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A lightweight model for pneumonia classification

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ABSTRACT: Madagascar suffers from pneumonia, a life-threatening disease that causes several deaths around the world every year. As a developing country, Madagascar faces lack of health infrastructures and radiologists to enable the early detection of this disease. That situation contributes to the high costs that most people could not afford. Thus, deep learning methods try to surpass these limits by providing models that could assists specialists and could run in a low-resource environment like a smartphone. That reduces considerably the overall expenses and contribute to save more lives. That perspective leads this work to propose a very lightweight model inspired from the architecture ofSSDLiteX that achieves a very great performance. To get further, preprocessing was used and a combination with LiteSRGAN was tested, too. After experiments, it achieves a 100% accuracy both with thecustom preprocessing techniques and with LiteSRGAN. A validation accuracy of99.07%, that is a very great metric showing high generalization, improved to 99.69% using liteSRGAN. The model is reliable and answers the need of the health domain in Madagascar and in other developing countries.

KEYWORDS: Pneumonia classification, Deep learning, lightweight model, Chest X-Ray, Medical imaging

I. INTRODUCTION

Pneumonia is a life-threatening infection that inflames the air sacs in one or both lungs. The air sacs may fill with fluid or pus, causing symptoms such as cough with phlegm or pus, fever, chills, and difficulty breathing. According to OWD [1], this is one of the most causes of death worldwide. It is contagious and can spread when a person coughs or sneezes. Pneumonia could be caught by people of all ages but it is particularly dangerous for infants, young children, people over 65 and those with weakened immune systems. That is 501910 children under the age of 5, 366522 people between 50 and 60 and 1.11 million of those over 70 years oldare still dead from pneumonia in 2021 corresponding to 3.23, 25.51 and 224.67 per 100 000 people in each range of ages. The difference between the death rates in different world regions is very large. The highest ones are shown in sub-Saharan Africa and South East Asia. There's a very strong correlation between a country's income and the child mortality rate from pneumonia [2]. It is more common in poor places where healthcare infrastructure is lacking and people are least able to afford the treatment [3]. Madagascar is among these situations, there are yet 5 323 children under the age of 5 and 2 281 over of 70 die due to pneumonia. The age standardized death rate from pneumonia is 156.9 and 569.9 for children in 2021.Bodily examination are conducted by professionals to diagnose patients using a chest X-ray, lung biopsy or other techniques to find exactly the disease. Rapid and accurate diagnosis is crucial to control the spread and improve the cure rate. Misdiagnosis could lead to incorrect treatment. Thus, the failure to recognize the disease will result ina patient's inability to lead a normal life. So, deep learning approaches are used to assist specialists to identify pneumonia in its early stage to provide suitable treatment to the patients. They use convolutional neural networks (CNN) that are reallyeffective in image analysis to extract features enabling the recognition of the images.This work aims to identify pneumonia using chest x-ray images to show if the patient has the disease or not. In other words, it

performs a binary classification of the chest x-ray into normal or pneumonia to avoid time consuming process and reducing the overall expenses and costs related to lack of infrastructures and specialists. This perspective leads to build up a lightweight model that would combine precision and speed at the same time. This is the other side where the present study focuses on. A lightweight model able to classify pneumonia, adapted to the constraints of resource-limited environments such as Madagascar, that would run fluidly in mobile device like a smartphone will emerge from this paper to enable rapid diagnosis even in the most remote areas.

The rest of this paper is divided in the following sections: Section 2 presents relevant previous studies. Section 3 develops the methodology presenting the dataset, pre-processing steps with and without LiteSRGAN and the model, while Section 4 gives a summary of the experimental results of the proposed approach. Finally, Section 5 concluded the study

II. RELATED WORKS

This work performs a binary classification of pneumonia using CXR images. Several works have already been carried out in this direction, which continue to evolve gradually using various approaches.

Nigus W., Ayodeji O., Aleka M. [4] propose to detect and classify pneumonia using CXR images. It exactly conducts a binary classification on the images to know if they are pneumonia-infected or not. Some preprocessing was used like histogram equalization to get useful features. For detection, it used YOLOV3 model and Support Vector Machine(SVM) and softmax for classification. The overall accuracy, precision, recall, andF1-score from this study are all 99%.

Alhassan M. and al. [5] an ensemble learning with three pretrained models: DenseNet169, MobileNetV2 and Vision Transformer. These models were trained with CRX images and fine-tuned. Combining the features obtained from the three models, the proposed ensemble learning achieves a great performance and records a testing accuracy of 93.91% and a F1-score is 93.88%.

In their work, Shagun S. and Kalpna G. [6] use VGG16 to detect and classify pneumonia. They did a lot of experiences using different structure of the model and two CXR datasets. They used VGG16 with SVM, K-Nearest Neighbor (KNN), Random Forest (RF), Naïve Bayes (NB) and VGG16 with Neural Networks (NN). The first dataset was collected from Kaggle, containing 5 856 anteroposterior CXR images. It was split into training and testing sets by the ratio 70:30. VGG16 with NN provides the best performance, giving an accuracy of 92.15%, recall as 93.08%, precision as 94.28%, and F1-Score of 93.7%.The second dataset was gathered from Kaggle also but it contains not only images for pneumonia, but also for covid-19. Among the 6 432 images, 80% were used for training the model and 20% were used for testing. So, the second dataset is used for multiclass classification, unlike the first one which were used for binary classification. Once again, VGG16 with NN achieves the best performance on classifying pneumonia. It provides accuracy, recall, precision and F1-Score of 95.4% each.

Using also a dataset from Kaggle, a CNN model was developed and training from scratch to classify pneumonia in [7]. The model provides an accuracy of 91%.

This same strategy was already used by Okeke S. and al.[8] when they adopted a CNN model from scratch and trained it to a CXR dataset. The results show an accuracy of 95.31% and a validation accuracy of 93.73%. Data augmentation was necessary during the process of training because the available dataset doesn't contain enough images to get the performance of the model.

Khalid El and al. [9] propose a comparison of recent deep CNN architectures for pneumonia classification. Instead of using only CXR dataset, they use also a compute tomography dataset with it. From VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50, MobileNet_V2 and Xception, fine-tuned finetuned version of Resnet50, MobileNet_V2 and Inception_Resnet_V2 gave better performance than the others. In training and validation, these models get an accuracy more than 96%, unlike Xception, VGG16, VGG19, Inception_V3 andDenseNet201that provide a performance more than 84% only.

Mujahid M. and al. [10] use transfer learning to classify pneumonia. They use also CXR images dataset available on Kaggle. Lots of pretrained model were used in this work: VGG16, Inception-v3, and ResNet50. They made an ensemble by incorporating CNN with each of these models. 80% of the dataset were used for training the models and 20% for testing. After experiments, Inception-v3 shows the highest accuracy and recall of 99.29% and 99.73%, respectively.

Sharma andal. [11] use CNN model with CXR images in Python by the help of OpenCV to classify pneumonia. The model achieves an accuracy of 98.06% and a validation accuracy of 84.10%.

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Having an objective to design a lightweight, deployable and accurate model to detect pneumonia by applying a binary classification,Harsh Bhatt and Manan Shah[12] use a CNN utilizing different models of varying kernel sizes. 3×3, 5×5 and 7×7 kernels were used. Then an ensemble from the models were used to combine predictions for higher expectation of results. A publicly available dataset of CXR images on Kaggle was used in their study containing 5863 images belonging to two classes: Pneumonia and Normal. Applying threshold on combined predictions provides thebest result by achieving accuracy, precision, recall and F1-Score of 84.12%, 80.08%, 99.23% and 88.56% respectively.

Rong Yi andal.[13] develop a deep CNN architecture that extracts useful features from CXR and CT dataset available on the UCI Kaggle databases containing 5856 images belonging to two categories. 70% of the dataset were used for training, 20% for testing and 10% for validation. Using some techniques of preprocessing like intensity normalization and CLAHE to improve the visual-in-formation and quality of images, and data augmentation, the deep CNN model provides a training accuracy of 98.02% and a validation accuracy of 96.09% after various experiments.

ReshanMand al.[14] present other approaches consisting of the use of 8 pre-trained models namely, ResNet50, ResNet152V2, DenseNet121, DenseNet201, Xception, VGG16,EfficientNet, and MobileNet to detect pneumonia from CXR images. Two different datasets were used for the experiments to ensure the robustness and effectiveness of the model. The first dataset contains 5856 CXR images that was split into 80:15:5 for training, testing and validation set. The second dataset is ChestX-ray14 containing 112 120 CXR images, but only 1 431 is labeled as pneumonia. So, with a ratio of 80:15:5 again for training, testing and validation, 1 431 of normal images were taken to balance with the pneumonia labeled images. After experiments, MobileNet provides the best results of accuracy as 94.23% and 93.75% in the first and second dataset.

Zhadra K. andal. [15] investigates a CNN model for pneumonia classification using CXR images. The publicly available Kaggle pneumonia dataset was used for the experiments. VGG16 is followed by a CNN as input layer. After experiments, the model demonstrated an accuracy of 96%.

Muazzez B. and al. [16] proposed 2 models made from CNN and an ensemble learning with CXR dataset to classify pneumonia. For transfer learning, they used Inception-V3. They performed both binary and multiclass classification applying Synthetic Minority Over-sampling Technique (SMOTE) method for balancing the dataset.95% average accuracy for binary classification and 78% and 75% average accuracy for multiclass classification were obtained respectively from the models.

Dalya S. Al-Dulaimiand al.[17] proposed a CNN model that encompasses two stages. The first stage consists of image preprocessing and the second one is responsible for features extraction and image classification. A CXR dataset were used with the model and other two models, VGG16 and ResNet 50 to see the model's performance.The proposed CNN model provideshigh results of precision, recall, F1-score, and accuracy by 98%, 98%, 97%, and 99.82%, respectively and outperformed the two other models.

Poonam A. Rajput, Dr. Sanjay Buch [18] develop a CNN model without max pooling for diagnosis of pneumonia in optic to be more accurate and take account all features that might be given by each image. They used a dataset from Kaggle containing 5 863CXR images. Some preprocessing is necessary and some were used to improve image quality for better feature extraction like histogram technique. The result of the model test accuracy, precision, recalland F1-Score were89.42%,87.67%,96.66% and91.95 respectively.

Dr. Sunil and al. [19] use CNN and VGG16 to detect and classify pneumonia from CXR images.5863 CXR pictures from Kaggle were used. Preprocessing techniques consisting on transformations like zoom, shear and horizontal flip were performed to the dataset before they enter into the VGG16 based CNN model. It reaches a categorization accuracy of 91%.

III. PROPOSED METHODOLOGY

This work uses CXR images to detect pneumonia. Two available pneumonia datasets were mixed together into one to evaluate the performance of the model. Both datasets are available on Kaggle: Pneumonia-ChestXray dataset containing two classes normal and pneumonia, and the Covid19-Pneumonia-Normal Chest X-Ray Images Dataset, containing Covid19 class in addition to normal and pneumonia. Thenthe study just mixed pneumonia and normal from them into corresponding classes. Some preprocessing was necessary to get higher features from the images. Thus, LiteSRGAN [20] model was utilized in that perspective. And as the mixed dataset was imbalanced, a balancing technique was used to ensure robustness of the model. Then the dataset is deployed into the proposed lightweight model to classify the image

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into normal or pneumonia. The overall methodology is shown in Figure 1.

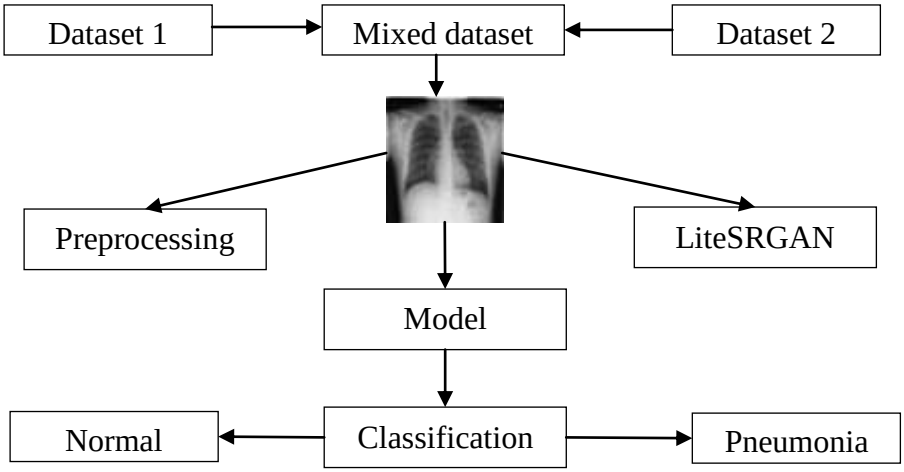

Figure 1-Overall methodology

3.1 Dataset and preprocessing

Two available datasets were mixed together into one and used in this work. The first one contains 5856 CXR images belonging to normal and pneumonia classes gathered from Kaggle. The second one contains also covid19 class in addition to normal and pneumonia, available on Kaggle also. Combining the same classes from both datasets, there are a total of 3385 normal CXR images and 6073 pneumonia CXR images gathered. Then a splitting ratio of 90:10 was applied for training and testing.The Table 1 and Table 2 give the repartition of the dataset into training, validation and testing sets for imbalanced and balanced datasets.

Figure 2 and 3 show some sample images from the mixed dataset before and after preprocessing

Types	**Total**	**Training**	**Test**	**Validation**
Normal	3385	2708	327	270
Pneumonia	6073	4858	602	607

Table 1-Dataset repartition: Imbalanced data

Types	**Total**	**Training**	**Test**	**Validation**
Normal	3500	4858	327	607
Pneumonia	700	4858	602	607

Table 2-Dataset repartition: balanced data

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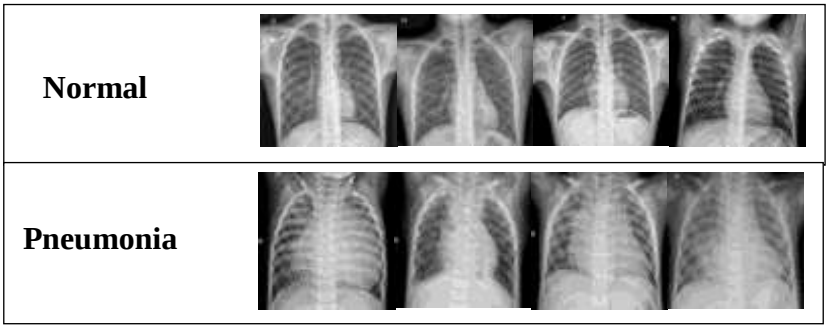

Figure 2-Sample CXR images from the mixed dataset without preprocessing technique

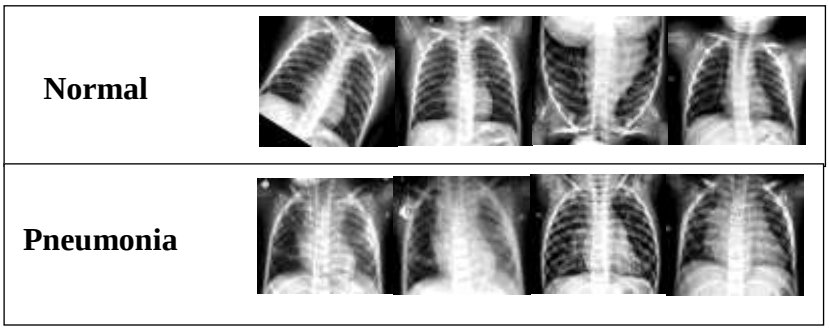

Figure 3-Sample CXR images from the mixed dataset after preprocessing

3.1.1 Preprocessing technique

There were 4 858 pneumonia images in the training set, but only 2 708 normal images. A balancing technique were performed to balance the dataset before deploying the model.
But before any balancing operation, a sharpening technique were used to improve image quality. Then, while balancing the data, three kinds of transformation were used: rotation, flip right left and flip top bottom.

3.1.2 LiteSRGAN

To go further into seeking image quality to ensure the effectiveness and robustness of the model, liteSRGAN [20] were applied to the dataset, performing the super-resolution task. This is the lightweight architecture version of SRGAN [21]which achieves a comparable super resolution image. As this paper aims to have a lightweight model, using LiteSRGAN contribute to achieve this goal. So, it was trained with the dataset to generate a model that is used into the proposed model to improve the image quality.

3.2 Proposed Model

This paper introduces a lightweight model to classify pneumonia. SSDLiteX [22] that is an enhancement of SSDLite [23]for small object detection, attract the attention on the possibility of having a more lightweight model but effectively accurate. Inspired from this model, this work adopts a new architecture using MobilenetV3Small [24] as backbone and a CNN with a smaller number of filters as auxiliary stage for the classification.

SSDLiteX , unlike SSDLite, uses a 3 × 3 depthwise convolutional layer and a 1 × 1 convolutional layer instead of a 1 × 1 convolutional layer, reducing the number of channels, a 3 × 3 depthwise convolutional layer with the reduced number of channels, and a 1 × 1 convolutional layer restoring the number of channels. Both use MobileNetV2 as backbone and attach the first layer of the auxiliary stage to the last feature extractor layer that has an output stride of 16 and the second layer is attached to the last feature extractor layer that has an output stride of 32 called C4 and C5 in [24].

The same architecture is used in this work but the difference is between the backbone and the number of filters at all auxiliary stages. The proposed model uses 32, 32 and 16 filters respectively at the first, the third and the last stage while SSDLiteX uses 256 filters in all stages. Then it is also designed for classification, and all customization led to this objective. It has It has 0.9 million parameters and 6.02 MB of size. The multiply-accumulate operations (MACs) are only 72 million.

The use of MobileNetV3Small and the reduction of the number of filters reduce

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considerably the number of parameters, contributing in a creation of a lighter model.

.The figure 4 below shows the auxiliary stage of the 2 models:SSDLiteX and the proposed model.

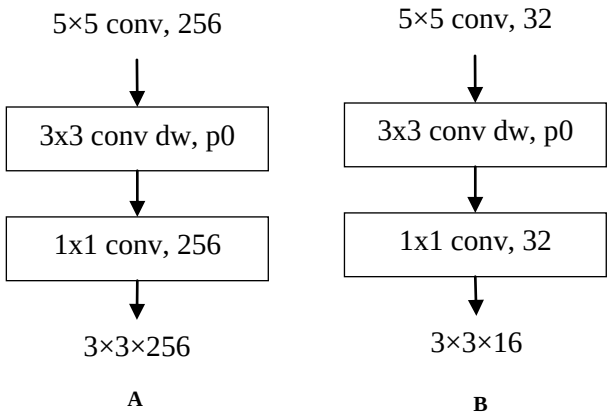

Figure 4-Auxiliary stage for (A) SSDLiteX and (B) the proposed model

IV. EXPERIMENTS AND RESULTS

4.1 Experiments

Lots of experiments were conducted to retain which is giving the best performance of the model. The main hyperparameters handled were the batch size and the epoch.

These manipulations were conducted on the preprocessed dataset without LiteSRGAN and the model with LiteSRGAN. The batch size of `16 were adopted and the model was implemented on Intel(R) Core (TM) i7-1255U CPU, 10 cores, 12 threads @ 2.30GHz, and 8 Gb RAM using TensorFlow and Keras with Python. The data were shuffled using a seed of 1000 to set the initial state of the random number generator to ensure the reproducibility and consistency in results.The epoch was 30.

To evaluate the model, usual metrics for classification were used. The next section gives more precision about them.

4.2 Evaluation metrics

To evaluate the model at the end of the training process, we adopted the following metrics:

The accuracy: This is the percentage of samples that were correctly categorized into corresponding classes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

TP represents the number of images correctlyclassified (True Positive). FP is thenumber of images misclassified to some other classes (False Positive), TN is thenumber of images correctly classified which does notbelong tothat class (True Negative) and FN is the number of images which belongs to a class but misclassified to another class.

It gives an overall effectiveness of the model and provides the ratio of the correctly predicted cases from the total number cases.

The precision:it calculates the number of correctpositive predictions from the total number of actualpredictions classified by the model as positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

The precision indicates how many of the predicted positive cases are actually positive.

Recall (Sensitivity or True Positive Rate): the score of true positive predictions to the instances thatactually belongto the positive class

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

The recall indicates how many of the actual positive cases the model correctly identifies.

F1-Score:an evaluation measure to estimate the model performance based on theaverage of precision and recall

$$\text{F1} - \text{Score} = 2\,\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

This metric is really useful to better measure the model's performance when there is an uneven class distribution.

The specificity (True Negative Rate): it measures the proportion of true negative predictions out of all actual negative instances.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

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The specificity indicates how many of the actual negative cases the model correctly identifies. High specificity means the model can identify most of the negative instances.

4.3 Results

4.3.1 Pneumonia classification without LiteSRGAN

Applying only some preprocessing mentioned in the subsection 3.1.1, the model shows a great effectiveness by providing an accuracy of 100% with a training loss of 0.01%. For the validation accuracy, the highest level of 99.07% is obtained with a loss of 6.09%. Talking about the test set, it shows an accuracy of 98.1% with a loss of 10.13%. The other metrics record great value, too. The precision, recall, F1-score and specificity are 98.05%,99.01%, 98.53%, 96.46% respectively.

The confusion matrix shows a slight misclassification

327	**12**
6	**602**

It shows that out of 327 normal cases, only 12are misclassified; and out of 602 pneumonia cases, 5 only are misclassified.

The ROC curve with a high value of AUC of 99% confirm these results and contribute in the effectiveness and robustness of the model.

The training and validation accuracy and loss go alongside during the process of training. Any overfitting might interfere in the training process.

The figure 5 below confirms the robustness of the model in discrimination of the classes from the ROC curve and AUC. The Accuracy and Loss of the model are shown in the figure 6.

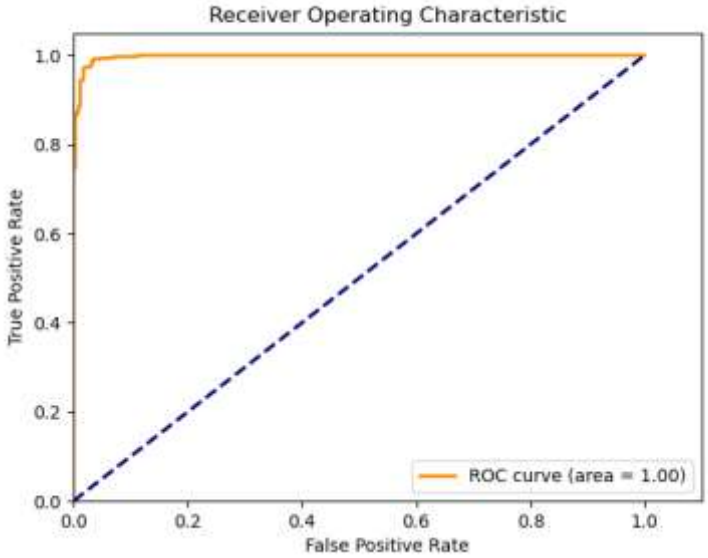

Figure 5-ROC Curvewith preprocessing techniques

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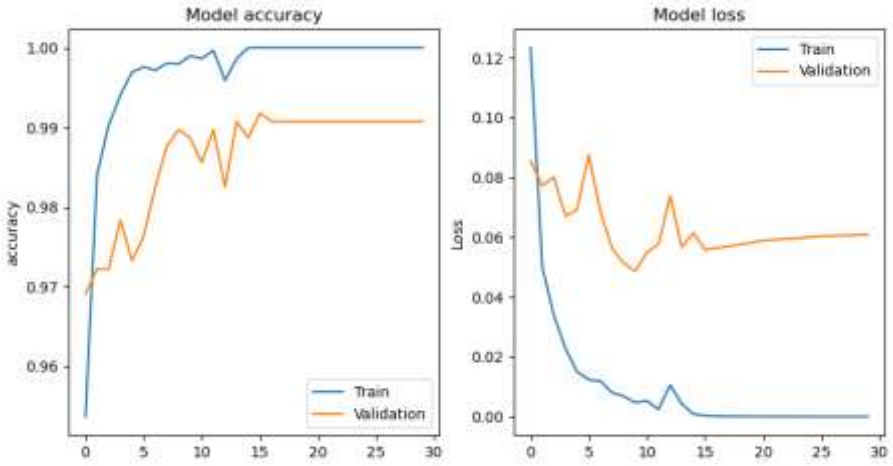

Figure 6-Preprocessed dataset - Model Accuracy and model Loss

4.3.2 Pneumonia classification with Lite SRGAN

Using preprocessing like sharpening and histogram equalization, the model has a great performance. If the input images had a super resolution, it might improve the performance of the model. So, the proposed model is used with LiteSRGAN to achieve this goal. The input image passes through LiteSRGAN first, to enhance its resolution, then the output goes to the proposed model for classification.

With a batch size of 16 and an epoch of 30, the results show a great accuracy of 100% with a loss of 0.02%. The model has learned the training dataset perfectly. Then, an improvement is noticed in the validation accuracy. It goes from 99.07% to 99.69% with a smaller loss of 2.05%. The model generalized well with new unseen data. The precision, recall, F1-Score and specificity are 98.05%, 99.34%, 98.77% and 96.76% respectively.The major contribution of LiteSRGAN is found in the generalization of the model, by considerably both reduce the lossand enhance the accuracy. The other metrics remain the same.

. The ROC curve and the AUC of 100% confirm the improvement shown in the validation accuracy. It shows more discrimination between normal and pneumonia.in fact, it demonstrates a perfect classification at all threshold levels.Figure 7 and figure 8 show the ROC curve and the accuracy and loss of the model.

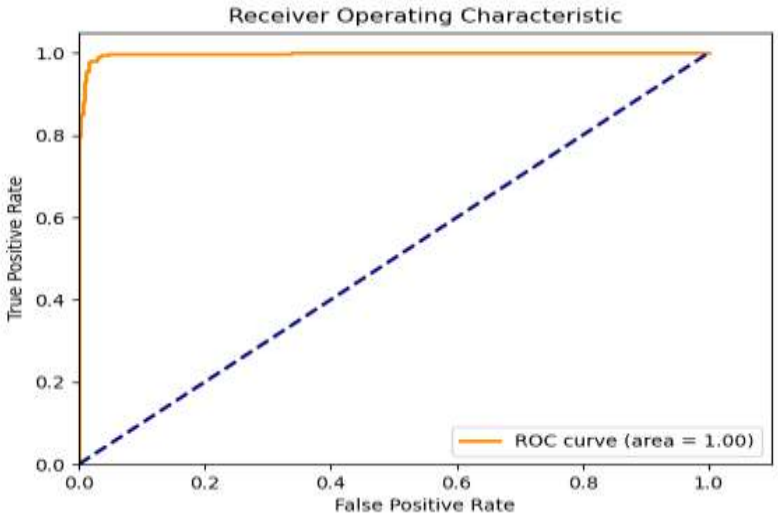

Figure 7-ROC curve and AUC with LiteSRGAN

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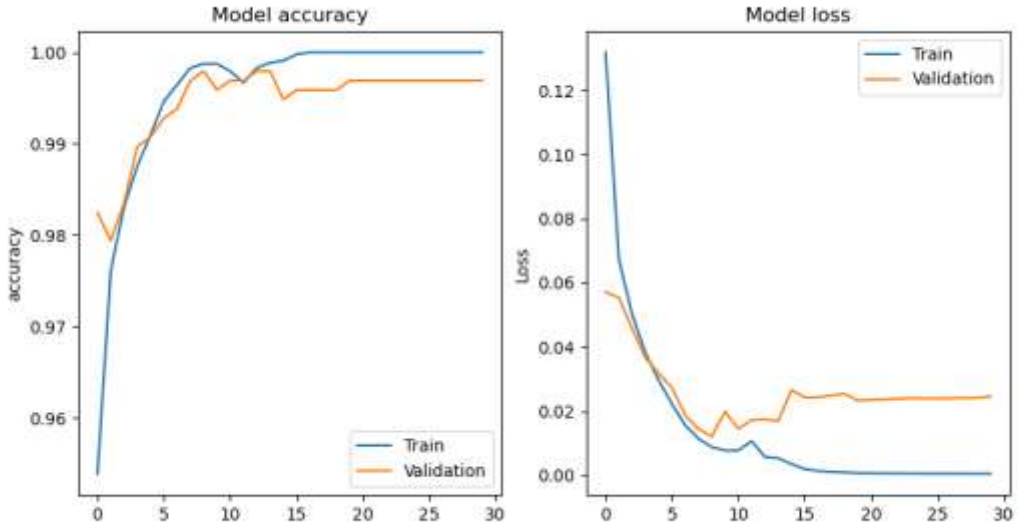

Figure 8-Model accuracy and loss-with LiteSRGAN

The confusion matrix remains the same as without the use of LiteESRGAN. It shows high ability into classifying each class.

327	**12**
6	**602**

So, only 12pneumonia caseswere classified as normal, which is minimal. And 6 normal only was misclassified into pneumonia. So, the present model worksexceptionally well also with improving the images quality with liteSRGAN. The Table 3 gives a comparison of the metrics values between the 2 types of datasets used in this paper.
LiteSRGAN contributed more in the model's generalization than the classical preprocessing.

Metrics	**Imbalanced dataset (%)**	**Balanced dataset (%)**
Accuracy	100	100
Validation accuracy	99.07	99.69
Precision	98.05	98.05
Recall	99.01	99.01
F1-Score	98.53	98.53
Specificity	96.46	96.46

Table 3-Metrics comparison between balanced and imbalanced datasets

CONCLUSION

This paper gives a deep learning-based model for pneumonia classification. A very lightweight but effective and robust model is presented. Applying some preprocessing techniques to improve the quality of images in the mixed CXR dataset, the results show accuracy, precision, recall and F1-Score of 100%,98.37%,99.18%, 98.77% and 97.05%. The validation accuracy of 99.07% implies the robustness and a great generalization to new data.As this study applies also another method to enhance the image quality, LiteSRGAN has been introduce to provide super-resolution images to extract better features. After using this methodology, the robustness in generalization improved from 99.07% to 99.69% with the corresponding loss decreased considerably. Image resolution play a great role in having higher results in a model. However, the proposed lightweight model is promising. Its reliability of use in such sensitive and critical health domain is shown. It would be accessible everywhere in Madagascar because it would run fluidly in a smartphone and any low-resource environment. The overall costs of pneumonia diagnosis are considerably reduced and it helps contributing in the health for all objective.

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