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Deep Learning-Based Automated Detection of Pneumonia from Chest X-Ray Using Convolutional Neural Network

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Abstract - *Pneumonia is considered a leading cause of childhood mortality worldwide, particularly in resource-limited settings where early diagnosis is challenging. Chest X-ray (CXR) imaging is the most widely used diagnostic tool, but its interpretation is highly prone to variability and error. To demonstrate this, we introduced a computer-aided diagnosis (CAD) system that leverages convolutional neural networks (CNNs) with batch normalization and transfer learning for automated pneumonia detection. Using the publicly available Kermany dataset, we pre-processed and resized CXR images, applied model checkpoints to minimize over fitting, and evaluated performance with a confusion matrix. Our proposed methodology achieved an accuracy of 85%, exhibiting that deep learning can provide reliable, scalable support for radiologists in distinguishing pneumonic from healthy lungs with early response. This work underscores the potential of CNN-based CAD systems to improve diagnostic consistency and accessibility in clinical practice.*

Key Words: Convolutional Neural Network, confusion matrix, keras, recall, hyper parameters, Pneumonia detection.

1. INTRODUCTION

Pneumonia is a serious infectious disease of the respiratory system that arises from bacterial, viral, or fungal pathogens. The infection primarily affects the lungs by inducing inflammation in the alveoli and may lead to the accumulation of fluid, a condition commonly referred to as pleural effusion. Globally, pneumonia remains one of the leading causes of mortality among children below five years of age, contributing to more than fifteen percent of deaths in this age group [1]. The burden of the disease is particularly severe in low- and middle-income countries, where factors such as dense population, environmental pollution, poor hygiene, and limited access to healthcare facilities significantly increase vulnerability. Consequently, timely identification and appropriate treatment are essential to reduce the risk of fatal outcomes.

Medical imaging techniques, including computed tomography (CT), magnetic resonance imaging (MRI), and chest radiography, are routinely employed to assist in the diagnosis of pneumonia. Among these modalities, chest X-ray imaging is widely preferred due to its non-invasive nature, affordability, and accessibility. Figure 1 illustrates representative chest X-ray images of healthy and pneumonic lungs. Infected lungs typically exhibit abnormal opacities, known as infiltrates, which appear as white regions and serve as key indicators of pneumonia. Despite their clinical usefulness, chest X-ray interpretations are often influenced by the experience and subjective judgment of radiologists, which can lead to diagnostic inconsistencies [2]. This limitation highlights the need for reliable automated approaches to support pneumonia detection.

To address this challenge, the present study proposes a computer-aided diagnosis (CAD) framework based on an ensemble of deep transfer learning models for accurate classification of chest X-ray images. Such systems have the potential to assist clinicians by providing consistent and objective diagnostic support.

Deep learning has emerged as a powerful branch of artificial intelligence, demonstrating remarkable performance in a wide range of computer vision applications [3]. In particular, convolutional neural networks (CNNs) have achieved significant success in image classification tasks across multiple domains [4]. However, the effectiveness of CNN-based models is highly dependent on the availability of large, well-annotated datasets. In the biomedical domain, obtaining extensive labeled image collections is challenging, as expert annotation by medical professionals is both costly and time-consuming. Transfer learning offers a practical solution to this limitation by enabling the reuse of knowledge from models trained on large-scale datasets. In this approach, pre-trained CNNs, commonly trained on datasets such as Image Net, which contains millions of natural images, are adapted to medical imaging tasks, thereby improving performance even when only limited training data are available.

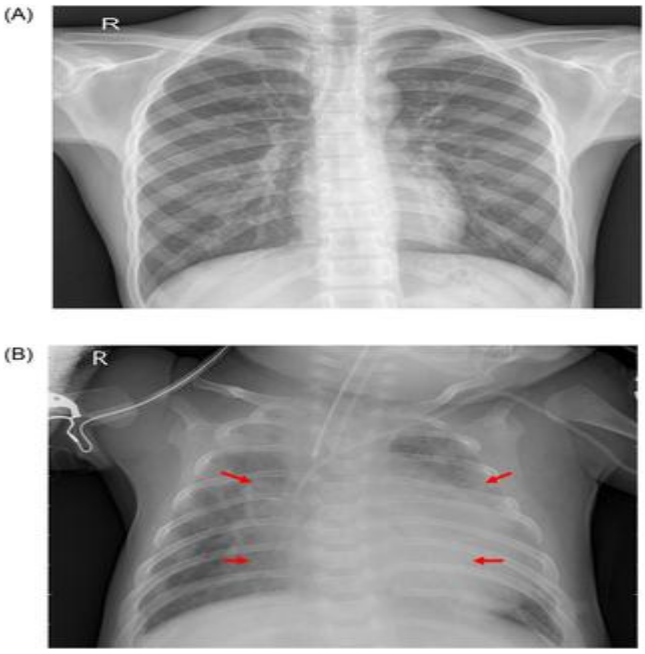

Figure 1: Examples of two X-ray plates that display (a) a healthy lung and (b) a pneumonic lung. The red arrows in (b) indicate white infiltrates, a distinguishing feature of pneumonia. The images were taken from the Kermany dataset

2. RELATED WORKS

Automatic detection of pneumonia from chest X-ray images has remained a challenging research problem for an extended period, largely due to the limited availability of large, publicly accessible medical imaging datasets. Early studies primarily relied on conventional machine learning techniques, where domain-specific features were manually designed and subsequently used for classification. For example, Chandra et al. performed lung region segmentation on chest radiographs and extracted a set of statistical features to characterize the images. These features were evaluated using multiple classical classifiers, including multilayer perceptron (MLP), random forest, sequential minimal optimization, classification via regression, and logistic regression. Their experiments, conducted on a dataset of 412 images, demonstrated that the MLP classifier achieved the highest classification accuracy of 95.39%.

Similarly, Kuo et al. investigated pneumonia detection in a cohort of 185 patients by extracting eleven handcrafted features from medical images and applying a wide range of regression and classification algorithms, such as decision trees, support vector machines, and logistic regression. Among the tested models, the decision tree classifier delivered the best performance, achieving an accuracy of 94.5%, while the remaining models showed comparatively weaker results. In another study, Yue et al. utilized six manually engineered features to identify pneumonia from chest CT images collected from 52 patients and reported a maximum area under the curve (AUC) value of 97%. Although these approaches yielded promising outcomes, their applicability is limited due to small dataset sizes and the reliance on handcrafted features, which restrict generalization to unseen data.

Unlike traditional machine learning pipelines that require explicit feature extraction and selection, deep learning-based approaches enable end-to-end learning, where discriminative features are automatically learned directly from raw input images. Convolutional neural networks (CNNs), in particular, have become the dominant choice for image-based medical diagnosis because of their ability to capture spatially invariant patterns through convolutional operations. Owing to these characteristics, CNN-based models have consistently demonstrated superior performance over conventional image processing and machine learning techniques in various image classification tasks.

Several studies have explored CNN architectures for pneumonia classification using chest X-ray images. Sharma et al. and Stephen et al. developed relatively shallow CNN models and employed data augmentation strategies to mitigate the challenge of limited training data. Using the dataset released by Kermany et al., both studies reported encouraging results, with classification accuracies of 90.68% and 93.73%, respectively [5]. However, while data augmentation increases the apparent size of training datasets, it introduces limited new semantic information, which may constrain further improvements in model

performance. Rajpurkar et al. applied a Dense Net-121 architecture for pneumonia detection and achieved an F1-score of 76.8% [6]. The authors attributed this modest performance, in part, to the absence of complementary clinical information, such as patient history, which also affected the diagnostic accuracy of human radiologists in their comparative analysis.

To improve model robustness and generalization, Janizek et al. proposed an adversarial optimization-based framework designed to reduce dependency on dataset-specific characteristics. Their approach achieved AUC scores of 74.7% in the source domain and 73.9% in the target domain, indicating improved cross-domain consistency [7]. Zhang et al. introduced a confidence-aware mechanism for lung X-ray anomaly detection by formulating the task as a one-class classification problem focused solely on identifying abnormal samples. Their method achieved an AUC score of 83.61%. In contrast, Tuncer et al. adopted a hybrid machine learning approach in which fuzzy tree transformation and exemplar-based partitioning were first applied to the images, followed by feature extraction using multi-kernel local binary patterns. The extracted features were then classified using conventional classifiers. Their method, evaluated on a small dataset containing COVID-19 and pneumonia cases, achieved an accuracy of 97.01% [8].

3. METHODOLOGY

The methodology and approach we've used has been describes step by step ahead. The task has been performed as per the following step. We have pre-processed the data and all the X-ray images were cropped to the ideal dimensions for computational needs. Next, we uploaded the data in the memory. Then we created a callbacks function and model checkpoint. Next, we reshaped the data and created the model through CNN. And last we did model fitting and found the accuracy and value loss using confusion matrix.

Pre-processing: In this we have resized the images for performing efficient operation on them. The images are originally 1000 pixels per dimension and they were resized to a compatible size for better computation. We also created a function in which pneumonia file in training dataset is given label = 0 and normal label = 1, else = 2. Two arrays, 'X' and 'Y' are created where 'X' stores pre-processed (resized image) data and 'Y' stores the label which is again stored back in the file we use the function 'resize' , and uploading the images in new h5py file whose main function is to store the data in binary format, means images of chest X-ray are converted to array of numbers as in figure 8. Uploading data in memory: Now, as the data has been pre-processed, we considered uploading it in the memory. We create a function to do so, it loads the training dataset and also the test dataset along with their labels. Afterwards, the shape of test and train datasets is obtained and the X-rays are displayed of both, with pneumonia and without pneumonia using "mat plot lib.

Callbacks and model checkpoint: We have imported "Model Checkpoint" from the "callbacks" library of "keras". We have done so as to reduce learning rate timely after monitoring a quantity. Model Checkpoint call back is utilized in addition with the training using model. Fit () function to save some the model or weights (in checkpoint file) at some interval, model/weights are hence loaded afterwards to continue with the previously saved model making checkpoints which helps in timely check and save the best model performance till last and also avoid further validation accuracy drop due to over fitting.Reshaping and model creation: Now we had imported various models from "keras library" for creating our model according to the dataset. We reshaped the "X_train" and "X_test" with ".reshape(5216,3,150,150)" and ".reshape(624,3,150,150)" respectively.
Model fitting and finding the accuracy: Next and final step in the completion of the project is fitting the training data set in the model using .fit() function in which the arguments are X_train and y_train and callback function to reduce the learning rate and the value of epochs (in our project the value epochs is set to be 10).

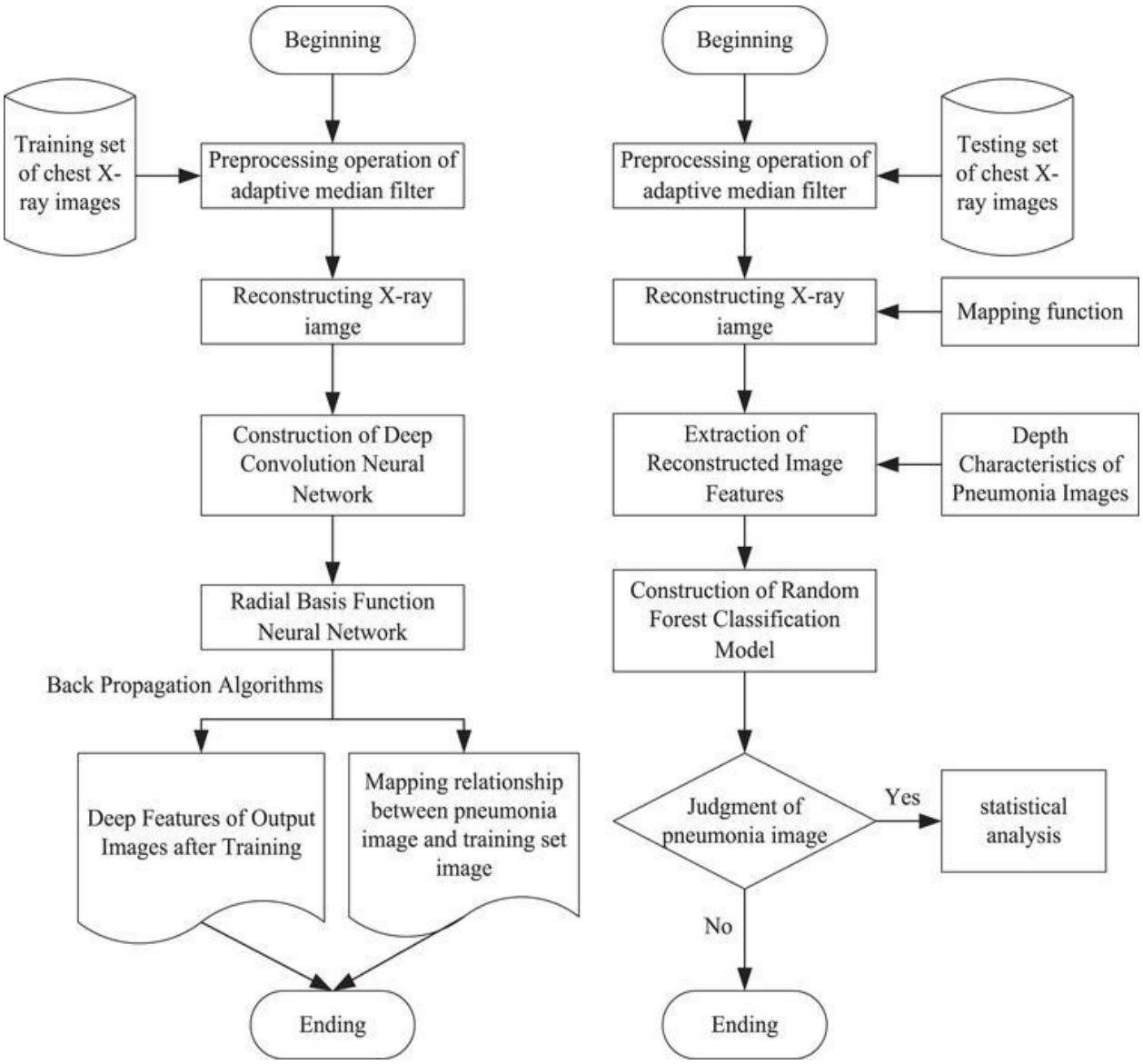

Figure 2: Flowchart of CNN model for pneumonia detection

4. RESULTS & DISCUSSION

The quality and adequacy of the dataset play a decisive role in determining the effectiveness of any machine learning project. A well-curated and sufficiently large dataset is essential for developing a reliable image classification model. In this work, the training process was carried out using the Create ML framework, which provides a streamlined and user-friendly environment by abstracting many of the underlying technical complexities. Unlike conventional development tools that require extensive expertise, Create ML enables model training through an intuitive interface while still allowing users to adjust key parameters. Furthermore, the framework supports multiple training runs under different configurations and automatically generates performance visualizations, which facilitate informed decision-making during model optimization, as illustrated in Figure 3. Image classification models consist of multiple interconnected layers, each designed to perform a specific operation and pass its output to subsequent layers for progressive refinement of the learned representation. Initial layers process the raw pixel intensities and extract low-level visual patterns, while deeper layers gradually capture more abstract and discriminative features. Through this

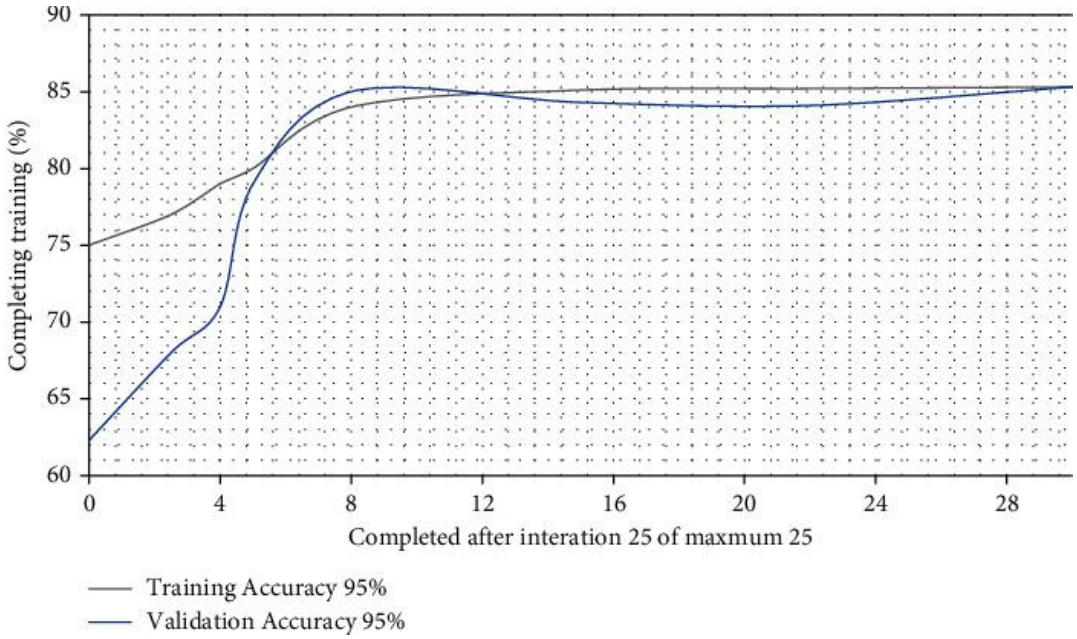

Figure 3: Training Vs Validation Loss

hierarchical feature learning process, the model becomes capable of different tilting between normal and pneumonia-affected chest X-ray images. Various architectural designs exist to define how these layers are structured and how information flows among them, with the choice of architecture depending on the nature of the classification task. In the Create ML framework, these internal operations are handled automatically, allowing model training without requiring explicit intervention in the underlying layer organization.

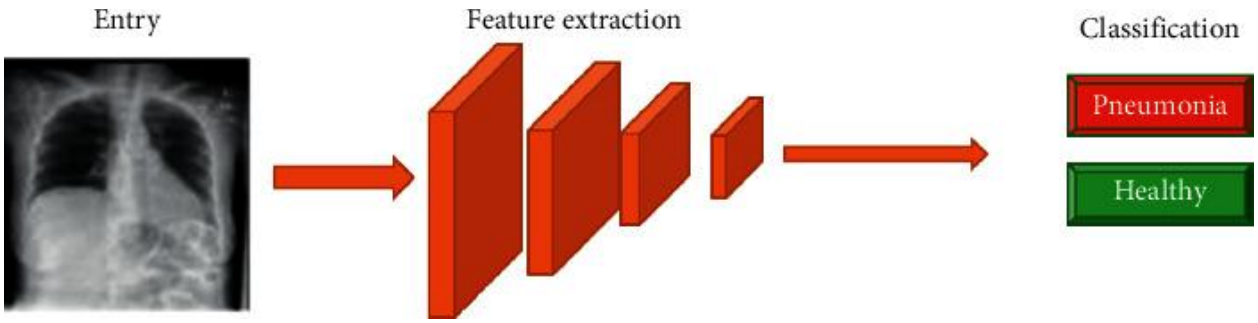

Figure 4: Feature Extraction

After carrying out several training processes with different configurations and variations in the parameters, it was possible to obtain a model with an accuracy of ~85% integrated into an iPhone application that is very easy to use and distribute. Since the model was trained with a set of data closed to two categories, NORMAL (Healthy) and PNEUMONIA, any image passed as input to the model will be categorized into one of these two groups since, during the training process.

5. CONCLUSIONS

This study presented a deep learning–based computer-aided diagnosis system for the automated detection of pneumonia from chest X-ray images. By leveraging convolutional neural networks and transfer learning, the proposed approach demonstrated effective feature extraction and reliable classification performance on the publicly available Kermany dataset. The experimental results achieved an accuracy of approximately 85%, indicating the potential of CNN-based models to assist radiologists in distinguishing between normal and pneumonia-affected lungs. The simplicity and scalability of the proposed framework suggest its suitability for deployment in resource-constrained clinical environments. Future work may focus on incorporating larger and more diverse datasets, integrating clinical metadata, and further optimizing model architecture to enhance robustness and diagnostic accuracy.

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