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Transfer Learning Based Model for Pneumonia Detection in Chest X-ray Images

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Abstract: Pneumonia is a lung infectious disease caused by viral bacteria. It damages one or both lungs in humans. Expert radiotherapists must evaluate chest X-ray to detect pneumonia. As a result, designing an automated system for detecting pneumonia would be valuable for quickly treating the disease, especially in remote areas. This paper introduces a convolutional neural network-based model for reliably detecting pneumonic lungs from chest X-rays. This model can be used by doctors to treat pneumonia in the real world. This study proposes a hybrid model of EfficientNetB0 as a transfer learning-based model and support vector machine (SVM) hinge loss. The functionality of the pre-trained EfficientNetB0 model is used as feature-extractors followed by SVM classifier for the classification of abnormal and normal chest X-Rays. The statistical findings show that using a pre-trained EfficientNetB0 model and supervised classifier algorithm to evaluate chest X-ray images, specifically to detect Pneumonia, can be very beneficial. The proposed model achieves higher classification accuracy, precision, recall, and AUC values outperforming other state of art models with an overall accuracy of 97%.

Keywords: Pneumonia, Deep learning, Transfer learning, EfficientNetB0, Support vector machine (SVM).

1. Introduction

Pneumonia is an infection of the lungs most frequently caused by a virus or bacteria [1]. According to the World Health Organization (WHO), pneumonia is the foremost vital reason behind death within the world for kids younger than five years (about 12.8\% of annual deaths) [2]. It's additionally the main reason behind morbidity and mortality in adults worldwide and in particular in China [3]. Pneumonia is the third leading reason behind death in Japan with a higher mortality rate for the aged, notably among individuals older than 80 years. Excluding lung cancer, in Portugal, Pneumonia is that the massive reason for respiratory death [4].

Chest X-ray is the most efficient method for the diagnosis of pneumonia, which plays an animated role in clinical nursing and medical specialty analysis [5]. However, some chest X-ray images are very similar. Doctors have compelled to decide according to lung texture, patchy shadow, shadow density, inflammation site, and so on. Even practiced doctors are prone to mis-judgment and misdiagnosis. Therefore, the detection of pneumonia in chest X-ray images is a difficult task that relies on the individual expertise of doctors [6]. Therefore, there is a need for computerized support systems to help radiologists for diagnosing pneumonia from chest X-ray images [7].

Artificial Intelligence (AI) and machine learning techniques would help doctors to detect pneumonia carefully and quickly. Over the last years, machine learning techniques have been quickly progressed and combined into computer-aided design systems (CAD) to supply careful and quick diagnosis. The salient success of AI brings more signs of advance in medical image analysis. The quality and quantity of the training data have a direct impact on the success of the learning model [8]. Deep learning (DL) is a branch of machine learning interested with algorithms inspired by the human brain called artificial neural networks. DL models are trained by utilizing large sets of data and neural network architectures that extract features directly from the data without the need for manual feature extraction.

Transfer learning (TL) technique is a recently utilized approach in the field of deep learning. Utilizing TL technique, weights of deep learning models trained utilizing large datasets are transferred to other network models for new similar tasks. The new network model can start with pre-trained weights [9].

EfficientNet is considering one of the recent pre-trained Convolutional Neural Networks (CNNs). It first introduced in Tan and Le, 2019 [10]. It is among the most efficient models that reaches State-of-the-Art accuracy on both ImageNet and common image classification transfer learning tasks.

This paper proposes a hybrid model CNN architecture and support vector machine (SVM) for detecting and predicting pneumonia from chest X-ray images. The transfer learning technique EfficientNetB0 is implemented instead of CNN directly in classification process. The classification process is performed utilizing hinges loss function [11] as SVM loss instead of sigmoid loss. In comparison to state-of-the-art models, the key contribution of this work is the use of transfer learning to provide a pneumonia diagnosis model with chest x-ray images. This work also contributes by using hinge loss as an SVM layer rather than a sigmoid classifier to distinguish between normal and abnormal chest. The proposed model's overall accuracy increases because of this substitution. The overall accuracy of the EffientNtB0 with sigmoid-based classifier is 96.7%, which is improved to 97% when using the SVM-based model.

The remainder of this paper is organized as follows: Related work approaches utilized for diagnosis chest X-ray are introduced in Section 2. In Section 3, the proposed model architecture based on EfficientNetB0 and SVM are proposed. Section 4 shows the experimental results with a comparative analysis to state-of-the-art models. Finally, conclusions and future work are introduced in section 5.

2. Related works

The detection of pneumonia from chest X-ray images attracts the attention of many researchers to diagnose and detect this disease. In this section, State of the art models with diagnosis methods based on deep learning architecture are explored and discussed.

Rajpurkar et al., [12] presented an algorithm to detect pneumonia for chest X-ray images, where the authors assure that the performance of the proposed algorithm exceeds the practicing radiologists. The algorithm is a CNN of 121 layers trained utilizing the set of images of ChestX-ray14, including more than 100,000 X-ray images with 14 diseases.

Kermany et al., in [13] proposed medical diseases diagnoses and treatment by utilizing image-based deep learning models to detect or classify several medical datasets including of the dataset utilized in this paper. The performance of the proposed method was comparable to human specialists and achieved accuracy 92.8%. This paper enhanced the performance, but the drawback was it depend on lower-level features.

Stephen et al., in [14] proposed an efficient deep learning approach to detect and classify pneumonia in healthcare based on the same dataset utilized in this paper. A deep learning model with 4 convolutional layers and 2 dense layers is applied in this work in addition to the traditional image augmentation technique and achieved 93.7% testing accuracy. This paper used only classical data augmentation to improve the accuracy with different data sizes.

Saraiva et al., in [15] proposed a classification of images of childhood pneumonia utilizing CNN. The deep learning model in this work contained 7 convolutional layers and 3 dense layers and achieved validation accuracy 95.03%. This technique improves the accuracy but this work had a problem of using small number of convolutional layer and limit size of data.

Liang and Zheng in [16] proposed a transfer learning method with a deep residual network for pediatric pneumonia diagnosis. The deep learning model utilized in this paper contained 49 convolutional layers and 2 dense layers to diagnose and detect childhood pneumonia. The testing accuracy of this model is 90.05%. The drawback of this technique was large execution time for using large number of convolutional layers.

Wu et al., in [17] proposed a hybrid model to predict pneumonia with chest X-ray images based on adaptive median filter convolutional neural network and random forest (RF). The author used adaptive median filtering to remove noise in the chest X-ray image, which makes the image more easily identified and achieved high accuracy. Then CNN architecture with two layers is established based on dropout to extract features. Although the adaptive median filter can improve the classification accuracy of CNN, it needs additional preprocessing.

El Asnaoui et al., in [4] proposed automatic methods for detection and binary classification pneumonia images using different CNN architectures such as VGG16, VGG19, DenseNet201, Inception ResNetV2, InceptionV3, Resnet50, MobileNetV2 and Xception. The Inception_Resnet_V2, Inception_V3, Resnet50, Densnet201 and Mobilenet_V2 models give highly satisfactory performance that outperform the baseline CNN, Xception, VGG16 and VGG16 that give low performance. This paper showed that the Resnet50, MobileNet_V2 and Inception_Resnet_V2 gave highly performance (accuracy is more than 96%). These models utilized the use of a deeper convolutional layer with huge number of parameters.

In this work we aim to improve the performance of pneumonia detection model over state-of-the-art models by using transfer learning based network, and hinge loss as an SVM layer instead of sigmoid loss function. The main different between our proposed model and state of the art models that we introduce a hybrid model based on deep learning and machine learning. This model can achieve high accuracy measures using small number of layers and parameters compared to other state of the art models.

3. The Proposed model

In this section, the proposed model based on a hybrid of pre-trained model and SVM classifier is designed for the prediction and classification of pneumonia from chest X-ray images. The pre-trained architecture utilized in the proposed model is EfficientNetB0. The features are extracted utilizing this architecture and fed into a linear SVM based on hinge loss function for the classification tasks. The hybrid model is then evaluated utilizing the test set. The proposed model is composed of four phases as shown in Fig. 1. The first phase is data pre-processing and augmentation. The second phase is the feature extraction utilizing pre-trained architecture such as EfficientNetB0 with transfer learning. The third phase is the classification of chest X-ray images based on the extracted features and, testing performance measurement are the fourth phase. Each phase of the proposed architecture is explained in detail in the following subsections.

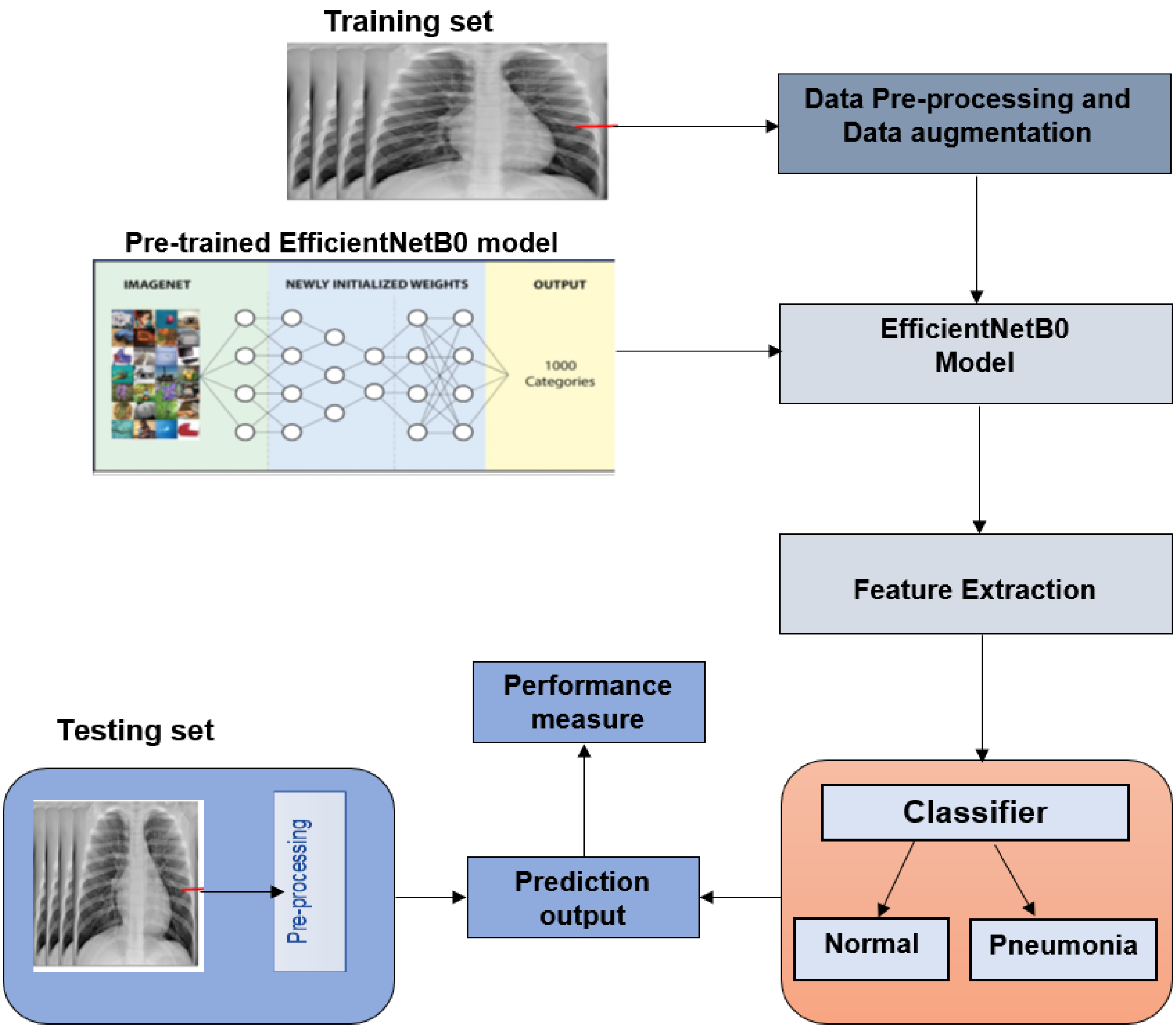

Figure. 1 Framework of the proposed model

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Table 1. Description of utilized dataset

Category	Training set	Validation set	Testing set
Normal	1070	234	279
Pneumonia	3115	390	768
Total	4185	624	1047

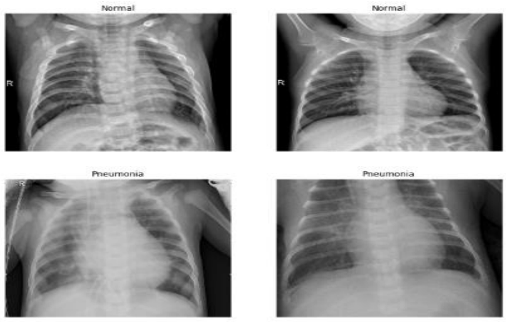

Figure. 2 Samples of chest x-ray images

3.1 Dataset description

The benchmark data utilized in this paper has 5856 chest X-ray images [18] with two categories (4273 pneumonia and 1583 normal). This dataset is available for free from Kaggle. The dataset contains three folders training, validation and test. The proportion of data assigned to training, validation and testing was highly imbalanced. Therefore, the dataset was combined and split into training, validation and testing sets as shown in Table 1. Finally, there were 4185 images in the training set, 624 images in the validation set and 1047 images in the test set. Fig. 2 shows a few sample chest X-ray images from the dataset.

3.2 Preprocessing and data augmentation

All input X-ray images are resized to 224×224×3 and normalized by converting each pixel value from 0-255 to a float pixel value in the range 0-1 as two basic two pre-processing steps.

Deep learning needs a large quantity of knowledge to get a reliable result. It's troublesome in some issues to induce enough information, particularly on medical issues since it's an awfully costly and long method. Data augmentation solves this problem by using existing data more efficiently. It is applied for the training process after dataset pre-processing and splitting to increase the training data, avoid the risk of over-fitting and improve the accuracy. Table 2 shows the parameter values for different data augmentation techniques such as rescaling, rotations, shifts, shears, zooms, and flips. The images after performing different augmentation techniques are shown in Fig. 3.

Table 2. The augmentation techniques and the parameter of each technique

Argument	Parameter value
Rescale	1/255
Rotation range	40
Zoom range	0.2
Shear range	0.2
Horizontal shift range	0.2
Vertical shift range	0.2
Horizontal flip	True

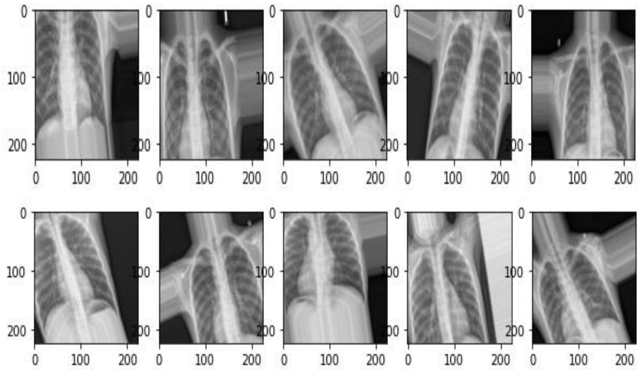

Figure. 3 Some samples generated by applying different augmentation techniques

3.3 Pre-trained CNN architecture for feature extraction

CNN models have shown to obtain superior results in medical image processing applications. However, training these models from scratch will be hard to predict pneumonia due to the limited availability of chest X-ray samples. The application of pre-trained models utilizing the concept of transfer learning (TL) can be beneficial in such settings. The TL technique is utilized to supply a pre-trained structure in an information base that can be from the same or another space, taking advantage of the information obtained to resolve new issues more quickly and viably [19]. One of the main steps of the TL process is a selection of the pre-trained model. pre-trained model is utilized as the starting point for a few specific tasks, rather than looking at the long method of training with arbitrarily initialized weights. Hence, it helps with saving the substantial computer resources required to develop neural network models to resolve these issues. The pre-trained CNN model utilized in this paper is EfficientNetB0.

EfficientNet [10] is a family of Convolutional Neural Networks (CNNs) that achieved high performance and accuracy in the ImageNet Challenge [20]. This family of CNNs is about 8 times smaller and 6 times faster to inference compared to

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Figure. 4 EfficientNetB0 architecture

the best existing groups such as SENet [21], GPipe [22]. EfficientNet utilizes a composite scaling method to create various models in the family that trade volume for accuracy. Composite scaling regularly measures the depth, width, resolution of the network. The depth of the network corresponds to the count of layers in a network. The width is related to the count of filters in a convolutional layer. The resolution is the height and width of the input image. The architecture of EfficientNetB0 shown in Fig.4.

In this work, the trained weights of EfficientNetB0 network are loaded from the Keras library and delete the classification output layers. The images of size 224 × 224 × 3 after applying augmentation is input to the pre-trained EfficientNetB0 model, then the feature extraction automatically using this model. These features may Represent the colour and the shape descriptor like circularity, roundness, compactness, ect.

3.4 Classification methods

After the features extracted automatically using pre-trained EfficientNetB0, two classifiers were used for the classification of chest X-ray images based on the extracted features.

3.4.1. Sigmoid-based classifier

The classification output layers of the EfficientNetB0 network are removed and proposed adding four layers for the classification task. The architecture of the proposed model for EfficientNetB0 show in Fig. 5. The first layer is a flattened layer used to convert a matrix of extracted features 7×7×1280 into a feature vector 62720. The second layer is a dense layer of neuron numbers 512 and Rectified Linear unit (ReLu) used as an activation function in a dense layer. The third layer is a dropout layer with dropout rate 0.2 which means 20% of the neurons will output 0 to reduce the over-fitting. In the last layer, a dense layer of neuron numbers 1 with a Sigmoid adds to the classification task. Sigmoid is an activation function that outputs a value between 0 and 1 only, so the result can be predicted easily to be 1 if the value is greater than 0.5 and 0 otherwise. It generally utilized when the number of classes is 2 and defined as [23]:

$$f(x_i) = \frac{1}{(1+e^{(x_i)})} \quad (1)$$

Where x_i denotes the input vector

For training the model, binary cross-entropy loss function is utilized. Binary cross-entropy function measures the performance of a classification model that is calculated as [23]:

$$L(y,p) = -y\, log(p) + (1-y)\, log(1-p)) \quad (2)$$

Where y is the actual value and p is the predicted value.

In the training step, because of the EfficientNetB0 was pre-trained, all the above layers of CNN architecture except the last twenty layers freeze to update their weights with the utilized dataset. The weights parameters of these layers are fine-tuned utilizing optimizer Adam. The hyperparameters for the network can be indicated in Table 3.

3.4.2. Hinge loss (SVM) based classifier

A novel hybrid model EfficienetNetB0-SVM is proposed by combining the EfficientNetB0 that is used for feature extraction with SVM that is used for classification. The architecture of the hybrid model was designed by replacing the Sigmoid classifier of the EfficienetNetB0 with a SVM classifier. The features are extracted from the pre-trained

Table 3. Training hyperparameters used while fine-tuning the deep learning model

Hyperparameters of Hybrid model	
Learning rate	0.00001
Optimizer	Adam
Batch Size	32
Max Epochs	100

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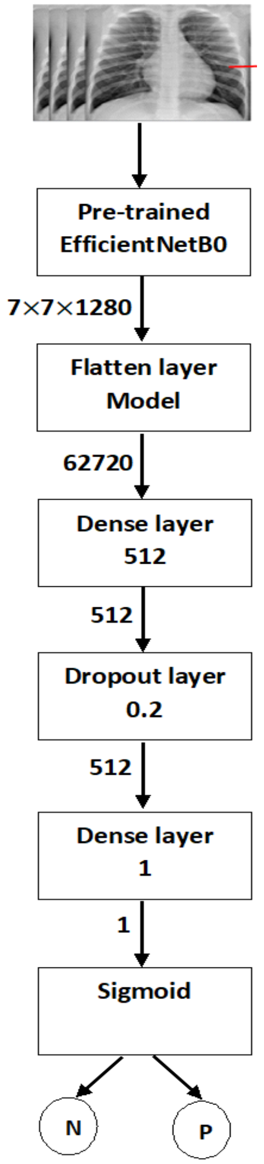

Figure. 5 The architecture of the proposed model using EfficientNetB0 structure

EfficientNetB0 model. These features are passed to the linear SVM classifiers to classify the output and predict the pneumonia chest X-ray images. The layers of the EfficientNetB0 architecture are freeze except the last twenty layers to update its weights with the utilized dataset. The fully connected layers of EfficientNetB0 are removed and adding a new four layers. The first layer is a flattened layer to convert the matrix of features to one feature vector. The second layer is a dense layer with 512 neurons. The third layer is a Dropout layer with a rate of 0.2 and the fourth layer is a linear SVM classifier based on the Hinge loss function. SVM is a binary classifier used to distinguish between the two classes instead of using the Sigmoid function. SVM understands these as class scores and its loss feature causes the appropriate class to score higher than other class scores by a margin. Instead, the Sigmoid classifier recognizes the scores for each category as unnormalized probabilities and then mapping them to normalized probabilities in the range [0,1] to be significant for the correct category. The main difference between sigmoid and binary SVMs is their objectives parametrized for the weight matrices. The sigmoid layer minimizes cross-entropy or maximizes the log-likelihood, while SVMs simply try to find the maximum margin between data points of different classes.

The SVM is trained to learn the weights parameter w by minimizing the hinge loss. Hinge Loss could be a loss function utilized in machine learning for training classifiers. The hinge loss could be a maximum [11]:

$$L(y) = \sum_i^N max(1 - y_i(w^T x_i + b), 0) \tag{3}$$

Where x_i the input i -th feature vector,
and $y_i \in \{-1,1\}$

y values are expected to be -1 or 1. If binary (0 or 1) labels are provided we will convert them to -1 or 1.

Fig. 6 Shows the architecture for the proposed hybrid model using EfficientNetB0-SVM.

3.5 Testing and performance measurement stage

The fourth phase of the proposed model is the testing phase, as shown in Fig. 1. The testing phase primarily deals with the testing dataset to evaluate the proposed model using the trained model based on the test accuracy and other performance measures, as shown in the next section.

4. Experimental results and analysis

This section introduces the results obtained from several experiments. Overall experimental analysis for pneumonia prediction from chest X-ray images utilizing a pre-trained CNN model and utilizing a hybrid model EfficientNetB0-SVM is presented. A comparative analysis among these models is introduced and to compared the results obtained from these models with recent state-of-the-art approaches. Finally, the most effective performing model is obtained.

The proposed models were trained on a Colaboratory (Colab) where a Google search project is created to supply everybody with free GPU resources for their deep learning projects and research. Each user is presently specified 12GB of RAM, and it will be up to 25GB. Google Colab gives a single 12GB NVIDIA Tesla K80 GPU and it can be utilized constantly for up to 12 hours.

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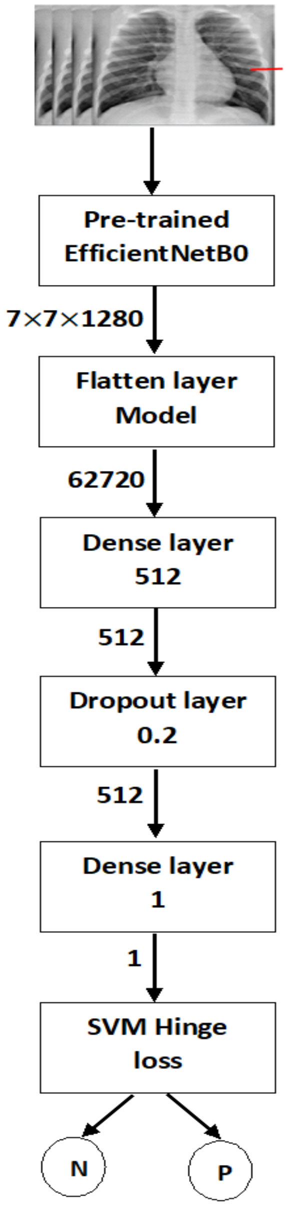

Figure. 6 The architecture of the proposed model using Hybrid structure

4.1 Evaluation metrics of model performance

The performance of the deep transfer models is evaluated utilizing various evaluation parameters such as testing accuracy, Precision measure, Recall measure, F1 score measure, Sensitivity, Specificity and area under the Receiver Operating Characteristic curve (AUC). Area under the ROC curve (AUC) is one of the most important evaluation metrics for classification model's performance that represents the degree of separability between classes. It indicates how much the model is able to distinguish between classes.

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

$$Recall = \frac{TP}{(TP+FN)} \tag{5}$$

$$F1-score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{6}$$

$$Sensitivity = \frac{TP}{(TP+FN)} \tag{7}$$

$$Specificity = \frac{TN}{(TN+FP)} \tag{8}$$

$$Accuracy = \frac{(TN+TP)}{(TP+TN+FP+FN)} \tag{9}$$

Where TP is the number of True Positive samples (i.e the model correctly predicts the positive category), TN is the number of True Negative samples (i.e the model correctly predicts the negative category), FP is the number of False Positive samples (i.e the model incorrectly predicts the positive category), and FN is the number of False Negative samples from a confusion matrix (i.e the model incorrectly predicts the negative category the negative result is false).

4.2 Training and validation accuracy

The training and validation accuracy/loss curves with the number of training epochs are displayed in Fig. 7 and Fig. 8 for both proposed models. As shown in the graph, the accuracy of the validation set and training set increases gradually with the increase of the number of epochs to reach a stability point; the curves of both training and validation loss for both models decrease gradually to reach a stability point with a small distance between the two. The error on the training data on the models decreases and so does the error on the validation dataset.

4.3 Confusion matrix and testing accuracy

Table 4 shows the performance metrics for EfficientNetB0 and Hybrid models. It indicates that the Hybrid model achieved the highest percentage for Precision, Recall, and F1 score metrics with a percentage of 100%, 95.8%, 97.9% and highest AUC score 98.0% compared with EfficientNetB0 model. Area under the ROC curve (AUC) is one of the most important evaluation metrics for classification model's performance that represents the degree of separability between classes. It indicates how much the model is able to distinguish between classes.

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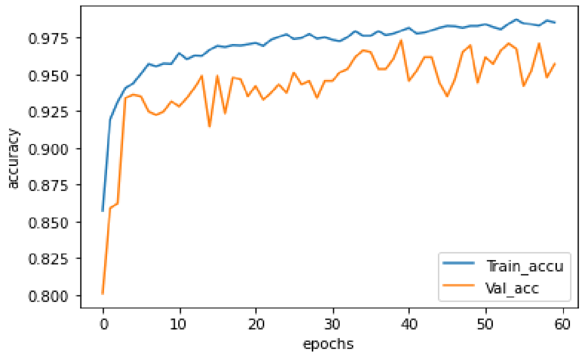
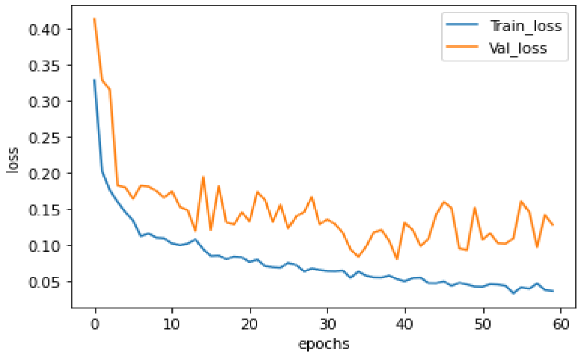
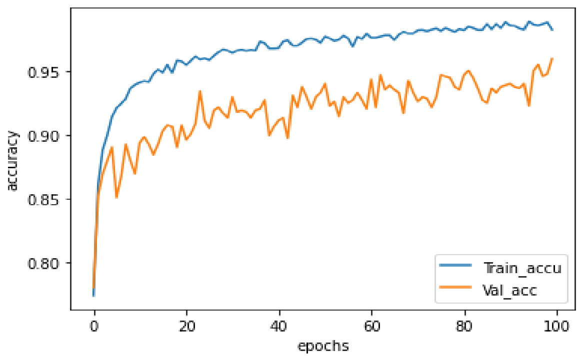


(a)

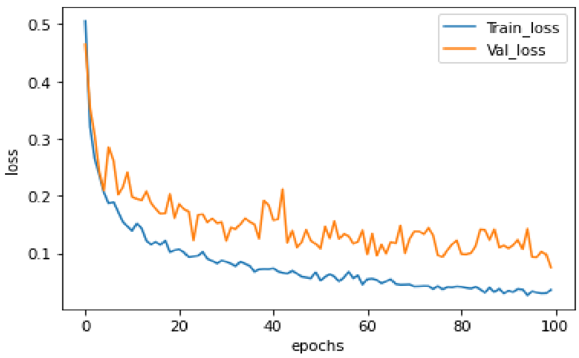


(b)

Figure. 7 Accuracy and loss curves for EfficientNetB0 model: (a) and (b)



(a)



(b)

Figure. 8 Accuracy and loss curves for Hybrid model: (a) and (b)

Table 4. Performance matrices for the proposed models

Metrices/Models	EfficientB0 model	Hybrid model
Precision	99.9%	**100.0%**
Recall	95.6%	**95.8%**
F1 score	97.7%	**97.9%**
Specificity	99.6%	**100.0%**
Sensitivity	95.6%	**95.8%**
AUC	97.6%	**98.0%**
Accuracy	96.7%	**97.0%**

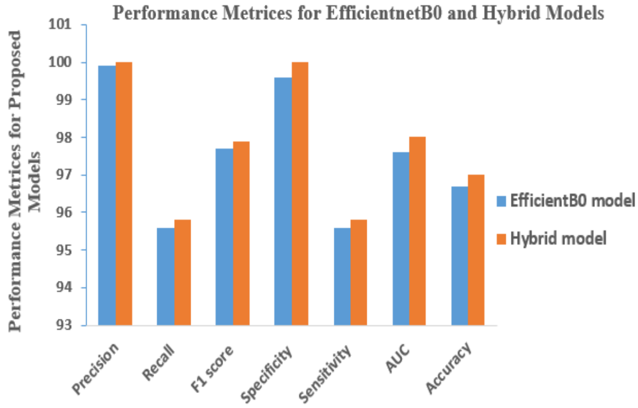


Figure. 9 Comparison of Precision, Recall, F1 score, Specificity, Sensitivity, AUC and testing accuracy for EfficientNetB0 and Hybrid models

Testing accuracy is an evaluation that determines the accuracy of the proposed model. The testing accuracy for EfficientNetB0 and Hybrid models are 96.7% and 97% consequently. The Hybrid model gives the highest accuracy compared with EfficientNetB0 model.

The comparative performance of Precision, Recall, F1 score, Specificity, Sensitivity, AUC and testing accuracy for two models are shown in Fig. 9.

Confusion matrix is a tabular method of visualizing the performance of prediction model. Each entry in a confusion matrix refers the count of predictions made by the model where it classified the classes correctly or incorrectly.

Fig. 10 displays the confusion matrices for the deep transfer model utilized in this paper with/without sigmoid.

In Fig. 10, The confusion matrix shows that, the EfficientNetB0 model was able to predict 278 images correctly as Normal. For the second class (Pneumonia), the EfficientNetB0 model was able to identify 734 images correctly, and fails with 34 images. On the other hand, The Hybrid model was able to identify 736 images correctly as Pneumonia and fails with 32. For Normal class, 279 were correctly classified as Normal and 0 images as Pneumonia.

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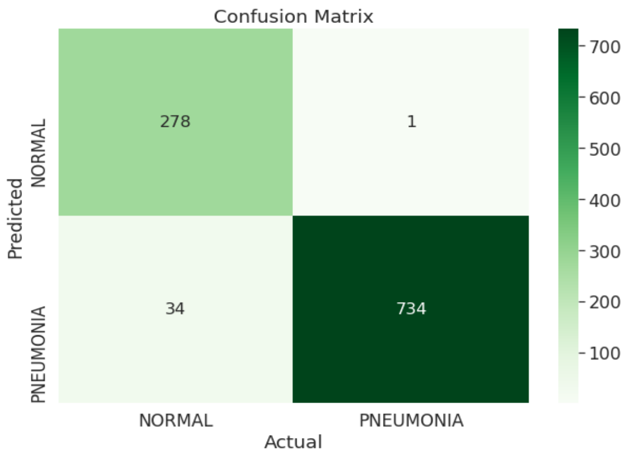
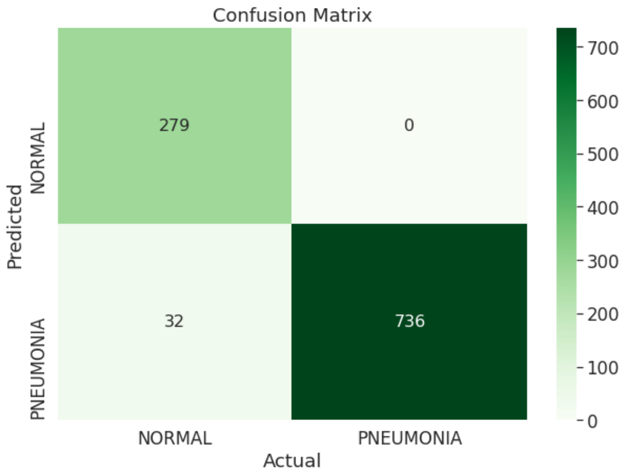


(a)



(b)

Figure. 10 Confusion matrices for EfficientNetB0 and Hybrid models: (a) Confusion matrices for EfficientNetB0 model and (b) Confusion matrices for Hybrid model

In Fig. 10, The confusion matrix shows that, the EfficientNetB0 model was able to predict 278 images correctly as Normal. For the second class (Pneumonia), the EfficientNetB0 model was able to identify 734 images correctly, and fails with 34 images. On the other hand, The Hybrid model was able to identify 736 images correctly as Pneumonia and fails with 32. For Normal class, 279 were correctly classified as Normal and 0 images as Pneumonia.

4.4 Comparative analysis

The dataset utilized [18] in this paper is a benchmark, and it is tested over many approaches since 2018. The Hybrid classification model is compared to previous related work on the same dataset which explained in Section 2.2. Table 5 illustrates the related works with the achieved testing accuracy. The comparative performance of different measures for the proposed model with the previous works are shown in Fig. 11. Table 5 presents the accuracy measures for related work and proposed models. The proposed Hybrid model achieved a superior testing accuracy of 97% more than the EfficientNetB0 model and compared related work. It also achieved the highest score for Precision, Recall, F1 score, Specificity, and Sensitivity metrics of 100%, 95.8%, 97.9%, 100%, and 95.8% sequentially compared with previous methods, except Liang and Zheng [16] achieved a high percentage for recall measure.

Results in table 5 show that integrating EfficientNetB0 output into an SVM improves classification accuracy.

Hinge loss is an effective method for SVM and EfficientNetB0 which contain lesser convolutional layers and parameters achieving high performance. So as combining can take advantage of both models due to the effectiveness of the SVM loss function and achieving high accuracy. It is deduced that the combination of transfer learning techniques and machine learning improves the accuracy of pneumonia detection and prediction, and strongly reduces the running time of pneumonia detection due to the lesser parameters and convolutional layers of EfficientNetB0 architecture and achieves high accuracy.

5. Conclusion

In this paper, a novel hybrid model base on SVM was introduced. This model was utilized in classification of pneumonia disease utilizing X-ray images. The linear SVM based on the hinge loss function was utilized to replace the Sigmoid function in EfficientNetB0. The experiments

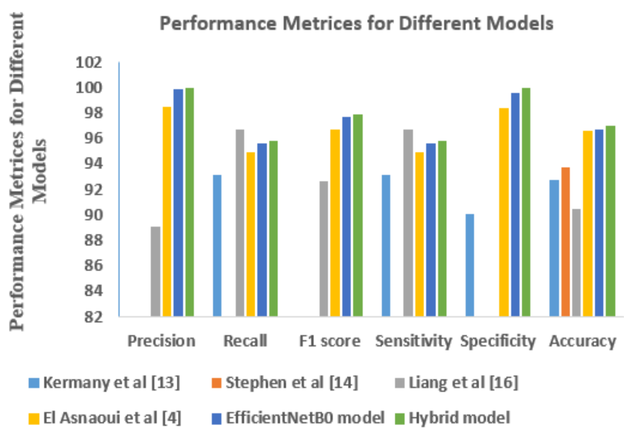


Figure. 11 Comparison of precision, recall, F1 score, specificity, sensitivity and testing accuracy for different models

Table 5. Performance matrices for the proposed models

Models	Precision%	Recall%	F1 score%	Sensitivity %	Specificity %	Accuracy%
Kermany et al [13]	-	93.2	-	93.2	90.1	92.8
Stephen et al [14]	-	-	-	-	-	93.7
Liang et al [16]	89.1	**96.7**	92.7	**96.7**	-	90.5
El Asnaoui et al [4]	98.5	94.9	96.7	94.9	98.4	96.6
EfficientNetB0 model	99.9	95.6	97.7	95.6	99.6	96.7
Hybrid model	**100**	95.8	**97.9**	95.8	**100**	**97.0**

have shown that the linear SVM outperforms Sigmoid function to solve the pneumonia recognition task. The proposed model superior the most state-of-the-art models concerning different accuracy measures (e.g., accuracy, precision, recall, F-score, specificity and sensitivity) and achieved a highest accuracy of 97%. This work proved the importance and benefits of utilizing transfer learning in combination with hinge loss as SVM in solving the binary classification problem of pneumonia diseases.

In future work, we plan to expand our research with other pre-trained CNNs to solve multi-classification problems. Expand this research to measure the grade of pneumonia that helps the physician know the patient's condition and Hyperparameter optimization for automatic parameter selection rather than manual. We also expand this research to utilize more than pre-trained CNN architectures as combined deep features extraction and will then use these features after.

Conflicts of Interest

The authors state no conflict of interest regarding the publication of this paper.

Author Contributions

Conceptualization, Ola M. El Zein gives the idea of the system, Ola M. El Zein; software and designed the experiments, Ola M. El Zein, Neveen I. Ghali, and Mona M. Soliman; formal analysis, investigation, resources, data preparation, Ola M. El Zein writing-original draft preparation, Neveen I. Ghali, and Mona M. Soliman; review and editing, Ola M. El Zein, Neveen I. Ghali, Mona M. Soliman, and A. K. Elkholy; supervised the study, analyzed the results, and verified the findings of the study.

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