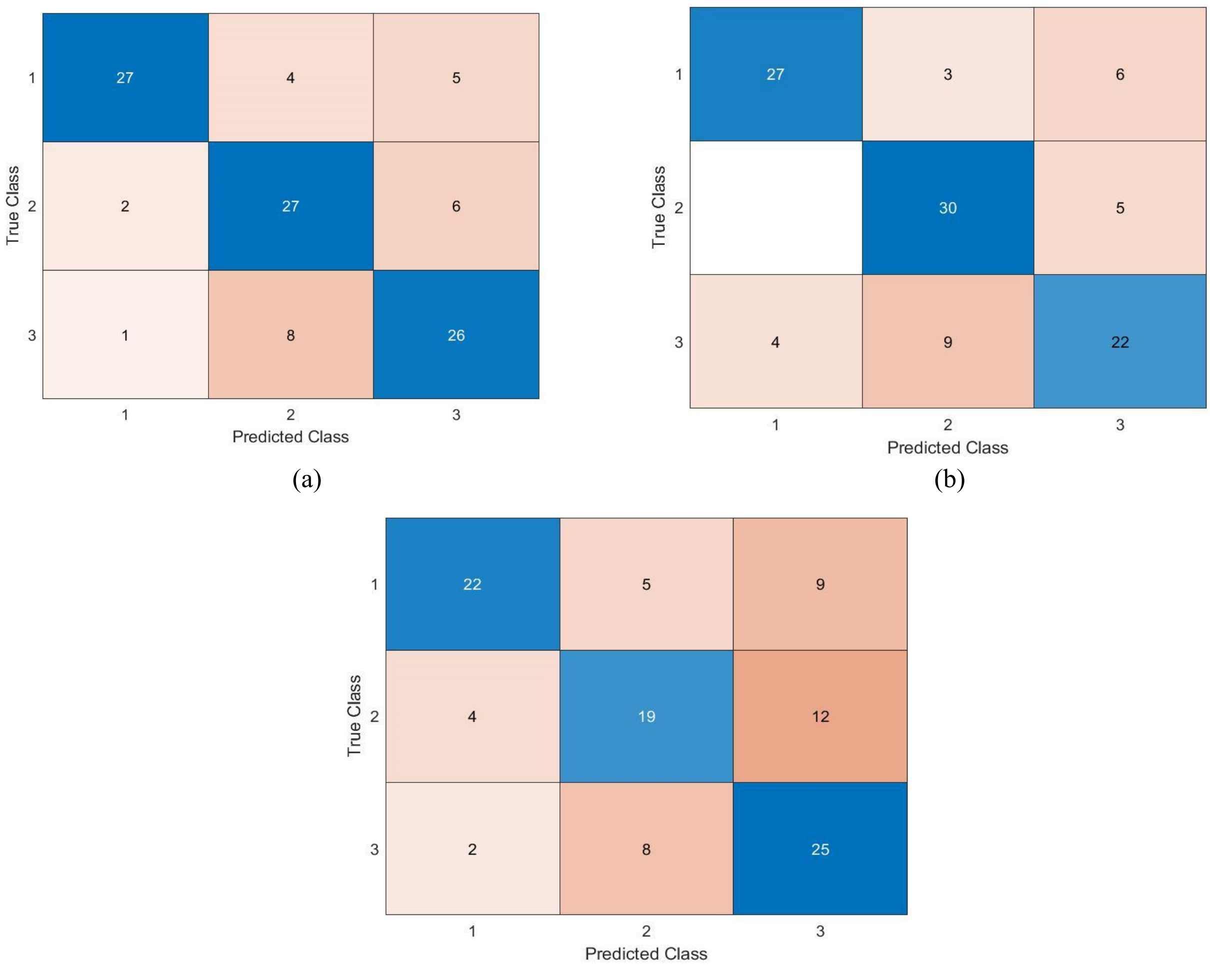


(c)

Fig. 2. Best of Receiver Operating Characteristic (ROC) Graphs (a) SVM, (b) KNN, (c) DT

TABLE IV. TESTING RESULTS OF THREE MODELS OF MACHINE LEARNING

Performance Matrix	**Quadratic SVM**			**Weighted KNN**			**Fine Tree DT**		
	Class 1	***Class 2***	***Class 3***	***Class 1***	***Class 2***	***Class 3***	***Class 1***	***Class 2***	***Class 3***
Accuracy	86.96%	80.00%	80.00%	85.87%	82.29%	76.70%	76.74%	69.47%	68.04%
Precision	94.64%	81.54%	82.81%	87.10%	69.23%	71.05%	78.57%	62.86%	51.16%
Recall	85.48%	86.89%	85.48%	75.00%	84.38%	67.50%	61.11%	57.89%	68.75%
Specificity	90.00%	69.23%	71.05%	92.86%	81.25%	82.54%	88.00%	77.19%	67.69%
F-score	89.83%	84.13%	84.13%	80.60%	76.06%	69.23%	68.75%	60.27%	58.67%



(a) (b) (c)

Fig. 3. Best of Confusion Matrix Performance of Testing (a) SVM, (b) KNN, (c) DT

IV. CONCLUSIONS

This study has successfully compared three machine learning methods for classification purposes. The early detection of Covid-19 computer-based using chest X-ray images could be performed by combining 2-D Haar Wavelet Transform as a feature extraction method and machine learning methods for classification. Three classification methods (Quadratic SVM, Weighted KNN, and Fine Tree DT) generated high-performance values for detecting Covid-19 in chest X-ray images. The optimal combination consisted of 2-D Haar Wavelet Transform and Quadratic SVM, acquiring accuracy rates for classes 1, 2, and 3 of 86.96%, 80%, and 80%. The precision values for classes 1, 2, and 3 obtained 94.64%, 81.54%, and 82.81%. The recall scores for classes 1, 2, and 3 were 85.48%, 86.89%, and 85.48%. The specificity values for classes 1, 2, and 3 were 90%, 69.23%, and 71.05%. The relative F-scores for classes 1, 2, and 3 were 89.83%, 84.13%, and 84.13%. Even though it yielded good performance values, more research is necessary to compare it to other methods.

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