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A DEEP CONVOLUTIONAL NEURAL NETWORK-BASED MOBILE APPLICATION FOR EARLY AUTO-DETECTION OF PNEUMONIA FROM CHEST X-RAY IMAGES

[1]Popoola, J. J.[*], [1]Dada, A. B. and [2]Odeyemi, C. S.

[1]Department of Electrical and Electronics Engineering, Federal University of Technology, Akure, Ondo State, Nigeria
[2]Department of Computer Engineering, Federal University of Technology, Akure, Ondo State, Nigeria
[*]Correspondence: jidejulius2001@gmail.com, adebolu4christ@gmail.com,charityodeyemi@gmail.com

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Abstract
Access to both reliable health services and experience medical personnel in rural communities in most developing nations of the world are great challenges. These challenges account for the reason rural dwellers in most developing nations of the world depend on traditional therapies in tackling diverse ailments. However, acute inflammation of the respiratory tract caused by bacteria and/or viruses, which lead to pneumonia is usually difficult to manage with traditional therapies. Thus, introduction of automated technology-base-driven approach for early detection of pneumonia becomes crucial. The indispensability of automated early detection of pneumonia necessitates the study reported in this paper, which focused on development of an automated early detection of pneumonia among rural dwellers using a deep convolutional neural network enabled mobile application (mobile app). The development of the mobile app involved five stages, namely data acquisition, data preparation, model training, development of mobile application, and performance evaluation. The results of the comprehensive performance evaluation tests conducted on the developed automated pneumonia early detector mobile app show detection average accuracy, precision, recall or sensitivity and F1 score of 80.8%, 73.3%, 97.3% and 83.6% respectively with average execution time less than 95 ms or 0.095 s. Furthermore, the results of both the validation and comparative performance evaluation tests conducted on the developed automated early pneumonia detector mobile app for this study show that the developed mobile app for this study performed relatively well with similar developed app in surveyed literature.

Keywords: *Pneumonia, Deep Convolutional neural network, Convolutional neural network model, MobileNets, Neural Network Performance Indices*

Introduction

Pneumonia is a main cause of childhood mortality and principal contributor to childhood morbidity worldwide. According to Siddiqqi and Javaid (2024); Munna et al. (2024); Kifle et al. (2023); Solomon et al. (2023); Seramo et al. (2022); Beletew et al. (2022); and Liu et al. (2016), pneumonia is currently the leading cause of death among children under the age of five globally. It is currently the main life-threatening lung infection disease resulting from various viral and/or bacterial infections. It is thus a deadly respiratory ailment that claims lives of more young children worldwide than any other infectious disease. It normally affects lungs and makes it difficult for the lungs to absorb oxygen by affecting both the alveoli and distal bronchial tree of the lungs. It is defined in Beletew et al. (2022) as a severe inflammation of the lungs' parenchymal structure. Although, pneumonia is an infection disease, the leading factors that contribute to its high incidence as reported in Kiconco et al. (2021), are malnutrition, lack of exclusive breast-feeding, low birth weight, in-door air pollution, overcrowding, and lack of immunization. Thus, children with compromised immune systems are at higher risk of having pneumonia.

Actually, incidence of pneumonia varies by age groups and between developing and developed countries. As reported in Gereige and Laufer (2013), annual incidence of pneumonia in children under the age of 5 years ranges from 150 million to 156 million cases resulting in an estimated death of about 2 million annually in developing countries of the world. For instance, as reported in Kiconco et al. (2021), pneumonia prevalence among children under the age of 5 years in studies conducted in most African nations ranges between 16% and 33%. Specifically, a global estimate made in year 2000 as reported in Beletew et al. (2022) revealed that approximately 156 million cases of pneumonia occurred annually in children under age five, which 5 million cases were in developed countries while the rest 151 million cases were in developing countries. In East African countries for instance, investigation of magnitude of pneumonia revealed a prevalence range from 5.5% to 89.8% among children below five years. Similarly in West African countries, especially Nigeria, pneumonia has been identified as the leading cause of child mortality killing over 140,000 children in a year (Wondi et al., 2020). On the other hand, in developed nations of the world such as the United States, children mortality rate as a result of pneumonia is relatively low. However, even in an advanced country such as the United Sates, pneumonia has been identified as the major reason children are being hospitalized (Quinton et al., 2017).

Globally, observations and experiences have shown that children under the age of five years are most vulnerable to pneumonia. Thus, the disease is a leading cause of both morbidity and mortality in children. According to Le Roux et al. (2015), up to fifty percent of consultations at healthcare facilities for sick children in low and middle-income nations or countries of the world are due to acute pneumonia. As a single infectious disease, pneumonia in 2018 claimed lives of about eight hundred thousand children. According to World Health Organization (WHO), nearly 1.6 million children under the age of five years die of pneumonia in a year. As reported in Yaguo-Ide and Nte (2011), over half of the world's annual pneumonia cases were concentrated in five countries: India (43 million), China (2.1 million), Pakistan (9.8 million), Bangladesh (6.4 million) and Nigeria (6.1 million).

Basically, pneumonia is classified based on place of acquisition. According to Torres et al. (2021), pneumonia is classified as either community acquired pneumonia (CAP) or hospital acquired pneumonia (HAP). According to these authors, the causative micro-organisms for CAP and HAP differ significantly. While Streptococcus pneumonia is responsible for CAP, Staphylococcus aureus are common microorganisms responsible for HAP. Apart from micro-organisms responsible for CAP and HAP, HAP is often developed in hospitalized child within forty-eight (48) hours after admission. Thus, while HAP is usually developed during a stay in the hospital as a result of another illness, CAP is the most common type of pneumonia that occurs outside of hospital or other healthcare facility. This accounts for the reason HAP is usually serious since the affected person is already sick. Specifically, patients who are on breathing machines or ventilators are high susceptible to HAP.

Irrespective of class of pneumonia, a lot of efforts have been geared toward reducing both the prevalence and burden of pneumonia locally, nationally and globally. For instance, in Nigeria measures to reduce both prevalence and burden of pneumonia include identifying and reducing the main risk factors causing pneumonia such as overcrowding, household air pollution, lack of breastfeeding and lack of immunization against Streptococcus pneumonia and Staphylococcus aureus. Unfortunately, these efforts have not yielded optimal and desired results as expected especially in rural communities in Nigeria where access to quality and reliable healthcare facilities is a problem. Thus, pneumonia has continued to be a major cause of sickness and deaths among children in rural areas in Nigeria, where rural dwellers depend on traditional therapies in tackling different ailments.

In actual fact, traditional therapies for managing pneumonia have been proved effective. However, insufficient number of research evidence on overall efficiency of traditional, complementary and alternative medicine (TCAM) utilization as well as lack of informs policy design and practice has hindered TCAM general acceptability by the WHO (James et al., 2018). Thus, conventionally laboratory methods involving capturing chest x-ray images have been used in detecting pneumonia and its etiology. However, since diagnostic facilities for pneumonia are expensive and unavailable in rural communities in most developing nations of the world such as Nigeria with acute shortage of hospitals and doctors, these demerits make early detection and diagnosis of pneumonia a difficult task for people in rural areas. Some of the patients who have obtained their chest x-ray images most often find it difficult to meet experienced doctors, so there is always long waiting periods. This delay most often aggravates the patients' health conditions and lead to death of pneumonia patients.

Actually, detection or diagnosis of pneumonia is usually performed manually through chest x-rays (CXRs) images examination by trained specialists. This non-automatic detection of pneumonia is not only tedious but often time-consuming and error-prone as the process depends on human judgment and interpretation. This non-automatic detection technique, as reported in Popoola (2014), is unpopular and unreliable because its success usually depends on the trained specialist's experience, such as doctor and radiologist. These disadvantages necessitate the need for the automatic or computer-aided detection of pneumonia using CXRs images, which currently is one of the fast-growing research areas over the past few years. In most of the researches on automatic detection or classification of pneumonia, applications of several deep learning (DL) algorithms using CXRs images had recorded huge successes.

These successes as reported in El Asnaoul (2021) are based on DL five layers architectures namely; input layer, convolution layers, pooling layers, fully-connection layers and output layer. In addition, the author added that better performance of several DL approached in automatic detection and/or classification of pneumonia disease is based on DL capability of reducing false-positive and negative errors in detecting and diagnosing the disease. As a result of DL efficiency in detecting pneumonia, several researchers had employed it to diagnosis pneumonia. For instance, Rajpurkar et al. (2017) developed DL algorithm, called CheXNet, to detect pneumonia disease from CXRs images. The CheXNet developed by these authors employed CXRs 14-dataset that contains 112,120 frontal view CXRs images of over thirty thousand patients. The developed CheXNet when tested by comparing it with that of expert radiologists using 420 CXRs images outperformed it in detecting pneumonia. Likewise, Abiyev et al. (2018) demonstrated the likelihood of classifying the chest diseases using deep convolutional neural network (DCNN), back-propagation neural networks with supervised learning and competitive neural networks with unsupervised learning. The comparative performance evaluation of the three forms of neural networks (NNs) algorithms showed that DCNN algorithm had a better generalization power than the two NNs algorithms though with high computation time and high number of iteration due to deep architectural structure of DCNN. However, the result of the study buttressed the finding reported in He et al. (2016) that DCNN is an efficient algorithm for detecting and/or classifying images.

Similarly, the study reported in Stephen et al. (2019) employed DL approach to classify pneumonia from samples of CXRs images. Though the study made use of insufficient repository CXRs dataset, the classification accuracy of the developed DCNN model achieved remarkable validation value as a result of several data argumentation algorithms obtainable in DCNN. Also, Hashmi et al. (2020) employed an ensemble like model that integrated five DL models to develop an efficient pneumonia detection model using CXRs images. The finding of the study showed that the developed model was efficient in quick diagnosis of pneumonia disease and as well as enhancing radiologists in easy diagnosis of pneumonia. Hashmi et al. (2021) also worked on another model for detecting pneumonia in CXRs, using compound scaled deep learning model, called ResNet50, which was an up-scaled version of ResNet50. The model when evaluated was found effective in detecting pneumonia disease as well as assisting radiologists in their clinical decision-making activities. Recently, Mabrouk et al., (2022) developed pneumonia detection model capable of detecting pneumonia in CXRs images using ensemble DCNNs. The pneumonia detection model, referred to as ensemble learning, was a computer aided pneumonia detecting algorithm developed to reduce pneumonia diagnosis process on CXRs images. The detection pneumonia model adopted the recent employed three well-known convolutional neural network (CNN) models namely, DenseNet169, MobileNetV2 and Vision Transformer, to enhance the performance of developed model. The developed ensemble learning pneumonia detection model when evaluated was found to outperform other existing models with performance accuracy of 93.91%.

However, all these developed automatic pneumonia detectors were neither developed for early detection of pneumonia nor currently available in any developing nation of the world. Thus, with the high mortality rate of patients suffering from pneumonia in developing nations of world, especially among the rural dwellers, there is an urgent need to develop an automated early pneumonia detection system that will aid effective identification and/or detection of pneumonia at early stage in order to drastically reduce high mortality rate of patients suffering from pneumonia. Thus, in developing nation like Nigeria, where inadequate medical facilities and experienced medical personnel are extremely scarce in rural areas, deployment of automated mobile app capable of automatic detection of pneumonia in the early stage will indeed help radiologists in early detection of pneumonia from CXRs images among the rural dwellers. This need necessitated the desired to design and develop the DCNN-based mobile app for early detection of pneumonia presented in this paper. The desired technology-driven solution for early detection of pneumonia for this study was developed using DCNN, which is a convolutional neural network (CNN) that has multiple layers. It is a group or class of artificial neural networks commonly used to classify patterns in video and images. DCNN works by receiving images as an input and then uses the input images to train a classifier. DCNN was employed in this study because of its acclaimed series of breakthroughs in image classification (Mohammed et al., 2024; Ma et al., 2020).

The primary goal of this study was to develop a DCNN-enabled mobile app for early detection of pneumonia among the rural dwellers from CXRs images. This goal was achieved through three objectives. The first objective was to train a TensorFlow model with CXRs images of pneumonia positive and pneumonia negative dataset. The second objective of the study was to design and develop a user-friendly mobile app for deploying the TensorFlow model trained in the first objective while the third objective was to evaluate the performance of the TensorFlow model trained in first objective and mobile app developed in the second objective. For sequential and logical presentation of the study reported in this paper, the entire paper is divided into four sections. In the first main section, we introduced the research and provide general information on pneumonia and its prevalence. The section also provides detailed information on the aim and objectives of the study alongside a comprehensive literature survey on the research topic. In the second main section, we present detailed information on the methodology employed in achieving the goal and objectives of our study. Detailed information on step-by-step approach in developing our desired automated early pneumonia detection mobile app was presented. The results obtained when the developed mobile app was evaluated are presented and discussed in the third section while the paper is concluded in the fourth section with summary of the findings from the study.

Methodology

The methodology involved in carrying out the study reported in this paper is divided into five main stages as shown in Figure 1. Activities involved in the first four stages are presented in this section while the fifth activity is covered in next section on performance evaluation and validation tests. Detailed information on each of the first four stages was thus presented in the following sub-sections.

Data Acquisition

The images dataset used in conducting this study was retrieved from Guangzhou Women and Children's Medical Center, Guangzhou, China, which comprised of CXRs images of one to five-year old children. Typical pneumonia patients' image dataset in .JPEG format is as shown in Figure 2. The dataset captured both patients with benign condition and those with malignant condition. The dataset was organized in three (3) folders, namely training, testing and validation folders, each of which contains subfolders of image categories that has been classified based on whether a patient has pneumonia or not. Overall, the dataset has 5853 x-ray images and two categories; pneumonia and normal. The folders and subdirectories that make up the entire dataset with the corresponding number of training set, testing set and validation set is shown in Figure 3.

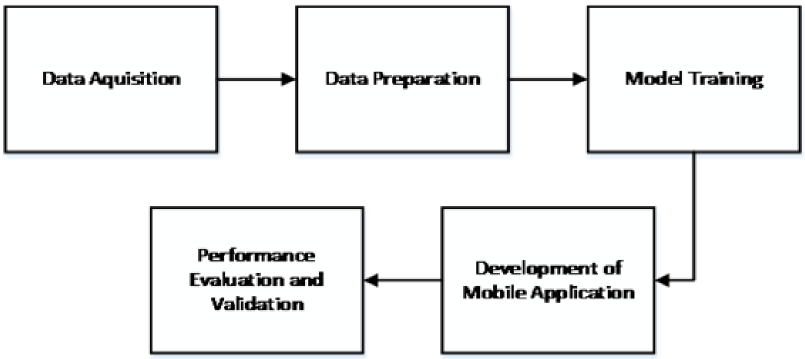


Figure 1: Methodical block diagram of the methodology

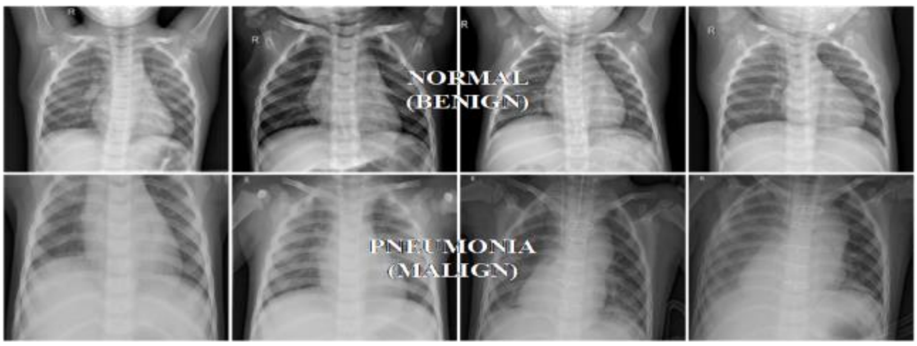


Figure 2: Sample Images of the Chest X-Ray Dataset

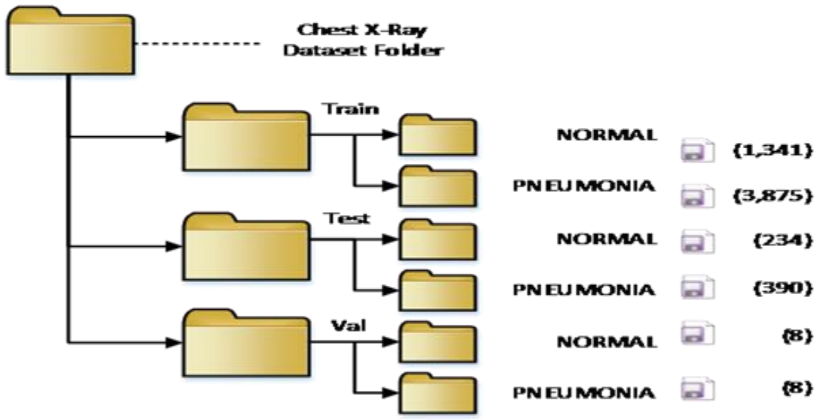


Figure 3: Organisation of the Directories in the Chest X-Ray Dataset

Data Preparation

Careful observation of the acquired chest x-ray datasets revealed that the images dataset were characterized by low contrast levels that could impact negatively the overall performance of the proposed mobile app. Thus, data preparation, which entails data preprocessing was conducted. The essence of the data preparation was to preprocess the acquired chest x-ray datasets in order to clean, enrich and transform the datasets so as to make the datasets suitable for further processing. In addition, the average dimension of each acquired chest x-ray image was rescaled to prevent the proposed mobile app complexity (Sabottke, and Spieler, 2020). Specifically, three different data preparation activities were conducted on the acquired chest x-ray images datasets, namely data rescaling, data stratification and data filtering.

Data rescaling was done to transform the dimension of the image dataset to the same range. The essence of the data rescaling is to prevent the image dataset with high dimension from dominating the learning process as well as to aid the desired algorithm to converge faster during training. Thus, data rescaling was implanted to downsize the image dimension from (1762×1430) to (224×224), which is in tandem with the recommendation in Howard *et al*. (2017). The data rescaling was implemented in MATLAB® programming environment using the *imresize* function predefined in the image processing package. Furthermore, data stratification was carried out on the 5853 acquired images in the image dataset consists of 1341 *Normal* class and 3875 *Pneumonia* class in the training folder. As a result of this huge disparity in the number of the image dataset, data stratification was implemented in order to prevent domino effect on the proposed mobile app. Both *Normal* class and *Pneumonia* class were shipped. Three different strata were finally created, namely *Strata 1*, *Strata 2* and *Strata 3*, which contained equal number of both the *Normal* class and *Pneumonia* class. Hence, in Strata 1, Strata 2 and Strata 3 datasets, there are 1,341 images in the *Normal* class and also 1,341 images in the *Pneumonia* class. Similarly, 234 images in the *Pneumonia* class from the test folder was drawn, which ensured equitable distribution of images across both the *Normal* and *Pneumonia* class. Sequel to implementing the stratification process, two extra datasets (the *Raw*folder and *Enhanced* folder) were created to segregate raw image dataset and histogram-equalized dataset. Finally, the whole chest x-ray dataset was copied to both the *raw* folder and *enhanced* folder. It was ensured that only images in the enhanced folder were filtered using a histogram equalizing filter. The filtering process was carried out to improve the contrast level of each image contained in the acquired chest x-ray dataset. The histogram equalizing filter implemented adjusted the image intensities and redistributed pixels uniformly across the image to enhance contrast. The resulted normalized histogram as expressed in Liu *et al*. (2020) is given mathematically in Equations (1) to (3) as;

$$p_n = \frac{number\ of\ pixels\ with\ intensity\ n}{total\ number\ of\ pixels} = 0,1,\cdots,L-1 \qquad (1)$$

The histogram equalized image g was defined by;

$$g_{i,j} = floor\left((L-1)\sum_{n=0}^{I_{i,j}} p_n\right) \qquad (2)$$

where $floor(.)$, which is flooring function means rounds down to the nearest integer. This is equivalent to transforming the pixels intensities, k, of I by the function;

$$T(k) = \left((L-1) \sum_{n=0}^{I_{i,j}} p_n \right) \quad (3)$$

As a result of limited space, a typical example of each of raw image dataset for normal class condition and pneumonia class condition before and after histogram equalization were shown in Figure 4 and Figure 5 respectively. After the normalization process, the contrasts of the image datasets for both classes were improved as opposed to the corresponding raw datasets. Some regions of the raw images for both classes that were blurry and invisible have become sharper and visible. This is perfectly illustrated by the obtained histogram plots shown in Figure 6 and Figure 7, respectively for both classes. Also, the outputs of the data preprocessing activities performed on the two classes of the datasets show that the bins of the two

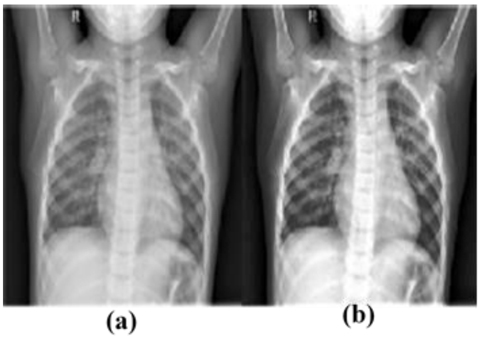


Figure 4: (a) Acquired raw Normal image (b) Histogram equalized Normal image

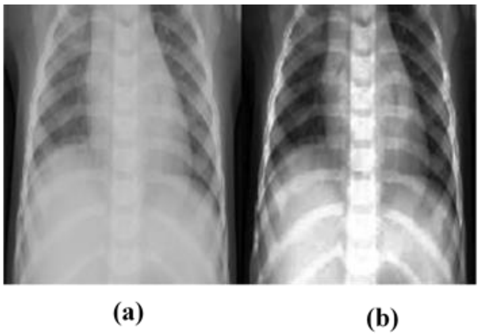


Figure 5: (a) Acquired raw Pneumonia image (b) Histogram equalized Pneumonia image

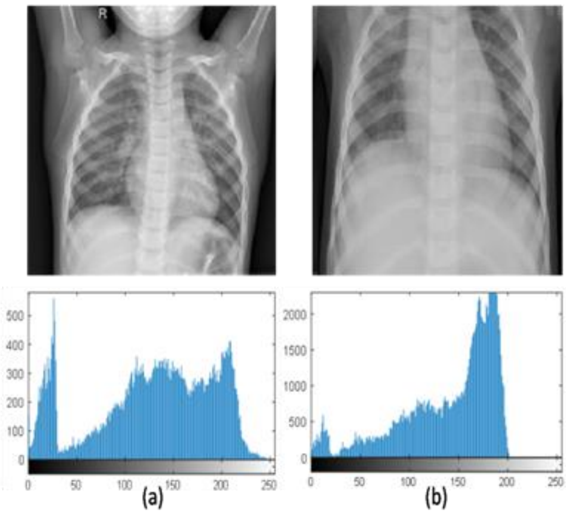


Figure 6: Image histogram for (a) Normal class and (b) Pneumonia class before applying histogram equalizer

datasets are evenly distributed after applying the histogram equalizer.

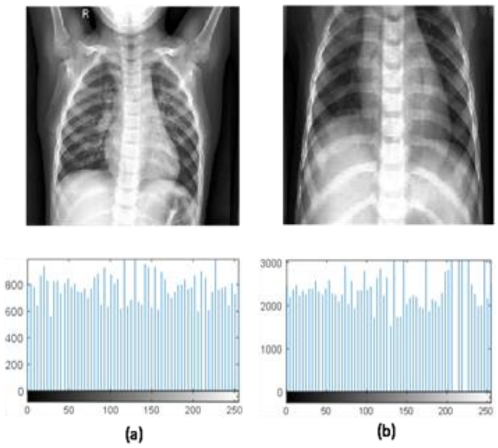


Figure 7: Image histogram for (a) Normal class and (b) Pneumonia class after applying histogram equalizer

Model Training

In this stage of developing the proposed mobile app, the training dataset acquired from the preparation stage was used to train a DCNN. The DCNN adopted in this research is the MobileNets, which are used specifically in mobile and embedded vision applications. The model training parameters employed are 50 epoch, 16 batch size and learning rate of 0.001. Basically, MobileNets are based on a relatively simple architecture that uses depth-wise separable convolutions to build on light-weight deep neural networks suitable for low memory applications. The MobileNets DCNN architecture was employed in this paper because the trained model will be eventually deployed to a mobile device. Also, because MobileNets architecture introduces two new global hyperparameters, width multiplier and resolution multiplier, that allow model developers to trade off latency for speed. During the training, both the normal and pneumonia classes were specified based on the strata in the training set. The 1341 images of the normal class in the training set were

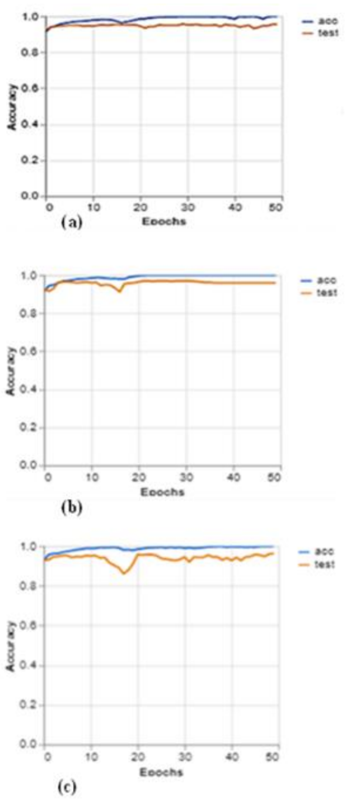


Figure 8: Normal Image performance (a) A/E for strata 1 (b) A/E for strata 2 (c) A/E for strata 3

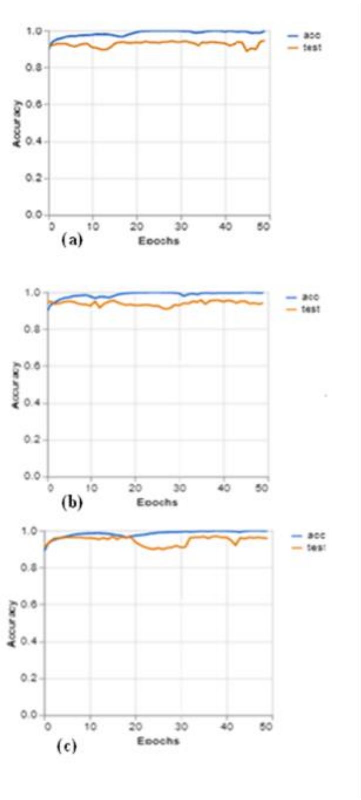


Figure 9: Pneumonia Image performance (a) A/E for strata 1 (b) A/E for strata 2 (c) A/E for strata 3

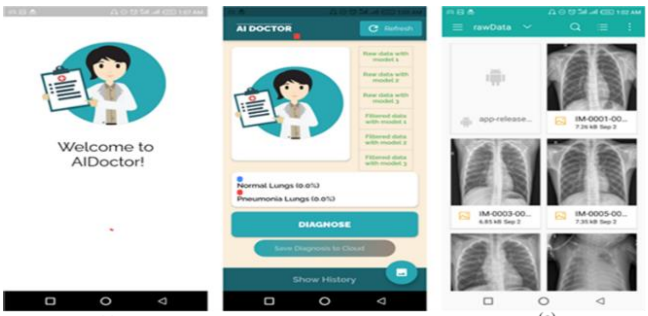
uploaded to the normal class while 1341 images of the pneumonia class were also uploaded to the pneumonia class. The training accuracies per epoch after training the model with both the normal class dataset and pneumonia class dataset for the three strata are shown in Figure 8 and Figure 9 respectively. Figure 8 and Figure 9 show clearly that developed model performs favourably well in predicting both the normal class and the pneumonia class with the normal class model outperforms that of pneumonia class model.

Development of the Mobile App

This stage, which is the fourth stage of the methodological activities employed in the study reported in this paper focuses on development of the proposed DCNN-based mobile app for early auto-detection of pneumonia. Google's cross platform mobile application framework called flutter, which was installed in Android Studio, was used in developing the diagnostic mobile app called "AIDoctor". The framework is written in a programming language called dart, which combines strengths and syntaxes of several other programming languages to form its own syntax. Summarily, this stage of the study reported in this paper entailed the installation of all the necessary packages for successful development of the proposed mobile app. Screenshots of some features of the developed mobile app or AIDoctor for early auto-detection or diagnosis of pneumonia from CXRs images are shown in Figure 10(a-c).

matrixes: True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP) obtained when the developed mobile app was evaluated. Likewise, the execution time of the developed mobile app was determined by measuring the time taken for the developed mobile app to detect or diagnose samples of pneumonia images. The obtained results for the two performance evaluation tests conducted were presented and discussed under the subsection on performance evaluation tests.

Similarly, two different validation tests, namely comparative test with radiologist and comparative test with recent related studies in literature, were conducted to validate the fitness of the developed mobile app in medical environment. In comparative validation test with radiologist, the results obtained using the developed mobile app was compared with results obtained when an expert or experienced radiologist applied his expertise to classify or detect pneumonia infection in the same sample images. The second comparative performance test with recent related studies in literature was to further validate the developed mobile app for this study. This test was conducted by carrying out a comparative performance evaluation test among the developed automatic pneumonia detection mobile app for this study and some similar studies in surveyed literature. The obtained results for the two validation tests conducted were presented and discussed under the subsection on validation tests.



(a) (b) (c)

(a) Developed app Welcome page **(b) Developed app Dashboard** **(c) Developed app selection modal view**

Figure 10: Screenshots of some features of the developed mobile app

Performance Evaluation and Validations Tests

This section is divided into four subsections. Results of the two performance evaluation tests conducted to evaluate the detection capability and detection time or execution time of the developed mobile app were first presented and discussed under performance evaluation tests. In order to determine the detection capability of the developed app, the four neural network performance indices; accuracy, precision, recall and F1 score rate, were computed based on the four confusion or error

Performance Evaluation Tests

Detection Capability Test

In conducting the detection capability tests for the developed mobile app, testing data set of pneumonia images in Figure 3 were used to test the detection potential capacity of the developed mobile app or MobileNet model. Three Strata samples were selected from the test folders. The obtained four error or evaluation matrices: True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP) obtained when the developed mobile app was evaluated were presented graphically in Figure 11. The four evaluation matrices were later used as key performance detection indices to compute the detection capability of the developed mobile app, which are: accuracy, precision, recall and F1 score rate of the developed mobile app. The evaluation metrics presented in Figure 11, were used because they are currently acclaimed standard metrics being used in medical image classification according to Mabrouk et al. (2022).

Critical observation of Figure 11 shows clearly that the developed mobile app for early detection of pneumonia in this study has high detection capability potential with its high TP values and extremely low FN values for the three pneumonia strata dataset used for the performance evaluation tests. The high TP results obtained implies correct identification of pneumonia in the sample datasets used to test the developed mobile app while the extremely low FN values obtained imply that the developed mobile app has extremely low incorrect detection of pneumonia in test data samples. Similarly, the relatively high TN values obtained indicate a correct detection of absence of pneumonia in samples without pneumonia infection. Further analysis of the four error matrixes values obtained using the mathematical expressions presented in Equations (4) to (7) give the results presented in Table 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{FP + FN} \quad (6)$$

$$F1 = 2\left(\frac{Precision}{Precision \times Recall}\right) \quad (7)$$

From Table 1, it is clearly shown that the developed mobile app for early detection of pneumonia in this study has detection average accuracy, precision, recall or sensitivity and F1 score of 80.8%, 73.3%, 97.3% and 83.6% respectively. The 73.3% average precision value obtained indicates that anytime the developed mobile app predicts that any patient has pneumonia, it is perfectly correct for over 73.0% of the cases considered. In addition, the overall average recall value obtained indicates that the developed mobile app has ability to correctly identify positive pneumonia images as positive with potential average value above 97.0%. According to Kassylkassova et al. (2023), the recall value for a good classifier is expected to be closer to one, which is true of the developed mobile app for early auto-detection of pneumonia for this study. The 97.3% average recall value obtained for this study indicates that the developed pneumonia

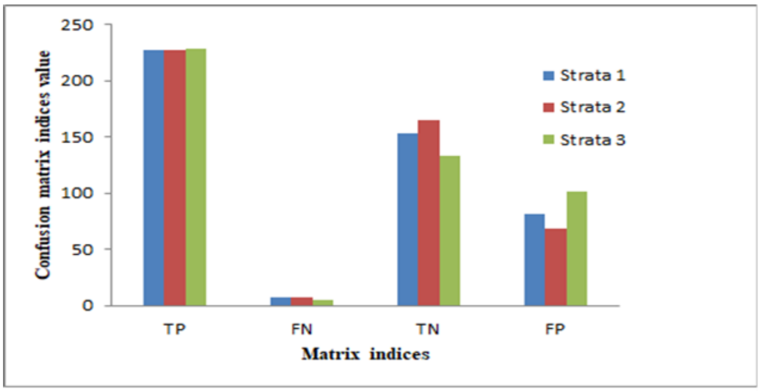


Figure 11: Detection Confusion Indices

Table 1: Developed mobile App detection capability result

Strata	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	81.2	73.7	97.0	83.8
2	83.8	76.7	97.0	85.7
3	77.4	69.4	97.9	81.2
Overall Average	80.8	73.3	97.3	83.6

detection mobile app for this study can perfectly detect over 97% of pneumonia affected patients subject to it for testing.

Detection Execution Time Test

The time taken for the developed mobile app to detect or diagnose image sample was determined. In measuring the response or execution time of the developed app, 15 random samples were selected from all the three strata. The time taken by the developed mobile app to detect or classify each sample was captured and recorded. However, as a result of limited space, only the calculated minimum execution time (MinET), maximum execution time (MaxET) and average execution time (AvET) in millisecond (ms) are presented in Figure 12. The time response or execution time obtained and presented graphically in Figure 12 shows that the execution time depends on the model as well as the image sample and computational resources of the device. The AvET values for strata 1, strata 2 and strata 3 respectively are 94.8 ms (0.0948 s), 94.3 ms (0.0943 s), and 92.7 ms (0.0927 s). These obtained low AvET values show that the developed early pneumonia auto-detection mobile app in this study performs favorably well when compared with study reported in Almaslukh (2021) with an AvET value of 0.33 s. The low AvET obtained in this study indeed indicates that the developed mobile app for early detection of pneumonia in this study is non-computational complex and indeed an energy saving mobile app that can be deployed for detection of pneumonia in rural areas where availability of regular power supply is a major challenge.

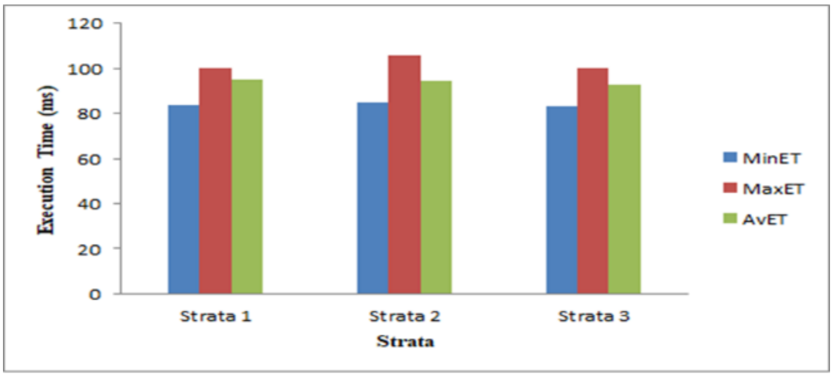


Figure 12: Developed Mobile app Average Execution Time

Table 2: Comparative results of the developed mobile app and radiologist detection tests

S/N	Number of Sample	Developed Mobile Diagnosis Result						Radiologist Diagnosis Result	
		Strata 1		Strata 2		Strata 3			
1	448	TP (%)	FN (%)	TP (%)	FN (%)	TP (%)	FN (%)	TP (%)	FN (%)
2	456	100.0	0.0	100.0	0.0	100.0	0.0	0.0	100.0
3	447	100.0	0.0	100.0	0.0	100.0	0.0	100.0	0.0
4	443	100.0	0.0	100.0	0.0	100.0	0.0	100.0	0.0
5	473	100.0	0.0	100.0	0.0	100.0	0.0	100.0	0.0

Validation Tests

Comparative Validation Test with Radiologist

The validation test was conducted by an experienced radiologist. The results obtained by the radiologist were compared with that obtained from the developed mobile app using the same 15 random samples earlier used as sample test images. Typical result obtained is presented in Table 2, where only five results out of the fifteen were presented as a result of limited space. However, all the obtained comparative results obtained were used to compute error incurred when using the developed app and trained radiologist to exam the same sample images. The error incurred was computed using Equations (8) and (9). The comparative validation results show that while the developed mobile app favourably diagnosed the pneumonia affected sample images in all three strata, the trained radiologist incurred some errors, amounting to 13.3% in diagnosing the same pneumonia affected samples images.

$$Error_{Radiologist} = \frac{|\#\text{Radiologist's Prediction} - \#\text{Actual Class}|}{\#\text{Actual Class}} \times 100\% \quad (8)$$

$$Error_{Mobile\ App} = \frac{|\#\text{MobileApp's Prediction} - \#\text{Actual Class}|}{\#\text{Actual Class}} \times 100\% \quad (9)$$

Comparative Validation Test with similar Studies

In order to further validate the accuracy of the developed mobile app in detecting pneumonia sample images subjected to it for testing, results obtained were compared with recent related studies in literature. The results of comparative performance accuracies of this work and three other recent related studies are presented in Table 3. The choice of the related studies used was based on some similarities, which include:

i. usage of CXRs images of one to five years old children;
ii. usage of *imresize* function of MATLAB to downsize the dimension of the image to 224 x 224;
iii. usage of simple architecture that uses depth-wise separable convolutions to build on light weight deep neural networks; and,
iv. usage of standard network performance indices in accurately identifying both normal lungs and pneumonia infected lungs

However, some differences are observed between this work and the reference studies. The first is the dataset used. While the study presented in this paper used 5853 chest x-ray images, the study presented in Togacar *et.* (2019) made of used of 5849 CXRs images, Saraiva *et al.* (2019) used 5840 CXRs images while Tawsifur *et al.* (2020) made used of 5247 chest x-ray images.

The second observed difference is the use of histogram equalization filter. While this work used both raw images and histogram equalization filtered images to train the developed models, the reference studies only used raw dataset to train their models. The third difference is that while the developed DCNN models in this work, were created from teachable machines, other were not created from teachable machines. The fourth difference is on the programming language employed. While the study presented in this paper made used of dart, the comparative studies made used of JavaScript and python programming language. The comparative validation results obtained are presented in tabular form in Table 3.

Critical observation of the comparative analysis results presented in Table 3 shows clearly that the reference studies outperform this present work in both precision and accuracy. This might be because the developed mobile app for this study made used of hyper-parameters, which was designed to trade-off accuracy for speed and low size. This is buttressed by the obtained low response time or AvET for this study when compare with the average response time of most of the reference studies in surveyed literature. This implies that the computation process of the present study is non-complex like most of the reference studies. In addition, observation of Table 3 also shows that the present work outperforms most of the reference studies in term of the obtained recall or sensitivity value. This implies that the present study is relatively more sensitive when compared with most of the reference studies in surveyed literature.

Convincingly, the overall comparative validation result presented in Table 3 shows that the present study performs favorably well with previous studies in the surveyed literature, which also validates the accuracy of the developed mobile app

Table 3: Comparative performance evaluation results of the developed app with similar studies

Study	Images used	Technique employed	Number of Image Samples	Recall/Sensitivity (%)	Precision (%)	Accuracy (%)
Togacar *et al.,* (2019)	Normal and Pneumonia	Deep CNN model	5849	96.83	96.88	96.84
Saraiva *et al.*, (2019)	Normal and Pneumonia	Neural Network	5840	94.5	94.3	94.4
Tawsifur *et al.*, (2020)	Normal and Pneumonia	AlexNet, ResNet18, denseNet201 and SqueezeNet	5247	99.0	97.0	98.0
	Bacterial and Viral Pneumonia	AlexNet, ResNet18, denseNet201 and SqueezeNet	5247	96.0	95.0	95.0
Present work	Normal and Pneumonia	Pre-trained DCNN model	5853	97.29	73.26	80.77

for early auto-detection of pneumonia.

Conclusion

This paper presents the overall procedural stages involved in developing, evaluating and validating a DCNN-based mobile app for early auto-detection of pneumonia from CXRs images. The chest x-ray images used in developing the mobile app were acquired from Kaggle, a subsidiary of Google's LLC. TensorFlow models were trained by the acquired Kaggle CXRs images dataset, which were subdivided equally in three strata. The performance evaluation tests carried out on the mobile app show good success detection performance with an average overall accuracy of 80.8%, precision of 73.3%, recall or sensitivity of 93.3% and F1 score of 83.6%.

Likewise, results of the validation tests conducted show that the developed mobile app for this study out-performed the results obtained by a trained radiologist using the same sample images. Also, the results of the comparative validation tests conducted between the developed mobile app for this study and other similar studies in surveyed literature show that the developed mobile app for early detection of pneumonia for this study performed favourably well with similar studies in searched literature. Furthermore, the low AvET value obtained when the developed mobile app for early detection of pneumonia in this study was evaluated show that the developed mobile app is non-computational complex and indeed an energy saving mobile app, which indeed is an ideal mobile app for early auto-detection of pneumonia in rural areas where limited access to both medical facilities and uninterrupted power supply are always major challenges.

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