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A Comparative study of BO-SVM plus different Residual Networks for pneumonia disease detection

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ABSTRACT

The term "pneumonia" is an ancient Greek word that means "lung," so, it is "lung disease". An inflammation of lung is not caused by infections only but there are many causes of pneumonia such as viruses, fungi, and internal parasites [6]. Deep learning advancements in recent years have aided in the identification and classification of lung diseases in medical images.

For clinical treatment and teaching tasks, medical image classification is essential. By using the traditional method, a significant amount of time and effort is required to extract and select classification features. A new machine learning method has proven its potential for various classification tasks, it is the deep neural network.[5]

Notably, the convolutional neural network dominates on varying image classon tasks with the best results[7].

KEYWORDS

BO-SVM, weighting method, convolution neural network, Resnet, pneumonia.

I. INTRODUCTION

Bi-Objective support vector machine(BO-SVM) is a mathematical model with two objective functions, the first one is maximizing the gap between two classes and the second objective function is minimizing the classification error. BO-SVM is used to classify two different classes of input points.

Therefore, in this paper, a system of a bi-objective support vector machine by using different types of Residual Networks (Resnet-18, Resnet-50, Resnet-101) is constructed to detect the pneumonia disease using X-ray images. Then, calculate the accuracy and the classification error of each Residual Network at different training to testing ratio and finally make a comparative study between them.

The remainder of this paper is organized as follows. Section 2 describes the mathematical model of BO-SVM. Section three shows the dataset description. Section four introduces the methodology of the proposed method. Section five shows the experimental results and finally, the conclusion and the future work present in section six.

II. THE MATHEMATICAL MODEL OF BO-SVM

In this section, the formulation of the bi-objective programming model for the SVM plus deep convolutional neural network is described,

$$\text{Min } \| w \|^2,$$

$$\text{Min } \sum_{i=1}^{l} \xi_i$$

$$\text{Subject to} \qquad (1)$$

$$y_i(w.x_i + b) \geq 1 + \xi_i \quad , i = 1,2, \dots , l$$

$$\xi_i \geq 0, \mathrm{i} = 1,2, \dots , l$$

This problem is a bi-objective quadratic programming problem. The first objective is to maximize the gap between the two hyperplanes which is used to classify the input points. The second objective is to minimize the errors in measuring the amount of misclassification in case of nonlinearity separable input points.

Problem 1 can be solved by the weighting method to get the set of all efficient solutions for the classification problem [4].

Then, in this paper the weighting method takes the form

$$\text{Inf } z = w_1 \| w \|^2 + w_2 \sum_{i=1}^{l} \xi_i$$

$$\text{Subject to} \qquad (2)$$

$$y_i(w.x_i + b) \geq 1 + \xi_i , i = 1,2, \dots , l$$

$$\xi_i \geq 0 \quad , i = 1,2, \dots , l$$

$$w_1 > 0, w_2 \geq 0$$

$$w_1 + w_2 = 1$$

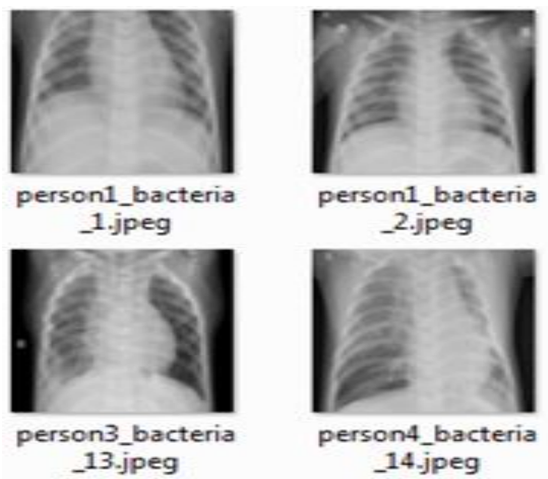
III. DATASET DESCRIPTION

The Chest X-ray dataset used is publicly accessible on the Kaggle website [3], consisting of 5,863 frontal chest X-ray images (JPEG) and 2 (Pneumonia/Normal) categories. All radio-graph images in the dataset have a resolution of 1024 by 1024. Of these images, 1341 images have been identified as having pneumonia. To complement the binary classification dataset, 1341 regular X-ray images (labelled 'No Findings') were selected from the dataset.

Before being granted input to the network, the images were downscaled from 1024 by 1024 resolution to 224 by 224 resolution. Figure 1 and Figure 2 represent a part of the dataset.

Fig.1. Images for the Normal cases

Fig.2. Images for the Pneumonia cases



IV. METHODOLOGY OF THE PROPOSED MODEL

The proposed pneumonia detection system using different types of the 'Residual Neural Network' (Resnet-18, Resnet-50, Resnet-101) is constructed to detect the pneumonia disease using X-ray images.[2]

these neural networks have different number of layers, number of connection, input name and output name as shown in Table 1[1].

Table 1: Specifications of Resnet-18,Resnet-50, Resnet-101

layer name	output size	18-layer	50-layer	101-layer
conv1	112×112	7×7, 64, stride 2		
conv2_x	56×56	3×3 max pool, stride 2		
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax		
FLOPs		1.8×10^9	3.8×10^9	7.6×10^9

By using Matlab2019b program, the confusion matrix describes how the different values of the weighting parameters affect performance of Resnet-18, Resnet-50 and Resnet-101 Models with BO-SVM at different training to testing ration and improve the accuracy.

V. EXPERIMENTAL RESULTS

The effect of the parameters different weights of BO-SVM and different training ratio(80%, 70%, 60%) on the accuracy of the different types of the residual networks will be presented in the following figures.

Fig 3: the relation between the weights and the accuracy of Resnet18 plus BO-SVM model at different training ratio.

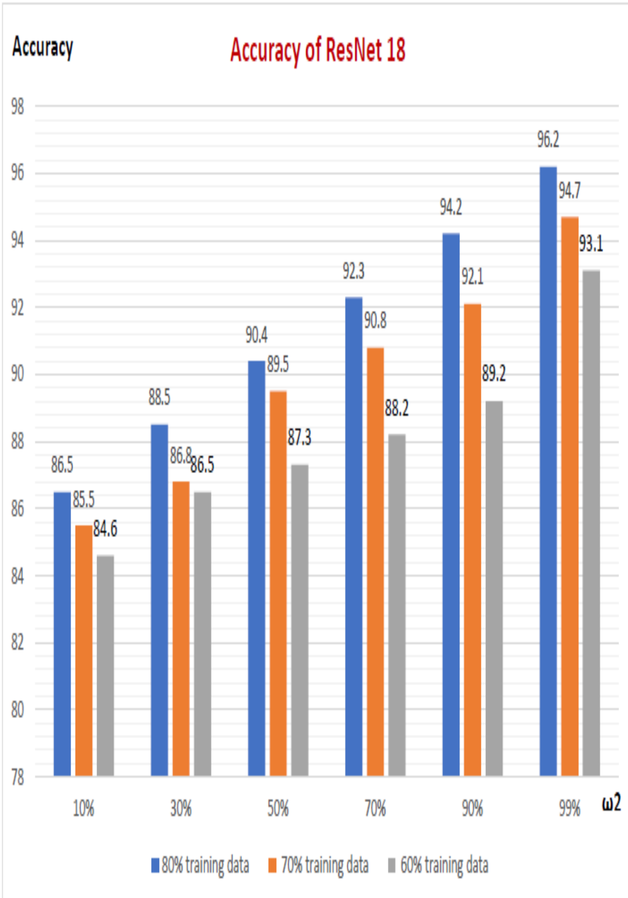


Fig 4: the relation between the weights and the accuracy of Resnet50 plus BO-SVM model at different training ratio.

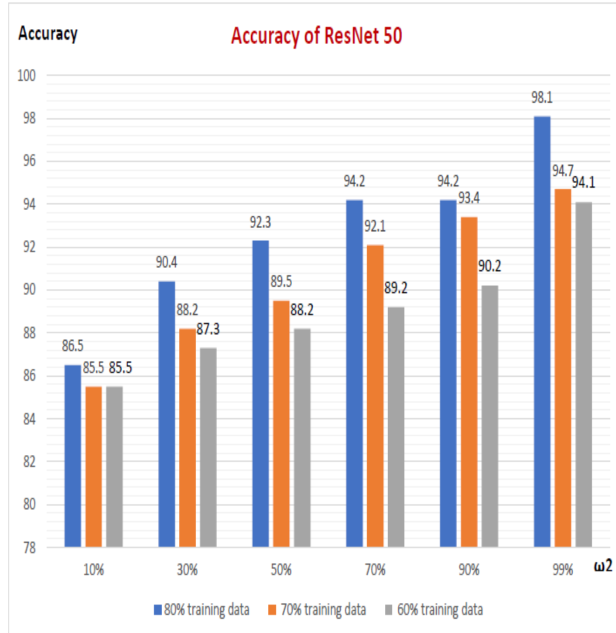
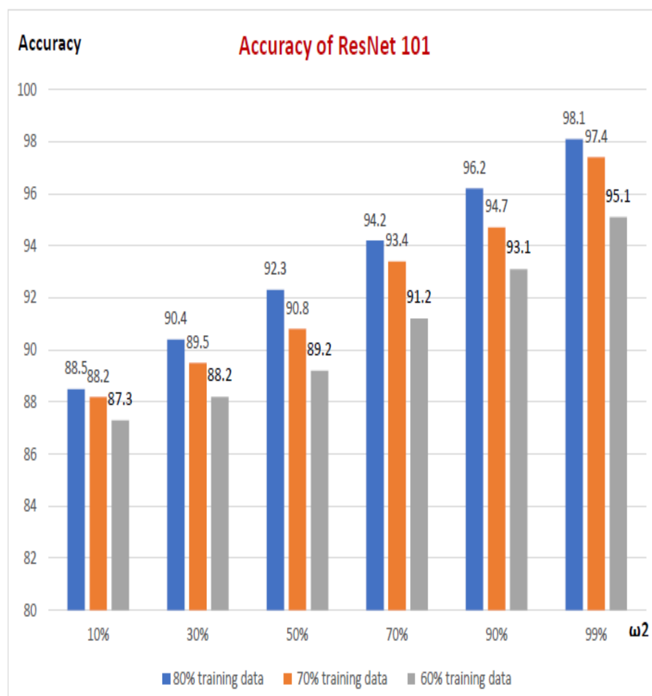


Fig 5: the relation between the weights and the accuracy of Resnet101 plus BO-SVM model at different training ratio.



the following figures represent the effect of the parameters different weights of BO-SVM and different training ratio(80%, 70%, 60%) on the classification error of the different types of the residual networks.

Fig 6: The relation between the classification error of Resnet18 plus BO-SVM model and the weights at different training data.

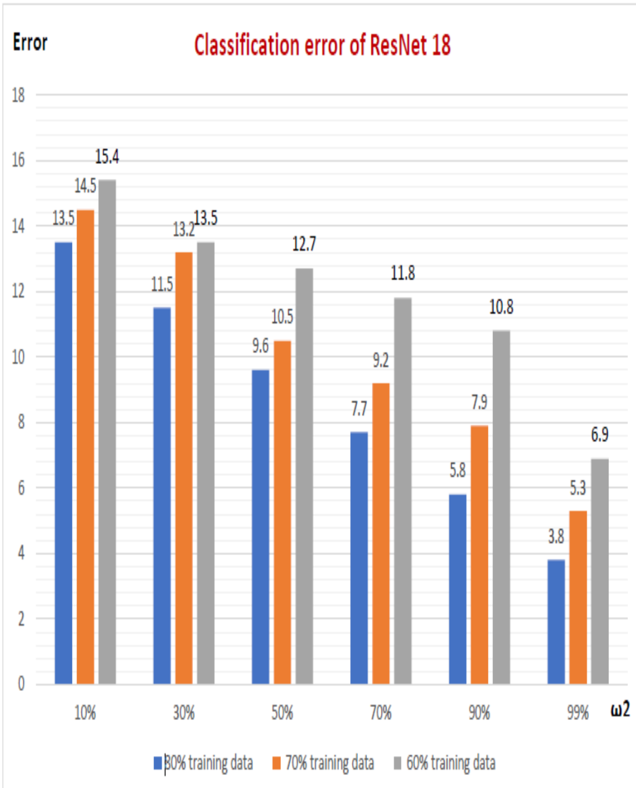


Fig 7: The relation between the classification error of Resnet50 plus BO-SVM model and the weights at different training data.

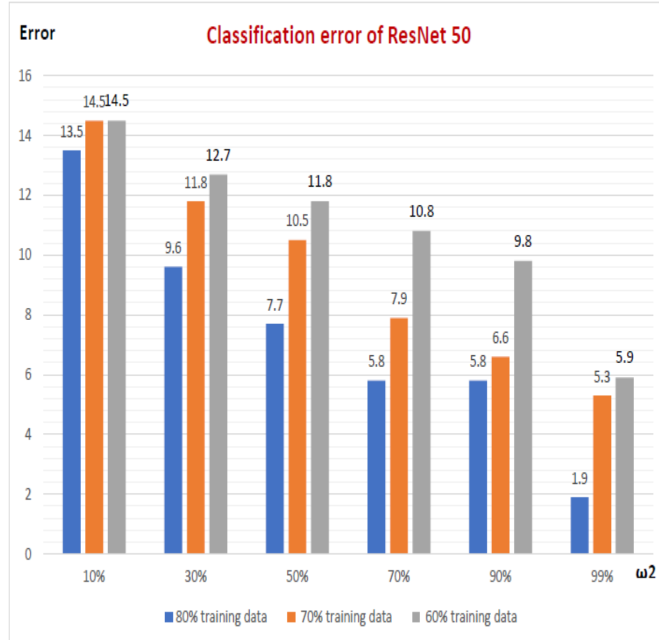
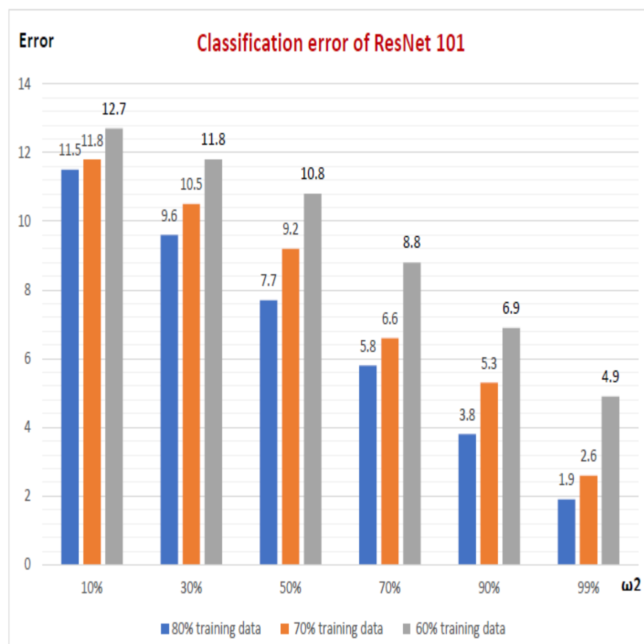


Fig 8: The relation between the classification error of Resnet101 plus BO-SVM model and the weights at different training data.



The previous figures show that by increasing the value of the weight of the summation of error, the accuracy of BO-SVM model increases and the classification error decreases and when the training data increases, the accuracy of the system increases.

The following table shows the comparison between the different types of Res-Net regarding to the accuracy and the classification error at weight 70% and training ratio 70%.

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Residual Networks	Accuracy	Classification error
Resnet-18	90.8%	9.2%
Resnet-50	92.1%	7.9%
Resnet-101	93.4%	6.6%

By comparing between the Res-Net101 , Res-Net50 and Res-Net18, the running time of Res-Net18 is less than the running time of Res-Net50 that is less than the running time of Res-Net101 but the accuracy of Res-Net101 is better than the accuracy of Res-Net50 that is better than the accuracy of Res-Net18 at different training data 60%, 70% and 80%.

VI. CONCLUSION

This paper introduced a comparison study of BO-SVM plus different types of Residual Networks (Resnet-18, Resnet-50, Resnet-101).

The experimental results proved that Renet-101 has the best accuracy and the best classification error at different weights and different training ration.

The future work, using different types of the convolution neural networks with BO-SVM and compare them by the results of Res-Net.

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