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A hybrid deep learning approach towards building an intelligent system for pneumonia detection in chest X-ray images

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ABSTRACT

Pneumonia is a major cause for the death of children. In order to overcome the subjectivity and time consumption of the traditional detection of pneumonia from chest X-ray images; this work hypothesized that a hybrid deep learning system that consists of a convolutional neural network (CNN) model with another type of classifiers will improve the performance of the detection system. Three types of classifiers (support vector machine (SVM), k-nearest neighbor (KNN), and random forest (RF) were used along with the traditional CNN classification system (Softmax) to automatically detect pneumonia from chest X-ray images. The performance of the hybrid systems was comparable to that of the traditional CNN model with Softmax in terms of accuracy, precision, and specificity; except for the RF hybrid system which had less performance than the others. On the other hand, KNN hybrid system had the best consumption time, followed by the SVM, Softmax, and lastly the RF system. However, this improvement in consumption time (up to 4 folds) was in the expense of the sensitivity. A new hybrid artificial intelligence methodology for pneumonia detection has been implemented using small-sized chest X-ray images. The novel system achieved a very efficient performance with a short classification consumption time.

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1. INTRODUCTION

Pneumonia is a respiratory condition in which lungs are affected by infection [1]. As the leading cause for the death of children under the age of 5, where it accounts for around 16% of all deaths of children [2]. Pneumonia kills over 800,000 children around the world every year [3], [4]. Adults can be affected by pneumonia as well, where over 50,000 people die every year, and more than one million people in the US (for example) are admitted to hospitals because of pneumonia; making it the most common cause of hospital admissions other than women giving birth [5]. Although pneumonia can be diagnosed by different imaging modalities such as magnetic resonance imaging (MRI) [6], [7] and computed tomography (CT) [8], [9], chest X-ray imaging is still the most common method for pneumonia diagnosis, because it is cheap, fast, and clinically more available.

Recent researches on diagnosis of pneumonia have focused on utilizing and developing automated computer-aided diagnosis (CAD) algorithms and methods to overcome the limitations of traditional (manual) diagnosis methods such as subjectivity, low accuracy, and time-consuming problems. Convolutional neural network (CNN) is one of the most common used deep learning architectures that has been applied for classification of many medical images because of its efficiency in extracting different level useful features [10]-[14]. Gu *et al.* [15], for example, were able to distinguish pediatric bacterial from viral pneumonia through chest radiography images using deep convolutional neural network (DCNN) model. The distinction between these two types of pneumonia using CAD methods was challenging because both types have similar and confusing features. They found that the accuracy, area under the curve (AUC), as well as the sensitivity were better when extracting DCNN features than when extracting the handcraft features; however, neither DCNN nor handcraft methods achieved satisfactory high results which was justified by the unbalance in their data and overfitting during the training process [15]. In addition, Abiyev [13] showed that for the classification of chest common pathologies that might be found in chest radiography, DCNN performed better, in terms of accuracy and minimum square error, than other conventional learning approaches such as backpropagation neural network with supervised learning and competitive neural network with unsupervised learning.

The use of CNN models has shown a high accuracy for classification of chest X-ray images to diagnose pneumonia. For instance, Omar and Babalik [16] introduced a CAD system based on CNN to detect pneumonia from chest X-ray images with an accuracy of 87.65%, which was higher than the accuracy obtained using different types of algorithms such as CheXNet [17], SMO, C4.5, and others [18]. On the other hand, Saraiva *et al.* [19] were able to achieve 95.3% average accuracy using k-fold cross validation compared to 92.8% achieved by Kermany *et al.* [20] who used CNN with a transfer learning technique which has been proven to be more efficient with limited data. CNN models have been found to perform better than multilayer perceptron (MLP) as well, where CNN achieved an accuracy of 94.4% compared to 92.16% for MLP [21]. In another recent study, Stephen *et al.* [22] constructed a CNN-based model that was trained from scratch to extract useful features from chest X-ray images and detect if pneumonia infection is present with training and validation accuracy of 95.31% and 93.73%, respectively.

The aforementioned studies have proven that CNN can be a reliable CAD model to diagnose and classify pneumonia from chest X-ray images because of the high accuracy it has achieved; however, there is still some loss (error) associated with all methods in the literature. Therefore, a novel hybrid artificial intelligence system has been proposed by this study. The proposed system is unique and distinguished from other existing systems by the use of convolutional neural network (CNN) along with other four different classifiers support vector machine (SVM), k-nearest neighbor (KNN), and random forest (RF), and Softmax. The main objective of this study was to investigate and evaluate the performance of this hybrid system in detecting pneumonia from small size chest X-ray images, which is another novel aspect of the study, by deep features extraction using a CNN fully connected layer.

2. RESEARCH METHOD

The block diagram of the proposed methodology is shown in Figure 1, where it started with transferring a learning applied technique to the pretrained CNN model. This transfer model was trained on the chest X-ray dataset to be used for deep feature extraction; then these features were fed to four types of classifiers; namely, Softmax, support vector machine (SVM), k-nearest neighbor (KNN), and random forest (RF). Finally, the performance of each classifier was evaluated and compared to that of other classifiers.

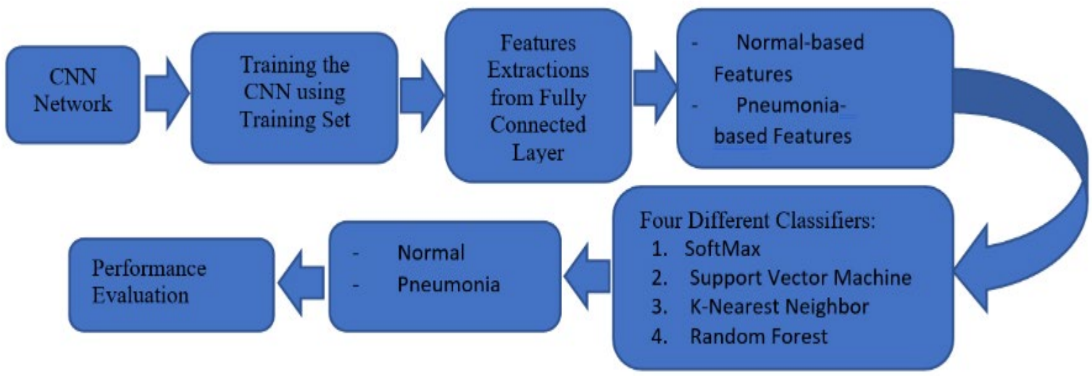
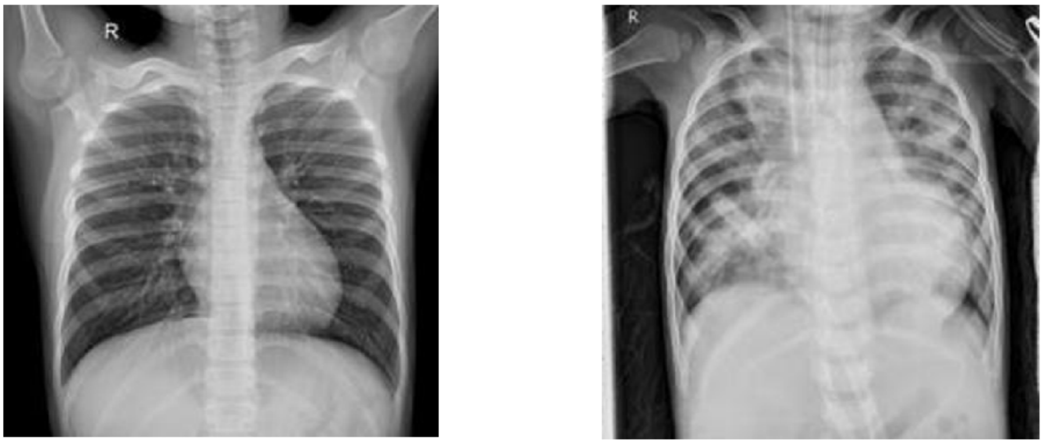


Figure 1. Block diagram of the proposed methodology

2.1. Dataset

The chest X-ray images dataset used in this study as shown in Figure 2 was published online (https://data.mendeley.com/datasets/rscbjbr9sj/3) by kermany *et al.* [20]. The dataset was divided into three groups (training, testing, and validation) and inside each group, there were two subgroups (Pneumonia and Normal) chest X-ray images. The dataset contained 5,852 anterior-posterior chest X-ray images which were carefully chosen from retrospective pediatric patients with age group between 1 and 5 years. For dataset balance purposes, the original data groups were merged and categorized into two main groups (Normal and Pneumonia) then these two sets were rearranged into three subsets: training set, validation set, and testing set with portions of 70%, 15% and 15%, respectively as illustrated in Table 1.



(a) (b)

Figure 2. This figure are; (a) chest X-ray images from the used dataset for a normal lungc, (b) an infected lung with pneumonia

Table 1. The distribution of images used in the system

Case	Number of training images	Number of validation images	Number of testing images	Total number of images
Normal	1,107	237	237	1,581
Pneumonia	2,990	640	641	4,271
Total	4,097	877	878	5,852

2.2. CNN architecture

This study has used a reconfigured CNN model that has been firstly proposed by Alqudah [23]. The model modification process included changing the input image layer size from 256×256 to 64×64 and the fully connected (FC) layer classes to 2 instead of 5. The modified CNN model layers details are shown in Table 2 while the architecture is shown in Figure 3. Like any CNN model, the proposed CNN model layers have been grouped into the following groups namely, deep features extraction layers and classification layers. For the deep feature extraction layers, each layer will take its input from the output of the preceding layer, then, the output of this layer will be processed as an input to the next layer; meanwhile, for the classification layers, this group of layers will take the features vector extracted using the previous group as an input received from the fully connected (FC) layer, usually, these layers are located at the end of all CNN model [13], [24].

2.3. Deep feature extraction using CNN

The modified CNN model used in this study has been applied to the chest X-ray images dataset using transfer learning technique, after which, the trained model has been used for deep feature extraction from each X-ray image. The fully connected (FC) layer has been used for deep feature extraction. The FC layer is the layer that precedes the classification layer Softmax so its output will be a feature vector that contains the features as columns where each column represents one type of the classes [25]. This type of feature extraction methodology is completely automated and produces a very deep and representative features for the entire dataset especially when the used CNN model is well designed and a large dataset used [26]. In this method the dimension of the extracted features is MxN where M represents the number of entered data (Images) and N is the number of classes [25].

Table 2. Layers specifications for the modified CNN architecture

Layer #	Layer name	Layer details	
1	Input layer	Size	64×64
2	Conv_1	Number of filters	48
		Kernel size	3×3
		Activation	RELU
3, 7, 11,15, 18	Batch normalization	Number of channels	32
5, 9,13,20	Max pool	Kernel size	2×2
		Stride	2×2
6	Conv_2	Number of filters	32
		Kernel size	3×3
4,8,12,16,19	RELU layer	Kernel size	2×2
		Stride	2×2
10	Conv_3	Number of filters	16
		Kernel size	3×3
		Activation	RELU
14	Conv_4	Number of filters	32
		Kernel size	3×3
17	Conv_5	Number of filters	32
		Kernel size	3×3

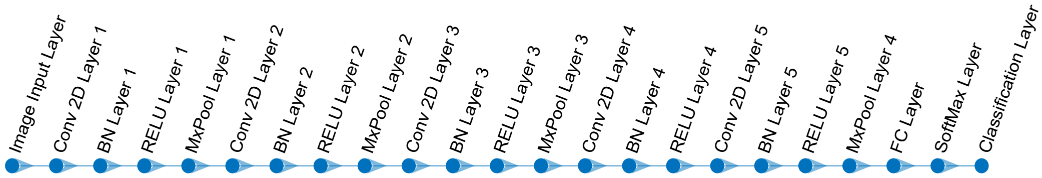


Figure 3. The architecture of the used CNN model

2.4. Classification stage

After the features have been extracted, different types of classifiers will be needed and used to find the corresponding label for every test image. For this purpose, four different types of classifiers have been used including SoftMax, SVM, KNN, and RF.

2.4.1. Softmax classifier

Softmax classifier is the most efficient and the simplest type of discriminatory classifier, which is used in CNN as the default classifier in the classification layer. The softmax discriminant classifier (SDC) finds the class of new features input of testing image by employing a nonlinear transformation function for the distance between the testing sample and training samples. In such a way, the learning method for the binary data in a softmax classifier is similar to the rule of standard binary data. The main difference between them is that softmax function is a generalization of the logistic sigmoid function, and it can deal with multiclass classification problems [25], [26].

2.4.2. Support vector machine (SVM) classifier

The support vector machine (SVM) classifier is a leading supervised machine learning algorithm that is widely used in medical applications to classify entire features into two classes. SVM builds the hyperplane model using training data that separates the entered data and can be used to anticipate the new feature class. The main aim of the SVM is mainly to find an optimal hyperplane that perfectly separates the entire data, and that maximizes the margin between the nearest data point called supporting points and the separating hyperplane [27], [28].

2.4.3. K-nearest neighbor (KNN) classifier

K-nearest neighbor (KNN) algorithm is an instant-based, unsupervised, and non-parametric machine learning algorithm, which is very simple, lazy, and widely used for classification of medical data. In general, usually, the KNN receives an input data that contains the feature space and the target label; the output class of the input features space will be determined based on the majority voting technique of the neighbor's classes. The majority voting is applied on the weights which represent the distance between each feature point and the center of mass of the vector [28].

2.4.4. Random forest (RF) classifier

Random forests (RF) classifier is an decision forests based ensemble classifier that has been proposed by Breiman [29] that is popular and widely used in multiclass medical data. The basic idea of RF methodology is to build classification trees by randomly selecting features from randomly selected samples with bagging strategy. Then, these trees are used to vote for a given input vector to get a class label. RF has many pros like efficiency on large-scale data, high precision, easy application, and overpowers in multi-class inputs, and it does not overfit.

2.5. Performance evaluation

In general, to make an evaluation and measure the performance of machine learning techniques used in this study, four well known statistical indices, namely, true positive (TP), false positive (FP), false negative (FN) and, true negative (TN) have been calculated. Then using these indices, the accuracy, precision, sensitivity, and specificity have been calculated according to (1)-(4) [30] shown:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{1}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FP+TN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{FP+TP}} \tag{4}$$

3. RESULTS

The methodology has been run using a desktop computer with Intel Core I7-6700 at 3.4 GHz and 16 GB of RAM and the code has been executed using a parallel environment. After feeding it with the training set, the CNN architecture has been trained using adaptive moment learning rate (ADAM) solver (initial learning rate of 10^{-3}, mini batch size of 128, and momentum of 0.9) in order to calculate the layers' weights; while the validation set was used for hyperparameters optimization. The training accuracy and loss for the used CNN architecture were plotted in Figure 4 which shows that after 620 iteration, the training accuracy achieved 100% while the loss reached 0%; which means that the model has been trained efficiently on the training dataset.

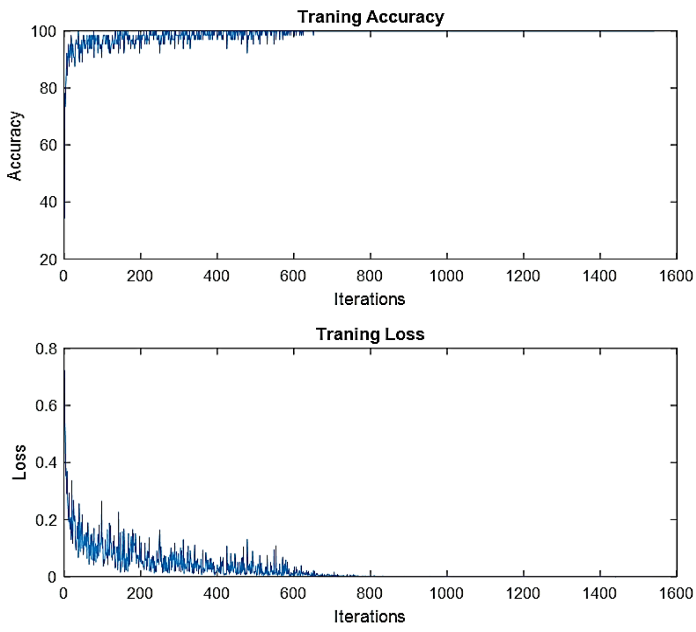
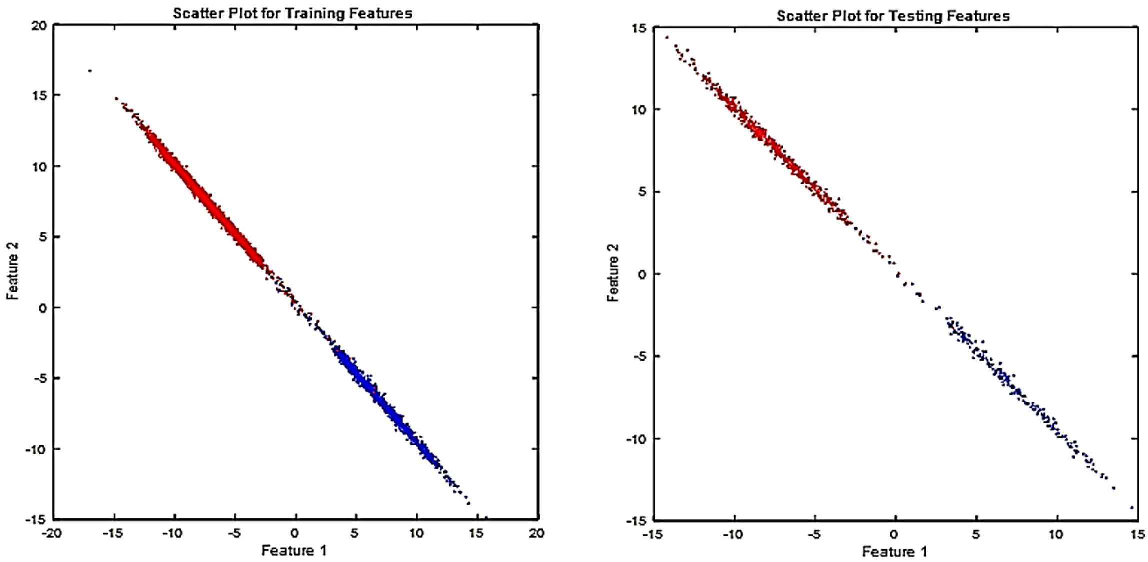


Figure 4. The training accuracy (top) and loss (bottom) change over the iterations

After training the CNN, the trained CNN has been used as a feature extractor from the fully connected (FC) layer. The output of this layer is a matrix with two columns representing the extracted deep features and rows representing the number of images for both training and testing datasets. Figure 5 shows the extracted deep features for both training and testing datasets.



(a) (b)

Figure 5. This figure are; (a) the extracted deep features for both training; and (b) testing dataset

To evaluate if the extracted deep features were significant, discriminant, and representative in the detection of the pneumonia, and to make a statistical check that extracted features were useful in detection pneumonia, a boxplot of each extracted deep feature among both classes was performed. As can be noticed from Figure 6, the range of holder exponents in the first feature and the second feature were far away from each other; which means that the extracted features can be used successfully in the detection of pneumonia. Also, it can be concluded from Figure 6 that the first feature was representative of the normal class (First Class), and the second feature was representative of the pneumonia class (Second Class).

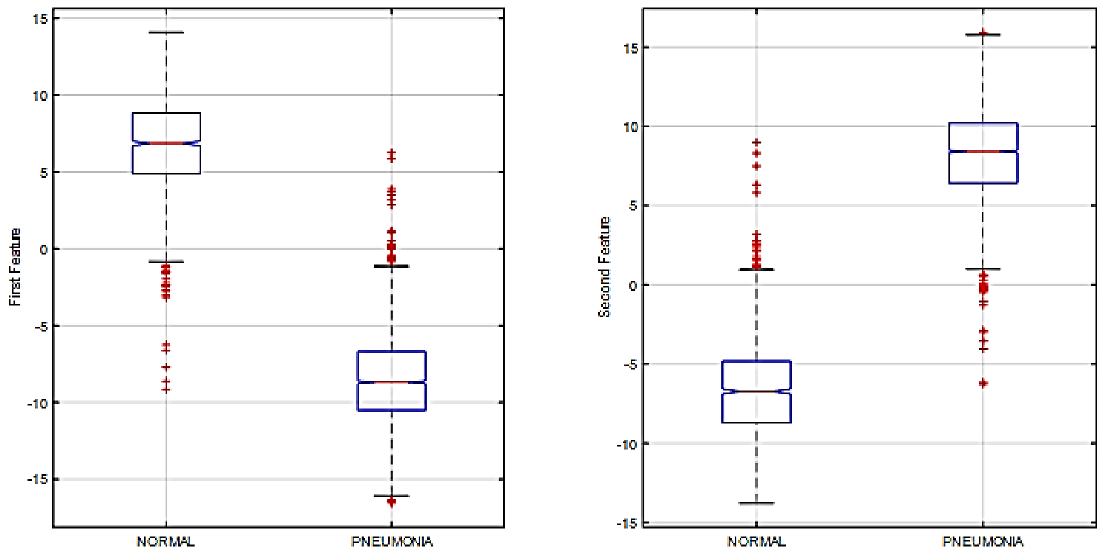


Figure 6. Boxplot for the both extracted features among the two classes

The extracted features from the training and testing images were then fed to four different classifiers (SVM, KNN, RF, and Softmax). The KNN classifier was implemented with a number of neighbors value of 2 and chebyshev distance measurement, while SVM was implemented with a 9th order polynomial as a kernel function. Finally, the RF was implemented with a 20 bags to be used for Bootstrapping. The choice of classifiers parameters was made by testing different combinations of classifiers parameters on the training and testing datasets, then the parameters that led to the best performance have been selected [31], [32]. To check whether the selected parameters can be generalized, the classifiers models were evaluated using 10 K-fold methodology. Figure 7 shows the confusion matrices for all classifiers, while Table 3 shows the training, testing, and overall accuracy of all classifiers. It can be noticed from Figure 7 and Table 3 that all classifiers performed very well in terms of overall accuracy of pneumonia detection with a small superiority of KNN.

Table 3. The accuracy of the four used classifiers

Method	Training accuracy %	Testing accuracy %	Overall accuracy %
Softmax	99	99	99
KNN	100	98.5	99.3
SVM	99	99	99
RF	100	97.15	98.6

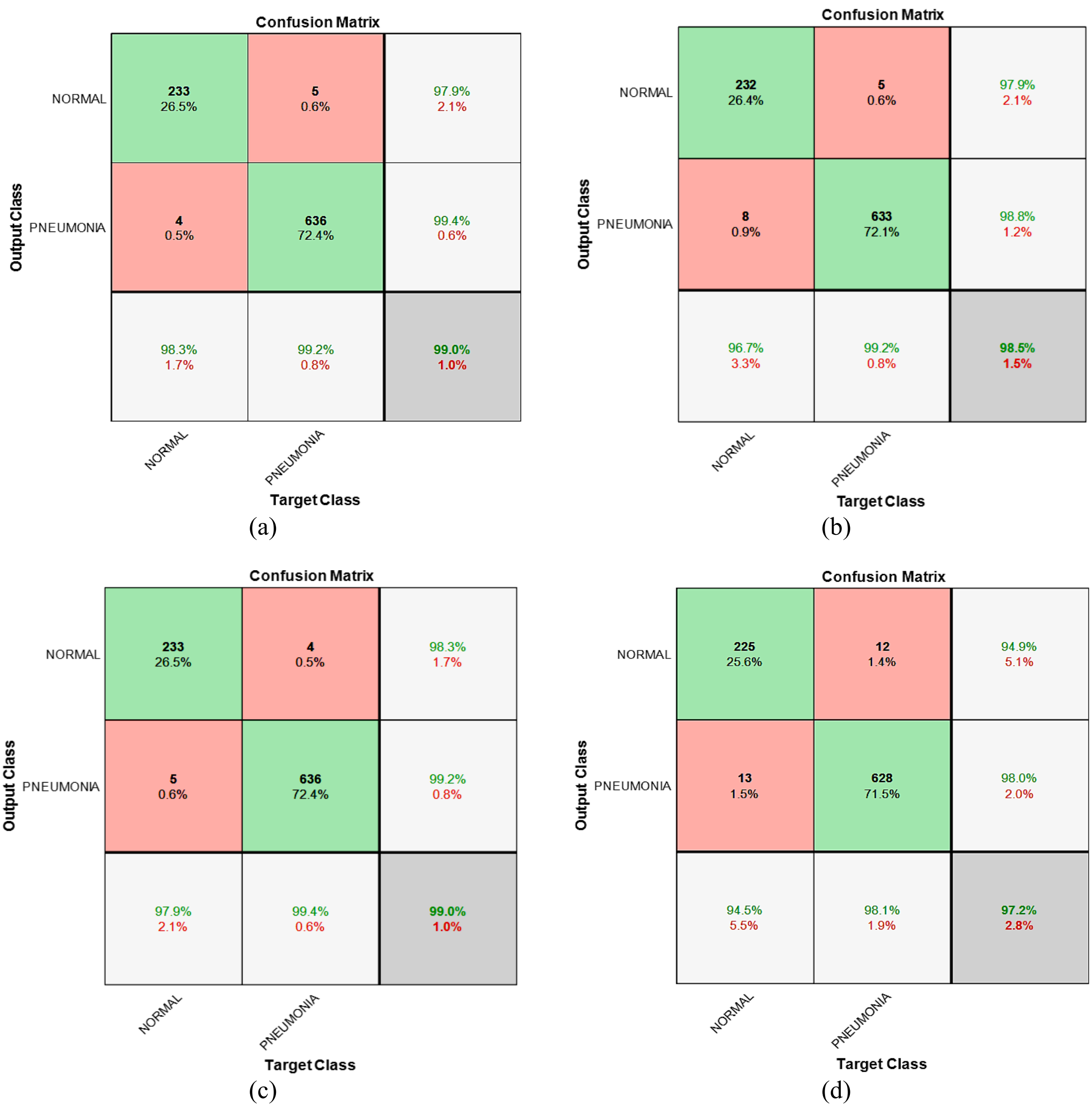


Figure 7. The testing confusion matrices for the used classifiers; (a) softmax; (b) KNN; (c) SVM; (d) RF

In order to make a comprehensive comparison between classifiers performances, the performance metrics of these classifiers including accuracy, sensitivity, specificity, and precision have been calculated, and the average time for classifying the image for both classes has been measured as well. Figure 8 shows that the statistical performance of the Softmax classifier was 98.97%, 99.22%, 98.31%, and 97.9%, for accuracy, specificity, sensitivity and precision, respectively. SVM classifier achieved the same accuracy, specificity, and precision as Softmax but with a lower sensitivity of 97.9%. KNN classifier, on the other hand, achieved a little lower performance evaluation with an accuracy of 98.51%, a sensitivity of 96.67% and a precision of 97.89%. Finally, RF classifier achieved the lowest performance with an accuracy of 97.15%, and a sensitivity of 94.56%, while the precision and specificity values were 94.96% and 98.12%, respectively.

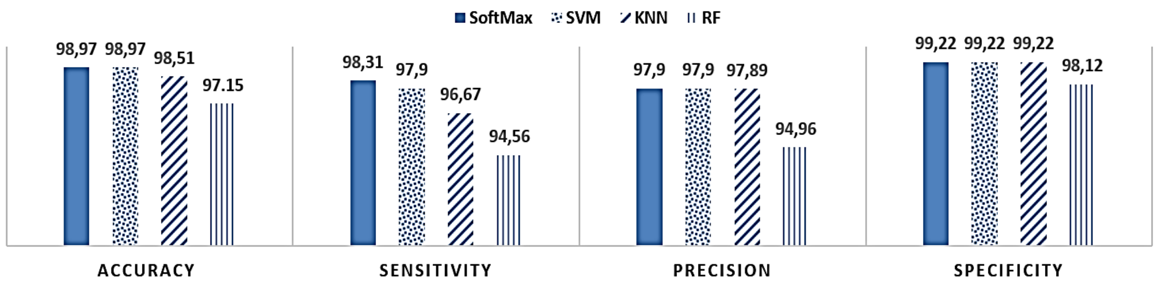


Figure 8. Performance comparison between different types of classifiers

Another evaluation of the system performance and stability using a 10 K-fold methodology was applied to all used classifiers. The results showed that all classifiers performed as expected. Table 4 shows the performance of the proposed hybrid artificial system for pneumonia detection using a 10 K-fold methodology. Figure 9 shows the time consumption for image classification using the different types of classifiers. The fastest classification was achieved by using KNN classifier, followed by SVM and Softmax; while the longest classification time was using the RF classifier.

Table 4. The accuracy of the four used classifiers using 10 K-fold methodology

Measures	Method			
	Softmax	KNN	SVM	RF
Accuracy %	99.72 ± 0.234	98.61 ± 0.117	99.61 ± 0.117	97.61 ± 0.234
Sensitivity %	99.52 ± 0.325	98.71 ± 0.406	99.71 ± 0.212	97.71 ± 0.523
Precision %	98.45 ± 0.483	96.24 ± 0.592	97.24 ± 0.592	95.24 ± 0.752
Specificity %	99.46 ± 0.254	98.58 ± 0.234	98.7 ± 0.234	97.58 ± 0.534

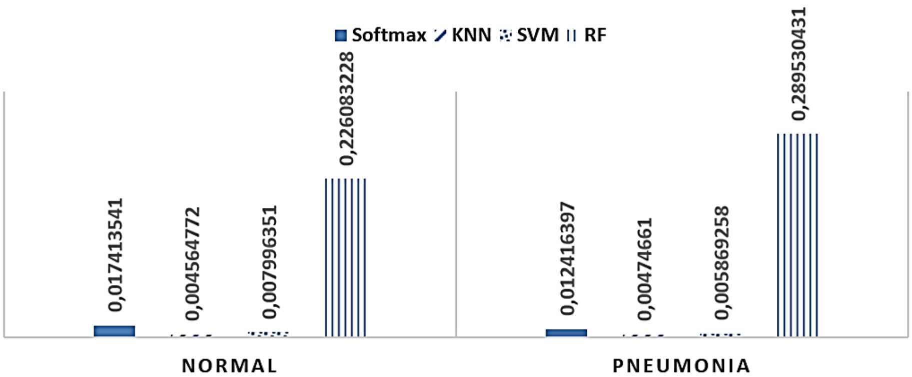


Figure 9. Classification time consumption for different types of classifiers

4. DISCUSSION

The goal of the current study was to investigate the impact of employing a hybrid artificial intelligence system on the performance of pneumonia diagnosis using chest X-ray images; as well as to examine the effect of using a new CNN architecture (AOCT-NET) with small image input sizes (64×64) on the efficiency of pneumonia detection. In the training phase scheme, all of the used classifiers (KNN, SVM, Softmax, and RF) achieved high accuracy using two extracted features; while during the testing phase, the four classifiers varied in their performance.

When comparing the experimental results of the proposed hybrid system to previous methods in the literature, it can be noticed that deep features extraction methods scored an accuracy less than that of the proposed methods (>97%). Rajpurkar *et al.* [17], for instance, proposed a CNN (ChexNet) that extracted deep features and used the Softmax classifier with an accuracy of 76.80%; while Saul et al. achieved a little higher accuracy with a value of 78.73% [24]. Both Rajpurkar *et al.* [17] and Saul *et al*. [24] used the NIH Chest X-ray 14 image dataset which contained more than 122,000 chest X-ray images of 15 different classes (normal and 14 diseases) among which 325 for pneumonia detection. The authors of the dataset have distributed the dataset into training, validation, and testing files. On the other hand, Kermany *et al.* [20] achieved a significant improvement in the accuracy (92.8%) when they used a transfer learning technique applied on Inception V3 CNN with Softmax classifier. More recently, Saraiva *et al.* [21] achieved an accuracy of 92.16% when they used deep features extracted using three hidden layers of MLP structure and Softmax classifier and an accuracy of 94.40% using deep features extracted using CNN architecture of three layers with Softmax classifier; both methods used the Kermany's X-ray pneumonia dataset that consisted of 5,852 images separated into training, validation, and testing files; they used image input size of 150×150 pixels. Also, Saraiva *et al.* [19] reported reaching an accuracy of 95.30% when using deep features with a Softmax classifier using ten layers CNN and input size of 300×300 pixels. A summary of the comparison between the proposed methodology and other methods in the literature is listed in Table 5.

Table 5. Comparison between the accuracy results in the proposed method and in other methods

Reference	Features Set	Classifier	Accuracy (%)
Rajpurkar *et al.* [17]	Deep features	Softmax	76.80
Saraiva *et al.* [19]	Deep features	Softmax	95.30
Kermany *et al.* [20]	Deep features using transferee learning of inception V3 CNN	Softmax	92.80
Saraiva *et al.* [21]	Deep features using multilayer perceptron (MLP)	Softmax	92.16
Saraiva *et al.* [21]	Deep features	Softmax	94.40
Saul *et al.* [24]	Deep features using nine layered ResNet CNN applied on increased contrast	Softmax	78.73
Current Study	Deep features	Softmax	99.00
		KNN	98.50
		SVM	99.00
		RF	97.15

The results of this study showed that Softmax and SVM achieved the highest performance in terms of accuracy, sensitivity, specificity, and precision, which can be explained by the fact that this study had only two classes (Normal and Pneumonia) and these two classifiers are well known to outperform other classifiers in binary problems because the Softmax classifier is a generalized version of binary logistic regression classifier, where SVM is known to be a generalized classifier for binary problems that use hyperplane to separate features into two classes. However, RF and KNN are more commonly used in multiclass classification (RF) and clustering (KNN) problems.

On the other hand, comparing the consumption time for testing image classification using the four classifiers, the fastest classifier for both: normal and pneumonic cases was the KNN, then SVM, Softmax, and lastly the RF. As mentioned before, KNN is a clustering technique which requires less time compared to other methods for making decision [33]; also, SVM is a hyperplane separation method which is a fast classification method [33]. Combining both characteristics of the system (i.e., the performance and consumption time), it was noticed that the consumption time can be reduced by a factor of 4 when using the KNN classifier compared to Softmax classifier, however, this decrease was traded off by sacrificing some sensitivity and accuracy. Similarly, the use of SVM classifier decreased the consumption time to half compared to Softmax classifier in the expense of sensitivity.

5. CONCLUSION

In conclusion, a novel hybrid artificial intelligence methodology for pneumonia detection has been implemented using small-sized chest X-ray images. The hybrid artificial intelligence system was built using a CNN model that was pretrained on OCT images. In contrary to other studies in the literature that utilized the transfer learning approach using pre-trained CNN architecture only, the hybrid system used in this work utilized the pre-trained CNN architecture for features extraction, and another classifier for making the decision. The hybrid system achieved a very high performance especially in terms of accuracy with short classification consumption time that varied with the classifier type.

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