ISSN No:-2456-2165

A Novel Approach for Detection of Pneumonia on Edge Devices Using Chest X-rays

Tejasri Kurapati
Department of ECE
JNTUH
Hyderabad, India

Siri Valluri
Department of ECE
JNTUH
Hyderabad, India

Lalitha Mulakaluri
Department of CSE
JNTUH
Hyderabad, India

Sunanda Datla
Department of ECE
JNTUH
Hyderabad, India

Abstract:- Pneumonia is the single largest infectious disease claiming the lives of 2.5 million people, including 672,000 children in 2019 alone. The mortality rate can be significantly reduced if early detection followed by proper treatment is made available. Our project aims to make early detection of pneumonia possible in remote and rural places that lack proper access to skilled radiologists. The diagnosis of this disease is predominantly done by studying chest X-rays. We built an application that can detect pneumonia by scanning chest X-ray images on mobile phones. We developed a convolutional neural network to detect pneumonia in chest X-rays. We converted the neural network into a TensorFlow Lite model to integrate it into an edge device application to enable on-device inference. Through this application, we also propose to help governments identify areas with high infection rates by collecting location data points of users.

Keywords:- *Pneumonia; Convolutional Neural Network; Edge Devices; Chest X-Ray; TensorFlow Lite; Deep Learning Inference.*

I. INTRODUCTION

Pneumonia is an acute respiratory infection that is caused by bacteria, viruses, or fungi. Though it is easily curable, the inability to detect the infection at its initial stages and access to proper treatment can be life-threatening. In 2017, 2.56 million people died from pneumonia around the globe, a third of whom were children [1]. It was reported by UNICEF that pneumonia kills more children than any other infectious disease, taking the lives of over 800,000 children under the age of five every year [2]. Approximately half of these early childhood deaths from pneumonia are estimated to result from lack of or delay in appropriate diagnosis and treatment [3]. Therefore, there is a critical need for computer-aided diagnostic research and development to reduce mortality associated with pneumonia [4]. Chest X-rays are primarily used for the diagnosis of this disease [5]. However, the lack of qualified medical professionals to read and analyze the X-rays in remote and rural areas makes early detection of pneumonia difficult [6].

A significant amount of research has been done on building convolutional neural networks that can detect pneumonia [7] [8] [9] [10]. The very high computational power they demand renders them inefficient to be implemented on mobile phones. In our project, we built a TensorFlow Lite model for efficient on-device inference. We developed an end to end solution by converting our neural network to a TensorFlow Lite model and integrated it into an application that can detect pneumonia throughedge devices. Since the TensorFlow Lite model doesn't require an internet connection, this application can be used in remote areas where network connectivity is not strong. The paper also discusses the idea of collecting the user's location to help governments identify areas with high infection rates to take remedial measures. The measures can be toset up immunization camps and to send appropriate medicines to the areas affected.

According to Indian Cellular and Electronics Association, the number of smartphone users in rural India will rise from 500 million smartphone users in 2019 to 820 million smartphone users by 2022 [11] [12]. This implies that about ninety percent of rural India will own a smartphone by 2022. This makes the idea of using on-device detection of pneumonia in rural health care promising.

II. METHODOLOGY

A. Data

The data used for this project are Chest X-ray Images (Pneumonia) taken from Kaggle [13]. The Chest X-ray images (anterior-posterior) are of paediatric patients aged between 1 and 5 years old. The dataset is appropriately chosen as it is observed that the majority of the infected population are children aged below 5 years. It contains annotated images of two categories: Pneumonia and Normal. A total of 5,856 images are divided into training (5216 images), testing (624 images), and validation (16 images) data sets in .jpeg format. We augmented the entire dataset by rotating, zooming in, and changing the width and height shift ranges.

Fig. 1. Left image is an x-ray of a child with normal lungs. Right image is an x-ray of a child infected with pneumonia.

TABLE I. Details of operations performed on the dataset

Operation	Value
Rotation range	10
Zoom range	0.1
Width shift range	0.1
Height shift range	0.1

B. Data Preprocessing

To pre-process the data, we converted the RGB images to grayscale images and re-sized them to 196x196 2-D images. It was observed that a class-imbalance problem existed in the training dataset where there were more positive pneumonia cases than normal cases. To correct this problem we augmented the normal case images by resampling. The final size of the training dataset is 7557 after resampling [Fig. 2].

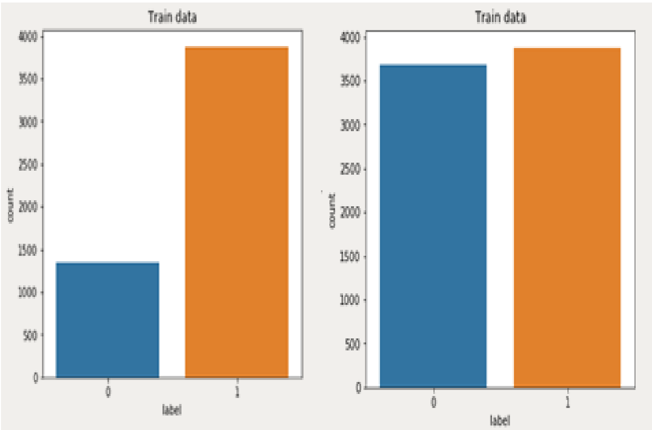

Fig. 2. Left image is the distribution of training data before resampling. Right image is the distribution of training data after resampling.

C. Convolutional Neural Network Model

Our model takes Chest X-ray images as input and outputs one of two results which are "Pneumonia" and "Normal", along with the confidence level of the output. The CNN model consists of five convolutional blocks, each block consisting of two convolutional layers followed by one max-pooling layer which extracts patches from input feature maps and outputs only the maximum value present in each patch while discarding the remaining values [14], effectively down-sampling the dimension of the feature maps. The five convolutional blocks are followed by a flatten layer which transforms an n-dimensional tensor into a 1-dimensional tensor [15]. The output of the flatten layer is connected to a dense layer in which every input is connected to every output [14]. The dense layer is followed by a dropout layer which aids in preventing overfitting. A dropout rate of 0.5 is chosen as it is optimal for a wide range of networks [16]. The model is concluded with a final dense layer with two output nodes, as there are two output classes.

In our model, the convolutional layers in the first and second blocks have 8 and 16 filters respectively. The ones in the third, fourth, and fifth blocks have 32, 64, and 128 filters respectively. This is because the responses from the filters in the first hidden layer measure certain attributes of the input. Hence the feature map from the first hidden layer is much richer than the input, representing higher-level abstract concepts. Therefore the second hidden layer which feeds from the first hidden layer needs to have an even larger number of filters to be able to properly measure the now richer projection of the input through hidden layer 1. Intuitively, the initial layers detect edges, the next layers combine them to detect shapes and the final layers merge this information to make inferences about the image.

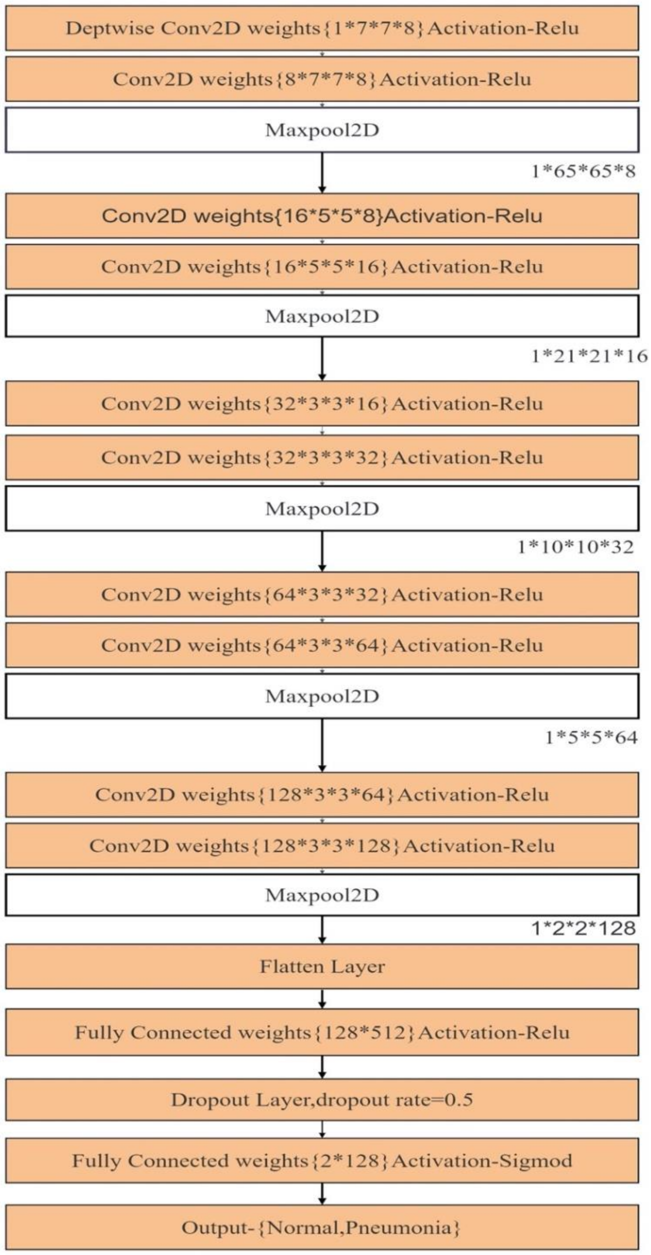

Fig. 3. Architecture of CNN consisting of five blocks. Each block consists of two convolutional layers and one max-pooling layer. The five blocks are followed by a flatten layer, a dense layer, a dropout layer and a final dense layer.

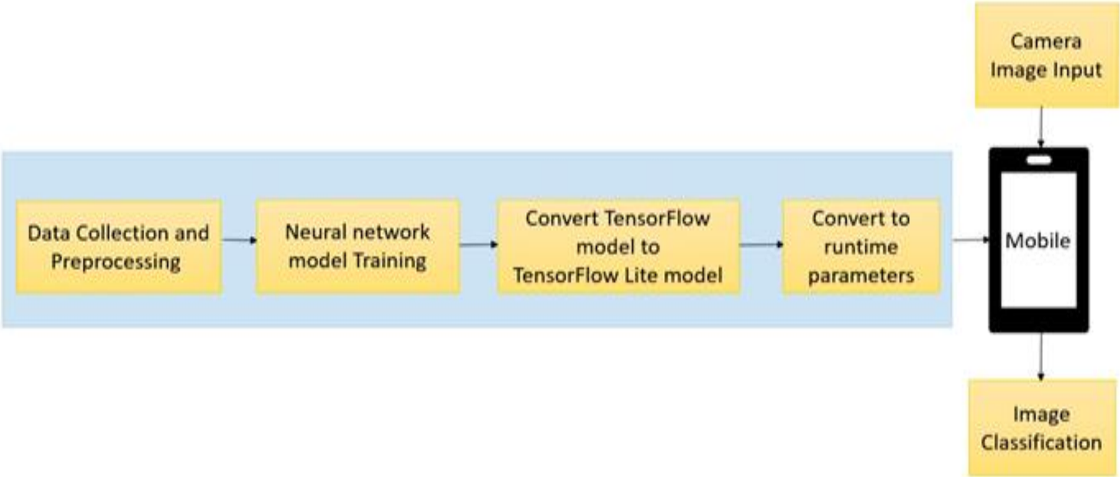

Fig. 4. Process Pipeline

The Activation Function used is "Relu" throughout the network except for the last layer where it is "Sigmoid" as it is the commonly applied last layer function for the task of binary classification [14]. We used the Binary Cross-Entropy loss function and Adam optimizer with an initial learning rate of 0.001 with a decay of 1e-5 for each epoch.

III. DEEP LEARNING INFERENCE IN THE EDGE

For areas such as healthcare, the most important aspect that should be considered while building technologies and applications is to reduce the turnaround time and provide real-time diagnoses. To enable this, we have incorporated on-device inference to make real-time detection of pneumonia possible. In our project, we use edge devices (smartphones) to collect X-ray images from the user and classify the X-ray as “Pneumonia” or “Normal” with the help of the pre-trained neural network. The usage of smartphones as edge devices to make inferences [17], facilitates the detection of pneumonia in real-time, thereby reducing the turnaround time in areas where access to medical imaging experts is scarce.

A. TensorFlow Lite

TensorFlow Lite is an open-source deep learning framework that enables on-device machine learning inference with low latency and small binary size. It is designed to perform high computational machine learning algorithms on edge devices and hence improving latency, privacy ,and power consumption.

TensorFlow Lite contains two main components - the interpreter and the converter. The converter does the job of compressing and optimizing the trained neural network. The Interpreter provides inference at the edge devices such as mobile phones. In our project, we built a convolutional neural network using TensorFlow and trained it with the dataset on our computer. The trained neural network is then converted into a TensorFlow Lite model to make on-device inference possible.

B. Implementation

In the project, we built a mobile application with Android Studio 4.1.0. We converted the trained TensorFlow model to a TensorFlow Lite model with the help of the converter function. The TensorFlow Lite model is binded to the application. This application takes in an X-ray image from the mobile camera and converts it into a grayscale image and resizes it into a 196x196 image before loading it into the TensorFlow Lite model. The application tags the X-ray image as either “Pneumonia” or “Normal” with a confidence level that helps the user decide if the X-ray belongs to an infected patient or not. Along with the detection of pneumonia, we also propose to collect the location data points of the users who test positive to help governments make data-driven decisions to slow the spread of the infection. Government agencies can educate people about the symptoms of pneumonia and can set up immunization camps. Seasonal outbreaks of the disease can also be identified with the data collected.

Fig. 5. UI of the application on the Edge Device

IV. EXPERIMENTAL RESULTS

To study the performance of the convolutional neural network, we recorded the F1 score, recall, precision and accuracy. In the equations below, tp is true positives, tn is true negatives, fp is false positives, and fn is false negatives. The confusion matrix is as shown [Fig. 6].

Precision = tp / (tp+fp)

Recall = tp / (tp+fn)

F1 score = 2*Recall*Precision / (Recall+Precision)

Accuracy = (tp+tn) / (tp+fp+tn+fn)

The recall of the model is 97.4 percent, the precision is 90.47 percent, the F1 score is 93.8 percent and the accuracy is 91.98 percent.

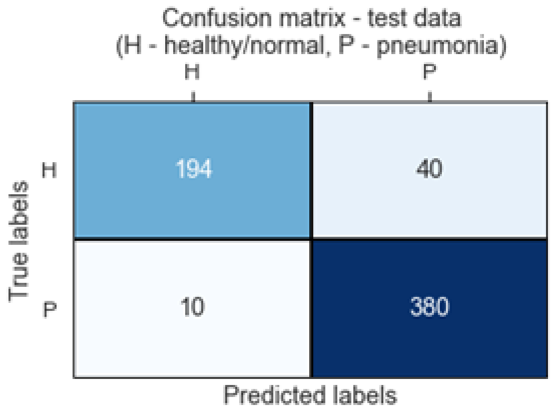

Fig. 6. Confusion matrix of test data

V. CONCLUSION

Pneumonia is a disease that is caused because of fluid or pus accumulation in the lung sacs. Children under the age of 5 are more susceptible to this disease as their immunity is not strong enough to fight the infection. Pneumonia is one of the leading contributors to the mortality rate in developing countries which have a large number of remote areas and where access to hospitals and skilled radiologists is scarce. The most common way to detect pneumonia is through identifying opacity in chest X-rays which indicates the presence of liquid or pus in the lung sacs.

Our project aims to provide means for early diagnosis by making real-time detection of pneumonia more accessible in remote areas using on-device inference. We built a convolutional neural network that was trained on chest X-ray images of children aged below 5 years. The CNN detects the presence of pneumonia in chest X-rays. The accuracy of the model was 91.98 percent and the recall was 97.4 percent. Though the accuracy is less, the high recall suggests that the model gives fewer false negatives which can help lower the risk to the patients' lives[17]. To make inference through the convolutional neural network possible on edge devices such as smartphones, we convert it to a TensorFlow Lite model. The TensorFlow Lite model enables on-device machine learning possible because of low latency and small binary size. We built a mobile application that takes Chest X-ray as input and labels the chest X-ray as either "Normal" or "Pneumonia" with the help of the TensorFlow Lite model that is binded with the application. The model also specifies the confidence level with which the prediction is made, which helps the user decide further course of action. We also propose to gather the location data points of the users to help governments locate places that have high infection rates. This can help the government to make data-driven decisions to set up immunization camps and spread awareness about the disease. The data can also be used to take precautions to curb seasonal outbreaks of the disease.

This application will help the world fight pneumonia by making early and real-time detection of the disease possible. The increase in the number of smartphone users in rural regions [18] gives us reason to believe that this application can be widely used for the early detection of pneumonia.

REFERENCES

[1]. Institute for Health Metrics and Evaluation (IMHE). (2014). Pushing the Pace: Progress and Challenges in Fighting Childhood Pneumonia.

[2]. McAllister, D. A., Liu, L., Shi, T., Chu, Y., Reed, C., Burrows, J., … & Nair, H. (2019). Global, regional, and national estimates of pneumonia morbidity and mortality in children younger than 5 years between 2000 and 2015: a systematic analysis.*The Lancet Global Health*, *7*(1), e47-e57.

[3]. What We Do- Pneumonia Strategy Overview, https://www.gatesfoundation.org/what-we-do/global-health/pneumonia

[4]. Oliveira, Leandro &Nouer, Simonne& Ribeiro, Luiza & Oliveira, Renato & Coelho, Clarimar& Andrade, Ana Lucia. (2008). Computer-aided diagnosis in chest radiography for detection of childhood pneumonia. International journal of medical informatics. 77. 555-64. 10.1016/j.ijmedinf.2007.10.010.

[5]. AnticonaHuaynate CF, PajueloTravezaño MJ, Correa M, et al. Diagnostics barriers and innovations in rural areas: insights from junior medical doctors on the frontlines of rural care in Peru. *BMC Health Serv Res*. 2015;15:454. Published 2015 Oct 5. doi:10.1186/s12913-015-1114-7

[6]. Rahmati MB, Ahmadi M, Malekmohamadi, Hasanpur S, Zare SH, Jafari M. The significance of chest ultrasound and chest X-ray in the diagnosis of children clinically suspected of pneumonia. *J Med Life*. 2015;8(Spec Iss 3):50-53.

[7]. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz,C., Shpanskaya, K., Lungren, M.P.: Chexnet Radiologist-Level Pneumonia Detection on Chest X-rays with Deep Learning (2017). arXiv preprint arXiv:1711.05225

[8]. Rachna Jain, PreetiNagrath, Gaurav Kataria, V. Sirish Kaushik, D. Jude Hemanth, Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning, Measurement,Volume 165,2020,108046,ISSN 0263-2241,

[9]. E. Ayan and H. M. Ünver, "Diagnosis of Pneumonia from Chest X-Ray Images Using Deep Learning," 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), Istanbul, Turkey, 2019, pp. 1-5, doi: 10.1109/EBBT.2019.8741582.

[10]. Jain, Rachna &Nagrath, Preeti&Kataria, Gaurav & Kaushik, V. & D, Jude. (2020). Pneumonia Detection in chest X-ray images using Convolutional Neural Networks and Transfer Learning. Measurement. 165. 108046. 10.1016/j.measurement.2020.108046.

[11]. Contribution of Smartphones for Digital Governance in India https://icea.org.in/wp-content/uploads/2020/07/Contribution-of-Smartphones-to-Digital-Governance-in-India-09072020.pdf

[12]. Panagariya A. The Challenges and innovative solutions to rural health dilemma *Ann Neurosci*. 2014;21(4):125-127. doi:10.5214/ans.0972.7531.210401

[13]. https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia accessed in November 2020

[14]. Yamashita, R., Nishio, M., Do, R.K.G. et al. Convolutional neural networks: an overview and application in radiology. Insights Imaging 9, 611–629 (2018). https://doi.org/10.1007/s13244-018-0639-9

[15]. Zijie J. Wang, Robert Turko, Omar Shaikh, Haekyu Park, NilakshDas,Fred Hohman, MinsukKahng, and DuenHorng (Polo) Chau (arXiv:2004.15004).CNN EXPLAINER: Learning Convolutional Neural Networks with Interactive Visualization.

[16]. Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, Ruslan Salakhutdinov;Dropout: A Simple Way to Prevent Neural Networks from Overfitting.

[17]. Kaushik, V. & Nayyar, Anand &Kataria, Gaurav & Jain, Rachna. (2020). Pneumonia Detection Using Convolutional Neural Networks (CNNs). 471-483. 10.1007/978-981-15-3369-3_36.

[18]. Xiaofei Wang, Senior Member, IEEE, Yiwen Han, Student Member, IEEE, Victor C.M. Leung, Fellow, IEEE, Dusit Niyato, Fellow, IEEE, Xueqiang Yan, Xu Chen, Member, IEEE Convergence of Edge Computing and Deep Learning: A Comprehensive Survey https://arxiv.org/pdf/1907.08349.pdf