IoT Enable Machine Learning Driven Pneumonia Screening and Referral System for Developing Countries

Sayed Mehedi Azim
011 162 097
United International University

Anika Tabassum
011 161 150
United International University

November 25, 2021

Abstract

Pneumonia is the major cause of death among children under 5 years mostly in developing countries. Around 15% of all deaths of children is caused by pneumonia. The numeric difference between the diagnosed patients and death rates show how significant the early diagnosis of pneumonia is. In Bangladesh, pneumonia is responsible for around 28% of the deaths of children under 5 years of age. Pneumonia is treatable but most of the time late detection increases the death toll. Doctors perform different detection methods like blood tests, chest x-ray to identify pneumonia. Most of the time doctors face difficulty in identifying pneumonia from x-ray images as images are not always clear to identify this disease. Therefore, it is necessary to find a way that can screen pneumonia at early stage. In this project, we aim to build a effective model using machine learning approach that can be easily use for pneumonia screening and as a referral system

Keywords Pneumonia · early screening · x-ray image · Convolutional Neural Network (CNN) · referral system

1 Introduction

Pneumonia is an acute respiration inflammation in lungs. Pneumonia is caused by different types of viruses, bacteria and fungi. There are different levels of pneumonia. Screening in lower level decrease complexity of this disease. Children and elderly people suffer the most because of pneumonia. Pneumonia is fully treatable if it can be identified in early stage. Most of the time late detection makes the situation really worst. Late detection or misdiagnosis increase the mortality rate significantly. According to a recent report of WHO [1], only in 2017 a number of 808 694 children under the age of 5 died of pneumonia. The death troll is really high even in developed countries. In developing countries, the situation is more critical.

Both children and elder are suffering terribly because of wrong detection and not having specialist radiologist to identify properly from x-ray. In many places, specialist are not found properly.

Sometimes specialist even get confused with other lung diseases. The whole process is time consuming. Within this time patient's condition can be worsen. Accurate detection of pneumonia can decrease the rate of death and other physical harm. Machine learning approaches are promising field in Artificial Intelligent. Machine learning approaches are quite effective in image classification. Use of machine learning for object detection, image classification are good opportunity in medical field for improving healthcare sector.
The objective of our project is to design a model that can identify pneumonia in absence of specialist and can give correct result getting confused with other lung diseases. We aim to build a model which can screen pneumonia at early stage with limited resources. Our goal is to make the screening procedure more affordable and sustainable. Another objective is to design a referral system to the specialist when needed.

2 Literature Review

Recent developments in deep learning field, especially convolutional neural networks (CNNs) showed great success in image classification [6]. The main idea behind the CNNs is creating an artificial model like a human brain visual cortex.

Rajpurkar et al. [4] developed a deep convolutional neural network (CNN) which is 121-layer dense. Authors [4] applied the model on publicly available ChestX-ray14 dataset. This dataset has 112,120 frontal-view chest X-ray images. Images are labeled individually with 14 different diseases. Dataset was randomly divided into training, testing and validation. Rajpurakar et al. [4] did a comparison among experienced radiologists results and ChexNet result and found that ChexNet performance is significantly higher than the radiologist. Some limitations are found here. Thr ChexNet dataset only have the frontal view image where both frontal and lateral chest view images are needed for proper detection.

In [3], authors solve the problem of dataset. CheXpert [3] dataset contains both frontal and lateral view cheast X-ray images. The dataset [3] has 224,316 chest radiographs of 65,240 patients. CheXpert [3] can predict the probability of different 14 diseases.

While the mentioned conventional and radiological methods might be effective, our study presents a deep learning approach to this pneumonia classification. Looking at the state of art, there has been two previous similar experimentations on this task. The initial one [8] uses Long Short Term Memory (LSTM) architectures for finding interdependencies among the X-ray data. While their study focuses on 14 interdependent diseases, our study focuses merely on Pneumonia. However, due to their experimentation for extracting 14 different diseases with one model, they have merely been able to reach an accuracy of 71.3%. Furthermore, LSTM uses multiple images for classifying a single image, whereas our proposed exper- imentation and model only need pre trained neural network weights for classifying images one by one. Additionally, our accuracy upon experimentation yielded 78.73%, which uses the same dataset.

Roth et al. [10] demonstrated the power of deep convolutional neural network (CNN) to detect the lymph node in clinical diagnostic task and obtained drastic results even in the presence of low contrast surrounding structures obtained from computer tomography. In another study, Shin et al. [11] addressed the problems of thoraco-abdominal lymph detection and interstitial lung disease classification using deep CNN. They developed different CNN architectures and obtained promising results with 85 percent sensitivity at three false positives per patient. Ronneburger et al. [12]

developed a CNN approach with the use of data augmentation. They suggested that even trained on small samples of image data obtained from transmitted light microscopy; the developed model was able to capture high accuracy.

All these studies have performed well on radiological data except that the size of the data was restricted to few hundred samples of patients. Therefore, a detailed study is required to use the power of deep learning over thousand samples of patients to achieve the accurate and reliable predictions. Kallianos et al. [9] presented a state of art review stating the importance of artificial intelligence in chest X-ray image classification and analysis.

Other than the above mentioned papers on pneumonia classification, Chest X-ray images have been widely subjected to experimentation with convolutional neural network architectures, as well as other image classification techniques. Bone structures were segmented within a paper [7]. This paper presents a segmentation method which utilizes additional steps after the classification algorithm. As a regular Convolutional neural network classifies the image as a whole, such segmentation methods utilize pixel wise classification, which, in the end, applies a deconvolutional layer for classifying each pixel one by one and eventually separating different objects within an image, bones being the most prevalent ones for the mentioned task.

In [5], authors aim to conduct early detection not for pneumonia but for thorax disease through weekly classifications with convolutional neural networks. This paper successfully detects patterns for patients who have thorax disease or one that might have the mentioned disease. Yet, has no activity on pneumonia classification.

3 Dataset

There are some publicly available dataset of chest X-ray. ChestX-ray14 [5] dataset is a large dataset containing over 100,000 frontal view images with 14 diseases. CheXpert [3] is another large dataset which contains over 200,000 chest radiograph. Dataset contains both frontal and lateral radiographs. We do not have enough resources to use these large datasets. Therefore, We choose a approximately small dataset to apply our model.

We used a publicly available dataset from kaggle. The dataset contains 5,863 X-Ray images which are in jpeg form. The dataset is in 3 folders which contains training, testing and validation set separated. Each folder has two categories of images which are pneumonia and normal. These x-ray images are collected from Guangzhou Women and Children's Medical Center, Guangzhou. Images are of children's aged one to five.

4 Methodology

We have applied convolutional neural network (CNN) on chest x-ray dataset. Dataset has different folders of training, testing and validation. Building of the model can be described in the following 5 steps.

1. We have used five convolutional blocks comprised of convolutional layer, max-pooling and batch-normalization.
2. On top of it we used a flatten layer and followed it by four fully connected layers.
3. Also in between we have used dropouts to reduce over-fitting.

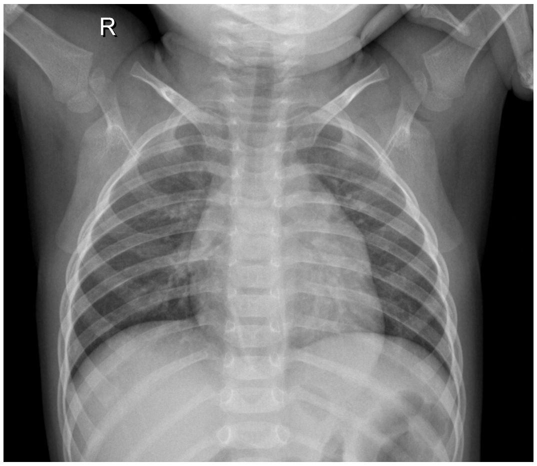

Figure 1: X-ray image from dataset

4. Activation function was Relu throughout except for the last layer where it was Sigmoid as this is a binary classification problem.
5. We have used Adam as the optimizer and cross-entropy as the loss.

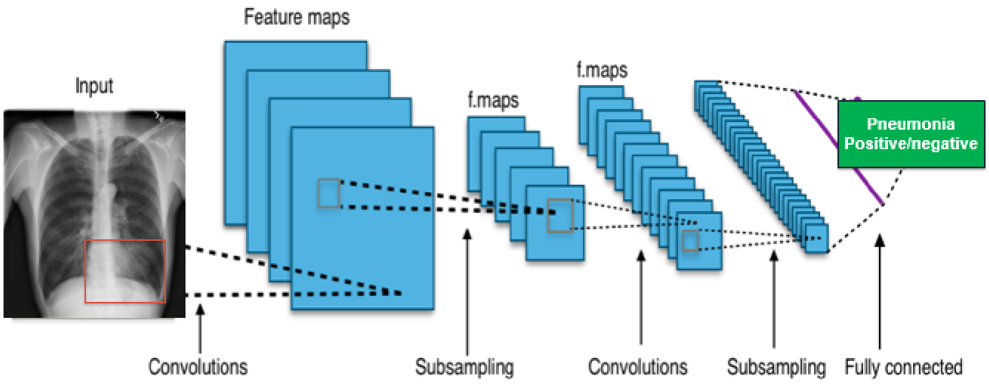

Figure 2: Pneumonia detection from chest x-ray

5 Result and discussion

The model is able to achieve an accuracy of 94% which is quite good considering the size of data that is used. We applied different model and found that CNN gives comparatively betterresults than other models.

```
Epoch 6/10
163/163 [==============================] - 81s 495ms/step - loss: 0.1639 - acc: 0.9423 - val_los
Epoch 7/10
163/163 [==============================] - 80s 492ms/step - loss: 0.1625 - acc: 0.9387 - val_los

Epoch 00007: ReduceLROnPlateau reducing learning rate to 2.700000040931627e-05.
Epoch 8/10
163/163 [==============================] - 80s 490ms/step - loss: 0.1587 - acc: 0.9423 - val_los
Epoch 9/10
163/163 [==============================] - 81s 496ms/step - loss: 0.1575 - acc: 0.9419 - val_los
```

Figure 3: Result

6 Limitations

There remains some limitations in pneumonia detection from chest X-ray. First, X-ray is not available in all areas especially in remote areas of developing countries. Therefore, it is not possible to perform an X-ray easily to identify pneumonia in needed situations. this method is not feasible for developing countries. Second, detection from chest radiographs is time consuming. Third, this detection method does not require any medical history of a patient.

7 Proposed Future Work

X-ray requires a number of setup and instruments, specialist radiologist and a huge amount of money. For developing countries like Bangladesh it is not possible to build a x-ray setup in all remote areas. This process is also time consuming. We are planning to make the screening method more flexible and affordable. We are proposing a screening model that will measure a patients temperature, heart rate and respiratory rate. A smartphone will be used to process the data collected from a patient. Within a few seconds anyone without any medical background can detect pneumonia through a smartphone. When a potential pneumonia patient use this device, he will know whether he has pneumonia or not. This process of detecting pneumonia will be very useful for the people living in remote areas. The proposed system is equipped with three simple component digital thermometer, oximeter and respiratory belt for skin temperature (T) heart rate (HR) and respiration rate (RR) observation.Physical signals from the sensors are processed and numerical vital signs are calculated by software that was developed. The whole process takes 10 seconds and can be performed by any person without medical background.

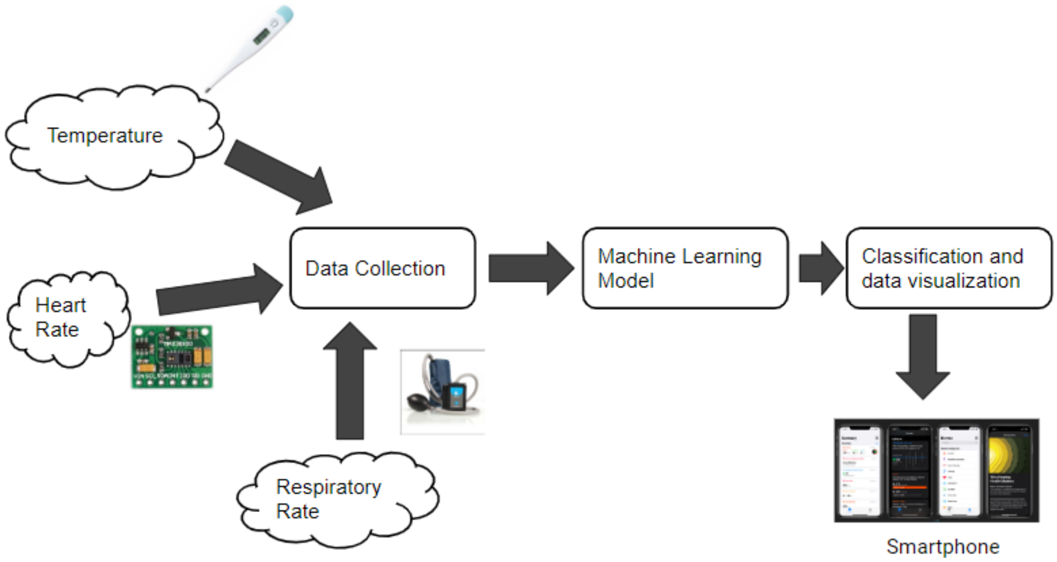

Figure 4: Proposed detection method using temperature, heart rate and respiratory rate

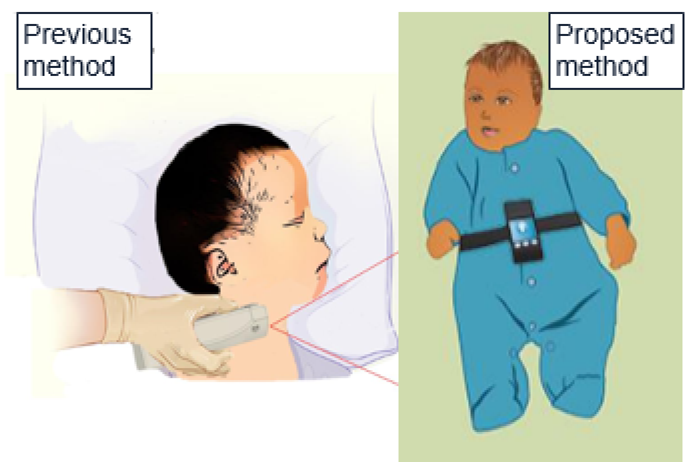

Figure 5: Screening procedure

8 Conclusion

Pneumonia is a major cause of mortality in children under 5 years mostly in developing countries. Lack of diagnostics equipment and human resources leads to delayed treatment and morbidity. In Bangladesh pneumonia is responsible for around 28% of the deaths of children under 5 years of age and around 3 million paediatric deaths are caused by pneumonia each year in developing countries all over the world. If identified in early stage pneumonia is fully treatable. In this paper, we applied CNN on chest X-ray images. Though the model gives a good accuracy, this screening method is not a good solution for developing countries like Bangladesh. We have tried ChexNet method since X-ray is not available in remote area, it is not feasible for developing countries. So a more flexible and affordable method is required. Our proposed model will be able to screen pneumonia more reliably in remote area since it is more convenient, portable and cost effective. The cost-effectiveness of the system means that it is feasible for low-income countries. The system operation is also user-friendly, meaning medical skills and experience is not required. To help developing countries with the early detection of pneumonia in children, we developed a IoT driven machine learning algorithm-based pneumonia screening system using multiple vital signs. This system is equipped with three biosensors and can distinguish potential pneumonia patients within 10 seconds. An applications on users smartphone calculates physical signals and performs the computation. Overall, the system cost is favorable for low-income countries. However, hospitals in developed countries that are equipped with high- technology equipment for simple vital sign measurements and industrialized countries often lack human resources and devices. Therefore, our proposed system may facilitate hospitals in developing countries such as Bangladesh and help pediatricians and nurses with time-consuming, complicated physical examinations as it measures multiple vital signs simultaneously in a short time.

References

[1] Who.int. (2019). Pneumonia. https://www.who.int/news-room/fact-sheets/detail/pneumonia

[2] Kaggle.com (2019) https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[3] Wang, Xiaosong and Peng, Yifan and Lu, Le and Lu, Zhiyong and Bagheri, Mohammadhadi and Summers, Ronald M Chexpert: A large chest radiograph dataset with uncertainty labels and expert comparison In arXiv preprint arXiv:1901.07031, 2019

[4] Rajpurkar, Pranav and Irvin, Jeremy and Zhu, Kaylie and Yang, Brandon and Mehta, Hershel and Duan, Tony and Ding, Daisy and Bagul, Aarti and Langlotz, Curtis and Shpanskaya, Katie and others Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. In *arXiv preprint arXiv:1711.05225, 2017*

[5] Wang, Xiaosong and Peng, Yifan and Lu, Le and Lu, Zhiyong and Bagheri, Mohammadhadi and Summers, Ronald M Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases In *Proceedings of the IEEE conference on computer vision and pattern recognition, 2019*

[6] Krizhevsky, Alex and Sutskever, Ilya and Hinton, Geoffrey E Imagenet classification with deep convolutional neural networks In *Advances in neural information processing systems,pages 1097–1105, 2012*

[7] Akçay, Samet and Kundegorski, Mikolaj E and Devereux, Michael and Breckon, Toby P Transfer learning using convolutional neural networks for object classification within x-ray baggage security imagery In*2016 IEEE International Conference on Image Processing (ICIP), 2016*

[8] Yao, Li and Poblenz, Eric and Dagunts, Dmitry and Covington, Ben and Bernard, Devon and Lyman, Kevin Learning to diagnose from scratch by exploiting dependencies among labels In *arXiv preprint arXiv:1710.10501, 2017*

[9] Kallianos, K and Mongan, J and Antani, S and Henry, T and Taylor, A and Abuya, J and Kohli, M How far have we come? Artificial intelligence for chest radiograph interpretation In *Clinical radiology, Elsevier, 2019*

[10] Roth, Holger R and Lu, Le and Seff, Ari and Cherry, Kevin M and Hoffman, Joanne and Wang, Shijun and Liu, Jiamin and Turkbey, Evrim and Summers, Ronald M A new 2.5 D representation for lymph node detection using random sets of deep convolutional neural network observations In *International conference on medical image computing and computer-assisted intervention, Springer, 2014*

[11] Shin, Hoo-Chang and Roth, Holger R and Gao, Mingchen and Lu, Le and Xu, Ziyue and Nogues, Isabella and Yao, Jianhua and Mollura, Daniel and Summers, Ronald M Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning In *IEEE transactions on medical imaging*

[12] Ronneberger, Olaf and Fischer, Philipp and Brox, Thomas Convolutional networks for biomedical image segmentation In *International Conference on Medical image computing and computer-assisted intervention, 2015*