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Medical X-RAY Image Classification Using CNN Based Model

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Abstract:

Viruses, bacteria, and fungus may all cause pneumonia, which one among the primary reasons of mortality in the globe. Detecting pneumonia from chest X-rays is challenging, however, this work is about simplifying the procedure for both experts and novices using a novel deep learning framework based on transfer learning. Previous studies have proposed a large amount of deep learning models as for pneumonia detection, but finding a successful approach that fulfils all performance measures. Therefore, this work proposes a pre-trained model called ResNet152V2, a Convolutional Neural Network (CNN), and evaluates it using Python. The suggested model outperforms other models in terms of f1-score, area under the curve, precision, accuracy and by 94.65%, 92.85%, 93.94% and 93.27%, respectively. An *important goal of this research is to offer effective deep learning model for the identification and categorization of pneumonia.*

Index Terms: *Deep Learning, Machine Learning, ResNet152V2, Convolutional Neural Network, Pneumonia*

1. Introduction

Medical imaging may be used to identify and treat a wide range of illnesses. Identification and categorization of several illnesses, such as pneumonia, cancer, and heart disease, is one of the most important uses of medical imaging. In recent years, machine learning (ML) models have shown remarkable progress in analyzing medical images and providing accurate diagnoses. Among these, the classification of pneumonia using ML models has attracted significant research attention due to its high prevalence and mortality rate. An estimated 1.4 million kids per year, or 18% of all kids under five years old, pass away from pneumonia. Also, every year, about two billion individuals globally deal with pneumonia, which can be fatal if immediate treatment is not performed. A timely diagnosis of pneumonia is essential [1][2]. The most popular and affordable method of detecting of pneumonia with the help of chest X-rays [3].

The accuracy of disease prediction using deep learning algorithms has already been demonstrated to be on par with that of a typical radiologist [11]. At this time, trained physicians cannot be replaced by deep learning-based algorithms in medical evaluation. Hence, deep learning-based computer-aided diagnosis techniques can be employed as an addition to clinical decision-making.

Medical image classification, particularly the categorization of X-ray images, is increasingly being done with convolutional neural networks (CNNs). These deep learning models are very good at finding patterns and characteristics in vast datasets, which enables them to accurately learn to distinguish between various kinds of medical images. CNNs have the potential to increase diagnosis accuracy and support doctors in making more informed decisions on patient care because of their capacity to recognize minute differences in medical images.

Traditionally, human specialists created deep neural network models and ran experiments on them using a continual trial-and-error process. It takes a lot of time, expertise, and resources to complete this process. This issue is solved by presenting a novel yet simple method to automatically perform the best task of classification with deep neural network architecture. The architecture of the neural network was created especially for challenges involving the classification of images of pneumonia. The suggested method convolves an image to extract important features using a collection of neurons. Convolutional neural network technology serves as its foundation. The effectiveness of the suggested strategy was demonstrated with a purpose to reduce the computing cost.

Although modern strategies for categorization based on CNN provide comparable trial-and-error system centered network topologies that they designed basis, Deep learning algorithms with CNN motivation have lately taken over as the default choice for categorizing medical pictures. Changes to the deep layered CNN's parameters to detect pneumonia have been tested in a number of articles. Pneumonia-related diffuse opacification on a lung radiograph might either have an alveolar or an interstitial pattern. Laboratory evidence of a bacterial infection is seen in individuals having chest radiographic evidence of alveolar infiltration, especially those with lobar infiltrates [4].

2. Literature Review

Enes Ayan et al. [5] compares the performance of two CNN models, Vgg16 and Xception, in diagnosing pneumonia using chest X-ray images. According to the test findings, Vgg16 performed better than Xception in terms of precision, accuracy, and F1 score for pneumonia. However, Xception was better at identifying pneumonia patients in general, but Vgg16 was effective at identifying typical instances. The authors suggest that combining the strengths of both networks through an ensemble approach could lead to more successful results in diagnosing pneumonia. The test's findings indicated that the Vgg16 network performs better than Xception network in terms of accuracy, specificity, pneumonia precision, and f1 score (0.90%) by 0.87%, 0.91%, and 0.90%, respectively. The Xception network surpasses the Vgg16 network in terms of sensitivity (by 0.85%), normal accuracy (by 0.86%), and pneumonia recall (by 0.94%).

Nitin Singh et al. [8] implemented an advanced technique such as Gray level Co-Occurrence Matrix and Wavelet Transform for detection of x-ray images of the chest to identify pneumonia. These methods are known for their ability to extract useful features from image data, particularly texture features, which can be informative for identifying patterns of pneumonia. Using K-nearest neighbors (KNN) and Support Vector Machines (SVM) for classification is also a popular choice in machine learning, and it's good to see that these techniques have been used in this study. The achieved accuracy of 94.6% with cubic SVM and 92.6% with weighted KNN is impressive and suggests that the proposed approach has good potential for the automated diagnosis of pneumonia. However, similarly to any machine learning approach, it's important to validate the performance of the model on a larger and more diverse dataset to ensure its robustness and generalizability. Moreover, the interpretability of the model's decision-making process should be investigated to ensure its clinical usefulness and avoid potential biases. Overall, this research is promising and has the potential to contribute to the development of automated diagnosis systems for pneumonia, this might possibly save lives by enhancing the speed and accuracy of diagnosis.

Abdullah Faqih Al Mubarok et al. [10] compares the performance of two deep convolutional architecture, Residual Network and Mask-RCNN, in classifying and detecting pneumonia. Because Mask-RCNN's RPN algorithm performs poorly at recognizing the characteristics of pneumonia, Residual Network outperforms it in terms of pneumonia identification. Due to an uneven dataset, the two networks also display a significant gap between sensitivity and specificity. Future study can concentrate on tweaking hyperparameters, utilizing more intricate network topologies, and enhancing the imbalanced dataset to enhance the performance of the two designs. Residual Network beats Mask-RCNN, which has an accuracy of 78.60%, with a precision of 85.60%. The study helps to improve the pneumonia CAD system, which is important for medical diagnosis and therapy.

Harsh Sharma et al. [6] elucidated deep CNN architectures to classify chest X-ray images for pneumonia detection. Both original and augmented datasets were used to assess how the amount of the dataset would impact CNN performance. Two CNN architectures were designed from scratch with data augmentation to prevent overfitting. The other models were outperformed by the CNN that used augmented data to train dropouts. To increase classification accuracy, future study will examine other optimizers and data augmentation strategies. Early stopping and batch normalization will also be tested to avoid overfitting. Their highest accuracy achieved was by Model 1 which was 90.68%.

Tej Bahadur Chandra et al. [7] puts forward a technique for applying machine learning to automatically diagnose pneumonia on segmented lungs. The technique concentrates utilize this knowledge to identify pixels in the segmented region of the lungs that are more indicative of pneumonia and uses it to extrapolate relevant attributes. On a series of 412 chest X-ray images with 206 pneumonic and 206 normal subjects, the approach was evaluated using five classifiers. The proposed method achieved significantly higher accuracy of 95.63% using Logistic Regression classifier and 95.39% with Multilayer Perceptron compared to the traditional method. This method could potentially improve pneumonia diagnosis and treatment using chest radiographs.

Saurabh Thakur et al. [9] propounded a methodology for using advanced artificial intelligence techniques, such as convolutional neural networks, for the diagnosis of pneumonia. The VGG16 model is a popular choice for image recognition tasks, and it's good to see that it has been applied to the diagnosis of pneumonia with promising results. Transfer learning and fine-tuning are popular techniques in deep learning that enable the use of trained models and the adaptation of those models to new tasks. It's good to see that these techniques have been used in this study, as they can significantly reduce the training time and improve the accuracy of the model. The achieved accuracy of 90.54% is impressive and shows the potential of using deep learning models in order to identify pneumonia. Moreover, the recall of 98.71% and precision of 87.69% suggest that the model has a specificity and high sensitivity which is crucial for accurate diagnosis. But it's crucial to highlight that the model's performance should be validated using a larger dataset with varied demographic and clinical characteristics. Moreover, the interpretability of the model's decision-making process should be investigated to ensure its clinical usefulness and avoid potential biases. Overall, this research is promising and has the potential to contribute to the development of automated diagnosis systems for pneumonia, which can accelerate and more precisely diagnose diseases and potentially save lives.

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3. Material and Method

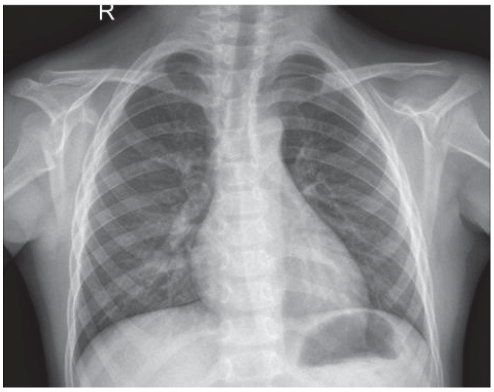
We outline the comprehensive tests and evaluation procedures used to determine whether the suggested paradigm is effective. The chest X-ray image collection used in our research was first proposed in [12].

3.1 Dataset

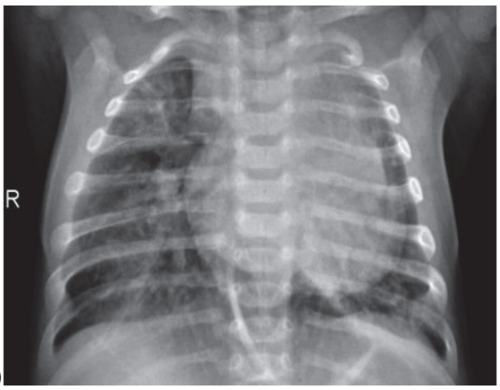
The three sections of the provided dataset are as follows: validation, train and test. Every image category that is Pneumonia and Normal have been provided with their own subfolder and dataset. The dataset has 5,863 X-ray pictures. that are in JPEG format. This dataset was provided by an author named as Paul Mooney. X-ray imaging displayed the chests of a group of individuals who were all younger than 5-year-old, from a Medical Center based in Guangzhou [12]. We have split the dataset into two parts, training and testing. Training contains 87% of the data and testing contains 13%.

Figure 1. Chest X-ray Images of a healthy individual (I) and an individual who has pneumonia (II).

I)

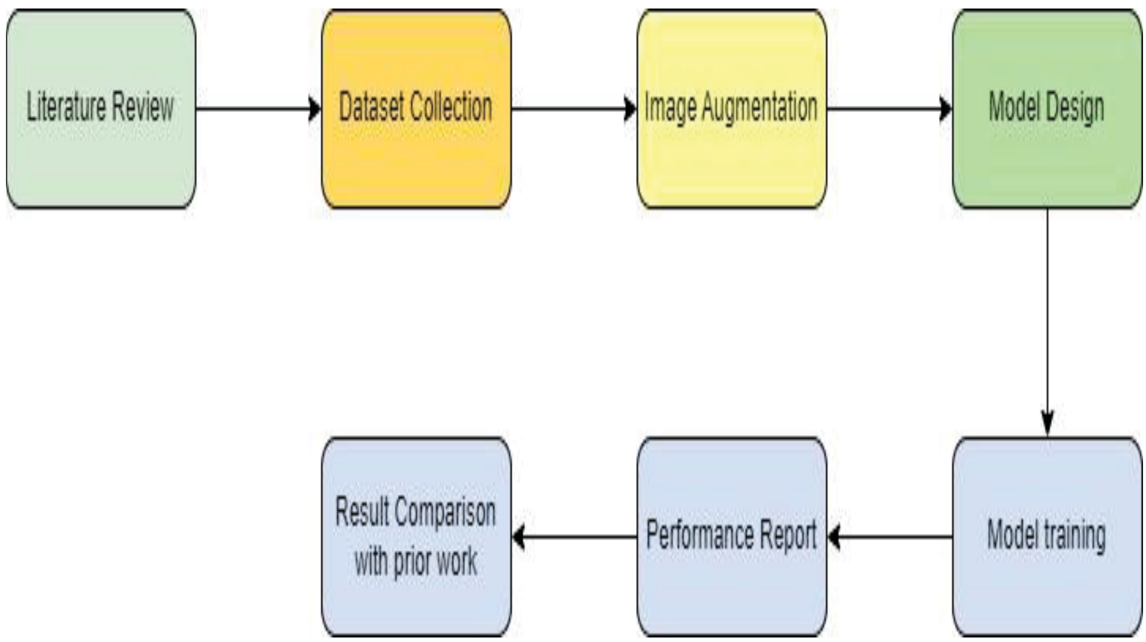


II)



3.2 Methodology

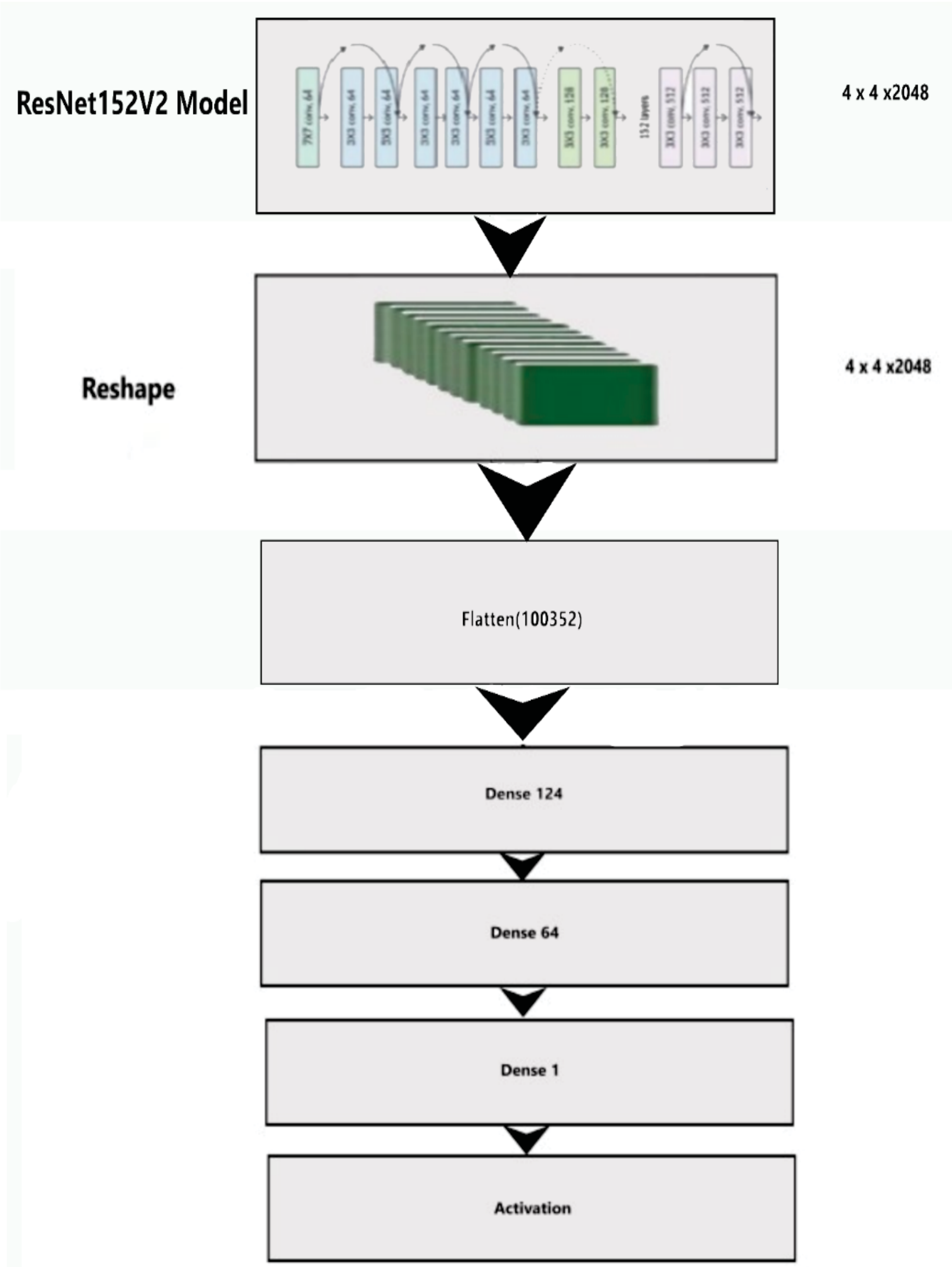
The results of earlier research articles were examined. Dataset collection and local storage were completed. Pre-processing of all relevant data was done. For training we used ResNet V2 cutting-edge CNN model. Following training on the dataset using this CNN model, the model's effectiveness was assessed. After that, the accuracy of the model was contrasted with models suggested by earlier research articles.



4. Preprocessing and Augmentation

The rescale operation during the augmentation procedure implies picture reduction or magnification. The rotation range adds the rotation of 40 degree. The image angles are clipped with a 0.2 percent shear range in the anticlockwise direction. The images were then randomly zoomed by the zoom range before being rotated horizontally, to a ratio of 0.2 percent. The validation spilt of 0.3 splits the data into 87% training and 13% testing.

5. Model Design



Model Name	Architecture Used	Specification
Model 1	ResNet152V2 (Pre-trained)	Pre-trained model with frozen weights

In the field of computer vision in particular, ResNet V2 has been demonstrated to be a very successful CNN architecture for image recognition and localization tasks. ResNet V2 uses residual connections to effectively train very deep networks, which was previously difficult for CNNs.

Residual connections were first introduced in the ResNet V2 architecture (V1) and allow information to travel over some network layers, making it simpler to train extremely deep networks. After each convolutional layer, the V1 architecture additionally employs batch normalization, which enhances training stability and generalization.

The batch normalization that is added before each convolutional layer in ResNet V2 expands on this. This is supposed to enhance information flow throughout the network and boost some task performance. The "bottleneck" architecture in ResNet V2 decreases the number of parameters in the network while still enabling the training of extremely deep networks. This update is in addition to the others.

In several image recognition tasks, including object recognition and detection, image segmentation, and others, ResNet V2 has been demonstrated to perform at the cutting edge.

6. Result

We compare our results to those of other authors who utilized the same dataset as we did. Table 1 provides the comparison. Kermany et al compared pneumonia to normal in their study [12].

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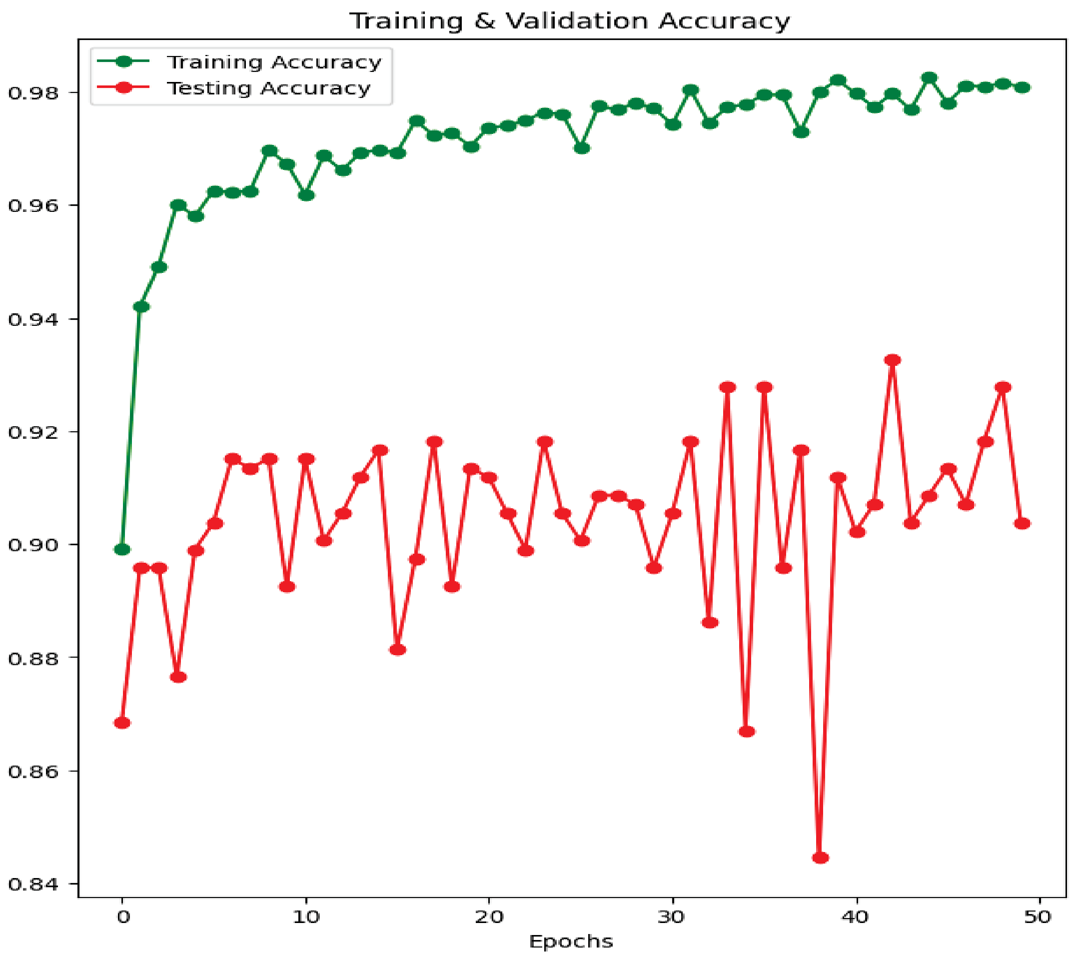
Table 1:

Paper Name	Author	Model Name	Accuracy
Diagnosis of Pneumonia from Chest X-Ray Images using Deep Learning [5]	Enes AYAN et al.	Xception	82%
		VGG16	87%
Pneumonia Detection with Deep Convolutional Architecture [10]	Abdullah Faqih Al Mubarok et al.	Residual Network	85.60%
		Mask-RCNN	78.60%
Chest X-Ray Images Based Automated Detection of Pneumonia Using Transfer Learning and CNN [9]	Saurabh Thakur et al.	VGG16	90.54%
Feature Extraction and Classification of Chest X-Ray Images Using CNN to Detect Pneumonia [6]	Harsh Sharma et al.	CNN	90.68%
Medical X-RAY Image Classification Using CNN Based Model	**Prashant Patil et al.**	**ResNet V2**	**93.27%**

Our transferring learning strategy's main objective was to accurately identify pneumonia among typical chest X-ray pictures. To do this, we taught each model individually after preparing them all as shown above. All of the models in this study were trained using a Tesla K80 GPU, 12GB VRAM, and 13GB RAM, and trained on Google Colab. We employed the Adam algorithm [13] during training. ResNet V2 was trained for 50 iterations at a very low learning rate of 0. 001.Our ResNet V2 model outperforms every other model from prior works, finishing with test and train accuracy of 93.27% and 98.02%, respectively. AUC came in at 98.30%. As show in Figure 2.

Figure 2:



7. Conclusion

Our purpose in writing this paper is to suggest a deep learning-based method for using transfer learning to categories pneumonia from chest X-ray pictures. The pretrained ResNet18 architecture trained on the ImageNet dataset and the transfer learning technique were utilized in this system to retrieve features. These characteristics were fed into the classifiers of the appropriate models, and each architecture's output was gathered. We found that efficiency could be further enhanced in the future by growing the dataset, applying a data enrichment strategy, and using manually created features.

Our findings support the hypothesis that deep learning techniques might be used to improve disease management and expedite the diagnosis process. Deep learning techniques may be compared to a two-way proof system, whereby a single doctor normally validates a diagnosis of pneumonia, allowing opportunity for error. The decision support system in this case provides a diagnosis based on images from chest X-rays, which the visiting physician may then validate, considerably minimizing both machine and human error. Our findings indicate that deep learning techniques can aid in illness diagnosis more correctly than traditional methods, which may result in improved therapeutic results.

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