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A Block Chain Based Health Care system for Pneumonia Disease Prediction

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Abstract
A Block chain network is used in the healthcare system to preserve and exchange patient data through hospitals, diagnostic laboratories, pharmacy firms, and physicians. Block chain applications can accurately identify severe mistakes and even dangerous ones in the medical field.This paper proposes efficient algorithm are used to detect the pneumonia in early stage. In this study, we successfully classified Block chain-based secure healthcare services for disease prediction in fog computing.Pneumonia is an infection that inflames the air sacs in one or both lungs. The air sacs may fill with fluid or pus, causing cough with phlegm or pus, fever, chills, and difficulty breathing. A variety of organisms, including bacteria, viruses and fungi, can cause pneumonia. Early detection of pneumonia is very important to avoid death rate. so many machine learning chest infection in chest X-ray images using deep leaning based on CNN with an overall accuracy of 99%.

keywords: Block Chain; Disease prediction; CNN; Pneumonia; Accuracy

1. Introduction

Pneumonia is one of the serious diseases which cause most of the deaths in adults globally. According to Health Metrics and Evaluation (IHME), the highest pneumonia mortality rates in 2017 were among people aged 70 and older. More than 1.13 million pneumonia-related deaths are reported every year were in this age group [1]. Pneumonia is a disease of infectious origin that causes inflammation in the air sacs or alveoli of one or both lungs [2]. The air sacs get filled with fluid which can cause difficulty in breathing and an over-generation of mucus and sputum. Pneumonia is most commonly caused by viruses or bacteria and, less commonly, other microorganisms [3].

Pneumonia is the single largest infectious cause of death in children worldwide. Pneumonia killed 808 694 children under the age of 5 in 2017, accounting for 15% of all deaths of children under five years old. Pneumonia affects children and families everywhere but is most prevalent in South Asia and sub-Saharan Africa.

it is a very common disease all across the globe. Due to poverty, people refrain from having access to trained radiologists. As far as diseases like pneumonia are concerned, the level of accuracy in the diagnosis should be good enough to assure proper treatment of this fatal disease [4]. Hence, to reduce the mortality of pneumonia, there is a need for research in the field of computer-aided diagnosis. There are many tests for pneumonia diagnosis, such as the chest ultrasound, chest MRI, chest X-ray, computed tomography of the lungs and needle biopsy of the lung [5]. X-rays are the most widely available diagnostics imaging technique [6].

The rest of the paper is structured as follows: Section 2 contains the discussion of the related works. Methods used in this paper are discussed in Section 3, while the dataset used has been introduced in Section 3. The proposed methodology and the results are discussed in Sections 4 and 5, respectively. Finally, Section 6 has the conclusion of the paper.

2. Related Work

Chuan Li et al introduced a frame work for detecting pneumonia on chest X-Ray by suppressing the non-pneumonia area and reducing noise to detect pneumonia. For this datasets were obtained from 8,964

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pneumonia labelled chest X-Ray images and the remaining 20,025 non-pneumonia chest X-Ray images. The study results the end to end identification model can undoubtedly be deceived to predict all the more bogus positive examples because of the variety and complexity of CXR pictures [7].

In paper [8] Here, It establish a diagnostic tool based on a deep-learning framework for the screening of patients with common treatable blinding retinal diseases. The performance of model depends highly on the weights of the pre-trained model. Therefore, the performance of this model would likely be enhanced when tested on a larger Image Net dataset with more advanced deep-learning techniques and architecture.

In paper [9], The proposed paper presents a deep neural network based on convolution neural networks and residual network along with techniques of identifying optimum differential rates using cosine annealing and stochastic gradient with restarts to achieve an efficient and highly accurate network which will help detect and predict the presence of pneumonia using chest x-rays.

In Paper [10], Here, it establishes a diagnostic system based on a deep-learning framework for detecting whether the patient has pneumonia or not. Only classification algorithm is used the Neural Network and there is no comparison between the accuracies of several algorithm. Automated detection of diseases from chest X-rays at the level of expert radiologists would not only have tremendous benefiting clinical settings, it would also be invaluable in delivery of health care to populations with inadequate access to diagnostic imaging specialists.

In [11], a modified CNN is presented, configured to localize the ROI based on a gradient for the detection and spatial localization of pneumonia. In addition, the authors of this work have released an extensive collection of datasets of frontal X-rays with a size of 112,120 images. At the time of writing, the authors achieved an accuracy of detecting pneumonia in 63.3%. In the gradient imaging method combined with heat maps was applied to the ROI's localization to identify pneumonia. The authors used a 121-layer tightly coupled neural network to assess the likelihood of disease and achieved an AUC of 76.8%. In another paper [12], the authors focused on visualizing the process of detecting pneumonia, using Class Activation Maps (CAMs) to interpret the results of an automated diagnostic system. As a result of VGG19 [13] modification, they achieved 93.6% of classification accuracy, and their imaging approach revealed what features CNN considers the most significant for the clinical decision. Another approach to visualizing and interpreting deep learning is fully-connected CNN, specifically, the U-Net architecture. For example, the study [14] proposes a modified U-Net architecture with convolution kernels of 3 × 3 × 3 to segmentation abdominal organs in volumetric images of computed tomography.

In order to make a summary about the task of pneumonia classification, Baltruschat et al. [15] compared the classification accuracy of currently widespread CNN models in pneumonia X-ray images by using the same hyper-parameter settings and same image pre-processing procedures. The method by Nahid et al. [16] proposed a novel CNN architecture which composed of two channels. The first channel processed the images, whose contrast was enhanced by the CLAHE method, while the second channel processed the images whose edges were enhanced by the Canny method. Then, these images were entered into a multichannel CNN model to detect if patients suffered from pneumonia. Researchers [17] developed a weak supervision approach to release a diagnosis burden of radiologists. They evaluated the model performance in a dataset of 30,000 chest X-ray images which were collected by the Radiological Society of North America (RSNA). In addition, they compared the region of interest (ROI) predicted by their proposed architecture and the ROI ground truth bounding boxes provided by RSNA. Finally, they proposed several model architectures, Xception, ResNet-50, Inception and Ensemble (which meant that they used a weighted mean of three models above). Their single best model was Inception net, which obtained an accuracy of 0.782 and F1 score of 0.6411 on the binary classification in detecting pneumonia

3. Proposed System

There are two main parts to a CNN architecture shown in Figure 2, convolution tool that separates and identifies the various features of the image for analysis in a process called as Feature Extraction .A fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages. There are three types of layers that make up the CNN which are the convolution layers, pooling layers, and fully-connected (FC) layers. When these layers are stacked, a CNN architecture will be formed. In addition to these three layers, there are two more important parameters which are the dropout layer and the activation function which are defined below.

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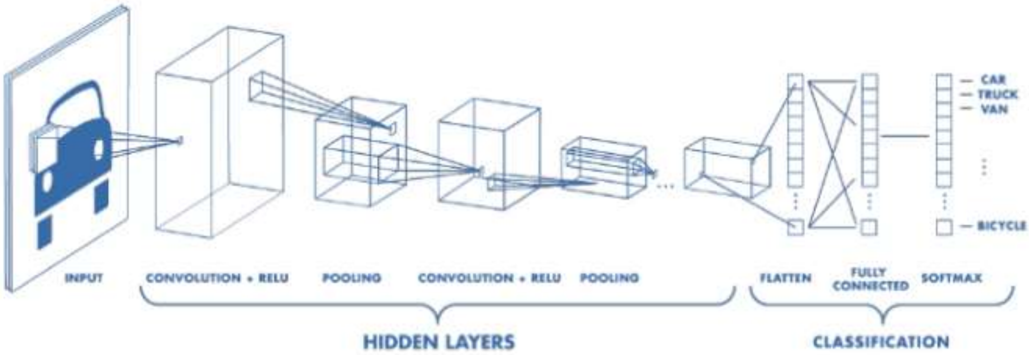

Figure 2: CNN Model

The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself. CNN is also computationally efficient.

4. Experimental and Analysis

4.1 Dataset Description

Pneumonia diseases have been verified for our experimental assessment, including the diagnosis of pneumonia from chest X-ray images. for instance, displays chest X-ray images from the selected data set. This data set is split into two sets: normal and pneumonia. The data set was provided by Kermany and Goldbaum and based on a chest X-ray scan images from pediatric patients from one to five years of age at the Guangzhou Women and Children's Medical Center. In the chest X-ray images (Pneumonia) data set, which is publicly available at https://www.kaggle.com/paultimothymooney/ chest-xray-pneumonia (accessed on 4 January 2022), there are in total 5856 normal and pneumonia chest X-ray images. To provide a fair comparison between our proposed method and the different methods, the training set, the validation set, and the test set were previously divided. The chest X-ray database was divided into two classes (normal and pneumonia). This data set contains two subsets for each class. The training subset consists of 1341 normal patients and 3875 pneumonia patients. Moreover, it contains 234 patients as normal and 390 pneumonia patients for the test subset. These data also consist of 16 validation data images, including eight pneumonia patients and eight normal patients.

Figure 3: Normal Cases

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Figure 4: Pneumonia Cases

4.1 Experimental Evaluation Metrics

Accuracy: Accuracy is defined as the percentage of correct predictions out of all the observations

$$Accuracy = \frac{Correct\ prediction}{Total\ cases} * 100\%$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100\%$$

Precision: Precision is defined as the percentage of true positive cases versus all the cases where the prediction is true.

$$Precision = \frac{True\ Positive}{All\ Predicted\ Positives} * 100\%$$

$$Precision = \frac{TP}{TP + FP} * 100\%$$

Recall: It is defined as the fraction of positive cases that are correctly identified

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$Recall = \frac{TP}{TP + FN}$$

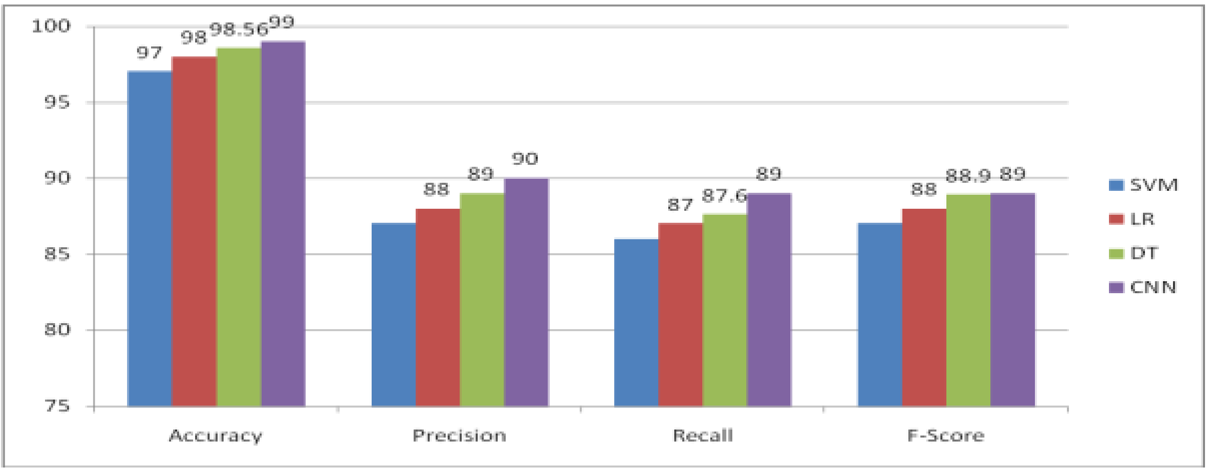
F1 Score: F1 score is defined as the measure of balance between precision and recall.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The proposed CNN model can be compared with other machine learning algorithm such as SVM , LR, and DT. CNN model achieves 99% accuracy, 90 % Precision, 89 % Recall and 89 % F score. The comparison of accuracy of disease prediction is shown in Table1.

Table 1: Comparison of Accuracy of disease prediction

ML Algorithm	Accuracy	Precision	Recall	F-Score
SVM	97	87	86	87
LR	98	88	87	88
DT	98.56	89	87.6	88.9
CNN	99	90	89	89



Comparison of Accuracy of Disease Prediction

Conclusion:

Early detection of pneumonia is crucial for determining the appropriate treatment of the disease and preventing it from threatening the patient's life. Chest radiographs are the most widely used tool for diagnosing pneumonia; however, they are subject to inter-class variability and the diagnosis depends on the clinicians' expertise in detecting early pneumonia traces. To assist medical practitioners, an automated CAD system was developed in this study, which uses deep transfer learning-based classification to classify chest X-ray images into two classes "Pneumonia" and "Normal." The weights assigned to the classifiers were calculated using a novel strategy wherein four evaluation metrics, precision, recall, f1-score, and AUC, were fused using the hyperbolic tangent function. The framework, evaluated on two publicly available pneumonia chest X-ray datasets obtained an accuracy rate of 99%, Furthermore, the proposed CNN model is domain-independent and thus can be applied to a large variety of computer vision tasks.

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