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Kidney stone classification with a lightweight model

Rahajaniaina Andriamasinoro[1], Ratiarison Adolph Andriamanga[2]

[1]*Associate Professor, Department of Mathematics, Computer Science and Applications, University of Toamasina, Madagascar*

[2]*Professor Emeritus, Department of physics and Applications, University of Antananarivo, Madagascar*

Corresponding Author: Rahajaniaina Andriamasinoro

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ABSTRACT: In this paper, we describe the use of deep learning-based model for classifying kidney stone images in order to overcome the lack of medical infrastructures within the hospitals in the development countries like Madagascar. Moreover, the use of mobile phones such as smartphone is very popularized in these countries. This situation leads us to perform a lightweight deep learning-based model inspired from the architecture of SSDLiteX. The Balancing technical was used to achieve higher performance. Our system provides 100% of accuracy, validation accuracy and F1-score. The result shows that this model surpass all lightweight models recorded to the state of the art about kidney stone classification. According to its nature, the proposed approach could run on the low resource environment like Smartphone. Thus, it is reliable and answer the need of the specialist within the hospitals in the development country.

KEYWORDS:kidney stone classification, lightweight deep learning, kidney stone imaging.

I. INTRODUCTION

Kidney stone has several causes such as medicines, individual's eating habit[13]. Kidney stone could amplify the risk urinary and kidney infection. So, it could provoke also the kidney damage and could result any problem into the bloodstream[14]. This disease could reach around 3 in 20 men and could be up to 2 in 20 women suffering them at some stage of their live[15].

Mobile phone is among the most popular products even in the development country. Furthermore, the advanced evolution of artificial intelligence has more impacts in several domains such as medical domain. In the last decade, Deep learning and transfer learning become essential to perform object classification task. Recently, more searchers use combination of methods or ensemble learning to achieve kidney stone classification such as [12][11][3]. So, their work permits early know the presence of the type of kidney stone. It aids the specialist to have an accurate diagnosis and prescribe the appropriate treatment. Unfortunately, their approach was more complicate and require an infrastructure more expensive. Like other African country, Madagascar suffers the lack of medical infrastructure mainly in the rural area. In fact, several specialists within the hospital practice manual recognition of kidney stone and these could be conducted to misdiagnosis. This situation is critical and precarious. it is time to ameliorate this one. For surpassing this situation, we propose an efficient lightweight deep learning based-model to achieve kidney stone classification task and permit automatic outcomes prediction. It could run on smartphone. Thus, it could alleviate the problems within the hospital in the African country like Madagascar because the cost of smartphone is more cheap than sophistically medical apparatus.

The remnant of this work is organized as follows. A brief related work on the different kidney stone classification methods is described in section II. Section III presents the material and methods. Results and discussion about our approach are discussed in section IV and section V conclude this paper.

II. RELATED WORK

In their paper, [12] developed two ensemble models named StackedEnsembleNet and PSOWeightedAvgNet for improving classification performance. They utilized a publicly available CT image dataset contains a total of 1799 CT images divided in two classes: normal and kidney stone. They resized all input images and they used 80/20%

train/test split distribution. In addition, data augmentation was applied to enhance the training data to avoid overfitting and improving performance. The StackedEnsembleNet is a two levels deep stack ensemble model. The first level was consisted of four transfer learning (TL) model formed by InceptionV3, InceptionResNetV2, MobileNet, and Xception. Each TL was trained separately on the kidney dataset and gave his prediction. They used the concatenation merge technique to combine the model predictions in order to form a unified feature representation. This one was treated by the second level of the StackedEnsembleNet that PSOWeightedAvgNet was the main component. The last one was based on optimization algorithm named PSO to determine the best weights for concatenating these predictions to obtain the final ensemble prediction. After experiment, the model achieved a maximum accuracy of 99.94%.

[8] presented the use of an array of classification methods such as light GBM, CatBoost, SVC, DNN, improved DNN…The dataset used for this study was a textual dataset which constituted by the textual information related to kidney stone classification. This information represented the medical reports, clinical notes, or patient histories. The dataset was pre-processed and split (80/20 as split ratio) by an essential library. After experiment, improve DNN was the most accurate. It gave an accuracy, precision, recall, and an F1-Score of 89 %, 90 %, and 89.5 %.

In [6], the authors proposed a comparison of various classification methods including deep convolutional neural networks (DCNN)-based approaches and classical ones. For this study, they used a dataset composed by 177 kidney stone images. The classification task was performed with the square patches in then surface or sections of kidney stone. They tested two methods (up sampling and down sampling methods) in order to balance the number of patches in each class. Thus, different combinations of geometrical transformations were applied to the original patches to augment the amount of data in each class. 10% of the original patches were used for test. For all experiments, they used ADAM as optimizer, 64 for batch size and early stopping. The DCNN-based approaches achieved the best precision and recall of 98%.

In their works, [1] performed a study to compare the suitability and performance of some deep learning approaches such as MobilNet, VGGNet19, InceptionNetV3 and ResNet50 V2 to know the presence or not of kidney stone. To achieve their goal, they used CRISP-DM data mining approach. The dataset used for this study was downloaded from GitHub. The dataset contains 1799 CT scan images of 500 patients. These ones consist of two classes: Kidney_Stone and Normal. During the data preparation, Various pre-process were applied to these images for obtain the format desired. To enhance the credibility and predictivity power, data augmentation was performed using some different parameters. The experiment showed that the InceptionNetV3 provided the best accuracy of 86%.

[11] described the use of some deep learning models such as VGG16, EANet, ResNet50, Inception, Swin Transformer and CCT for identifying kidney stone from CT scan images. The dataset consists of a collection of the pictures from some hospitals. Pre-processing techniques such as scaling, normalization and noise reduction were applied to the images to minimize the variability and ameliorate the result of future extraction. The scaling operation change for each base model. The splitting ratio 80/20 % for train/validation set was used. Thus, data augmentation approach was used to avoid the risk of overfitting and to enhance the performance of the models. In addition, various transformations were achieved for each model in order to improve the accuracy. Extensive hyperparameters tweaking was used to improve also the models' performance. They used Grid search or random search to alter iteratively these hyperparameters for optimizing the precision of the model and its generalizability. After experiment, the Swin Transformer offered the maximum in terms of accuracy and recall of 99,30% and 1.

[9] made a literature review of the kidney stone detection approach. Their study showed that the problem caused by the medical imaging for detecting the kidney stone could be resolved by the deep learning models. Their study also demonstrated that [4] achieved the best accuracy of 99,59%.

[7] compared some machine learning approach and convolutional Neural Network including Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF),Multilayer Perceptron (MLP), K-NearestNeighbour (kNN), Naive Bayes (BernoulliNB), and deep neuralnetworks using CNN. The dataset was formed by 221 x-ray images provided by the urology Department of Ataturk University. Various pre-processes (resizing, grayscale conversion, …) were applied to the x-ray images. Thus, these data in the dataset have been labelled as patient (182 images with kidney stone) or healthy (39 images) after consulted the opinion of the specialist in this department. As the dataset was imbalanced, resampling approaches were applied for balanced this one. 80% of the dataset was used for train and

20% for test set. StratifiedKFold crossvalidation(kFold = 5) was performed to the train data. The experimental results showed that DT had the highest F1score rate with a success rate of 85.3% using the combiningSMOTE – RANDOMUNDERSAMPLER (S+U) sampling method.

In their paper, [10] proposed deep learning model for classification the dataset into stone or not. In their study, they used an open-source dataset contained 1000 data of 0 or 1 downloaded from Kaggle. Then, they split the dataset into 80% for training and 20% for test set. Thus, sigmoid activation was used at the output layer to provide binary classification result. Data augmentation process was applied to improve the performance of the model. The model shows an approximative accuracy of 95%.

[3] developed an ensemble learning in order to combine the results of the three DCNN models for taking a decision. Majority voting approach was applied for final classification decision. The ultrasound kidney images consist of normal, stone, cyst and tumor types downloaded from various locations was used for testing the models. During the experiment, three others models were tested with the proposed ensemble model. The experimental result shows that the ensemble model achieves the highest performance in all evaluation metrics as accuracy, sensitivity, specificity, F1-score, precision, recall and dice coefficient of 98,49%, 98,7%, 98,21%, 98,5%, 99,51%, 97,69%and 98,82%.

III. MATERIALS AND METHOD

3.1. Proposed approach

Dataset publicly available in Kaggle web site was used to train and evaluate the model. Among 12446 images in dataset, 70% were used for training and the rest of this one was divided equally in to validation and test set. Thus, down sampling approach was applied to balance the data in train set for having better results. Then, this data was injected to the model to be classified into one of three types of kidney stone or healthy kidney. Figure 1 illustrates proposed approach.

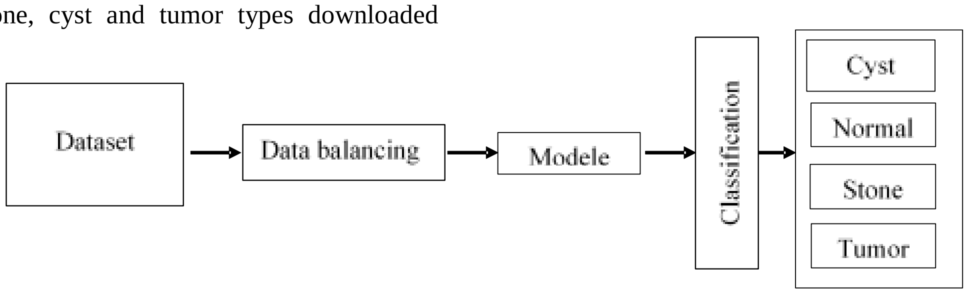

Figure 1- Proposed approach

3.2. Dataset description

The dataset consists of 12446 images formed by four classes cyst, normal, stone, and tumor. From this, 3709 are cyst, 5077 are normal, 1377 are stone and 2,283 are tumor. This dataset was downloaded from Kaggle web site. Figure 2 below shows samples images from the dataset.

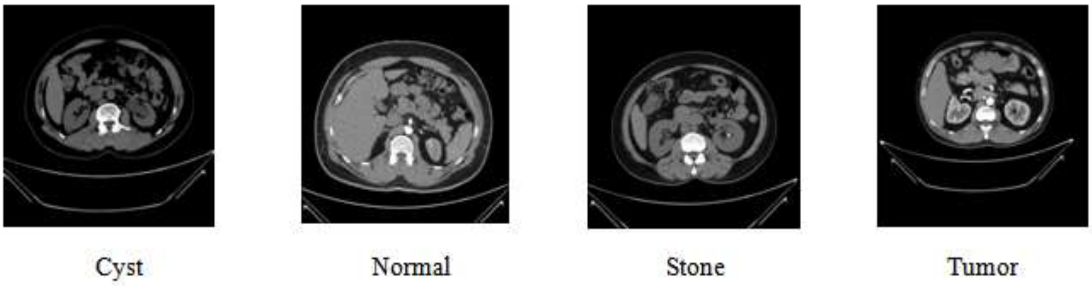

Figure 2- Sample images from the dataset

3.3. Proposed method

The aim of this study is to perform a lightweight model for classifying kidney stone. In fact, we used transfer learning technique. For this, we choice as backbone of the proposed model MobileNetV3Small. This one is the lighter version of MobileNetV3. The SSDLiteX auxiliary stage composed of a 3 × 3 depthwise convolutional layer

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and a 1 × 1 convolutional layer was used with a reduction number of filters. Rather than used 256 filters, our system was used 32, 32 and 16 filters at the first, the third and the last stage respectively. The last feature extractor layer that has an output stride of 16 called C4 is attached to the first layer of the auxiliary stage and the last one that has an output stride of 32 called C5 is attached to the second layer of auxiliary stage. These tricks ameliorate the performance and the quality of the model. The proposed model has only 0.9 million (3.44 MB) of parameters and has a size of 6.17 MB. So, it demonstrates that our model outperforms several lightweight models such as MobileNetV3Small that has 2.4 million of parameters and has a size of 9.83MB. Our model is already tested for other dataset [5] and it gave higher performance. Figure 3 illustrates the architecture of the proposed model.

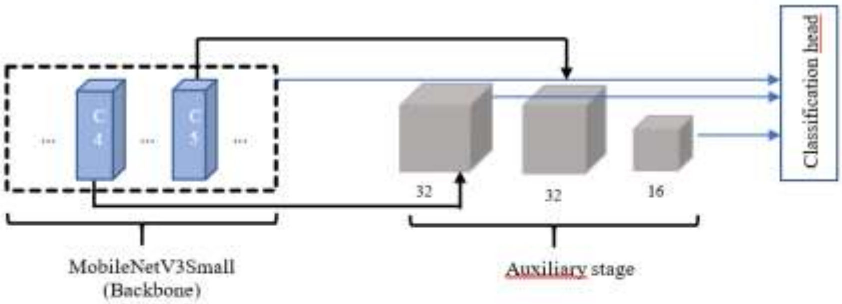

Figure 3 - Model architecture [2]

IV. RESULTS AND DISCUSSION

We present the proposed model's experiment result in this section. During the training process, a lot of experiments were conducted. Then, the batch size of 30 and an epoch of 40 achieve best result. Our model was implemented on Intel(R) Core (TM)i7-1255U CPU, 10 cores, 12 threads @2.30GHz, and 24 Gb RAM. The development task was performed in python, using TensorFlow, Numpy, Matplotlib, Scikit-learn, OpenCV, Panda and Keras libraries. A shuffling technique with a seed of 123 were performed in order to minimize loss, to have a lower variance and ameliorate the generalization of the proposed model. To evaluate the model, we refer to two metrics: the accuracy and F1-score. The accuracy gives the proportion of the correct prediction made by the model. Thus, this statistical measure performs the ration for both true positives and true negatives to the true total number cases. F1-score on the over hand can be interpreted as a harmonic mean of the precision and recall. It gives a balance between these two metrics.After experimental step, our model provides 100% for an accuracy, validation accuracy and the global F1-score. It shows that the proposed model is more efficient for the kidney stone dataset and outperforms all registered models for this domain. Figure 4 below illustrates the training and validation loss, the training and validation accuracy and the training and validation F1 score.

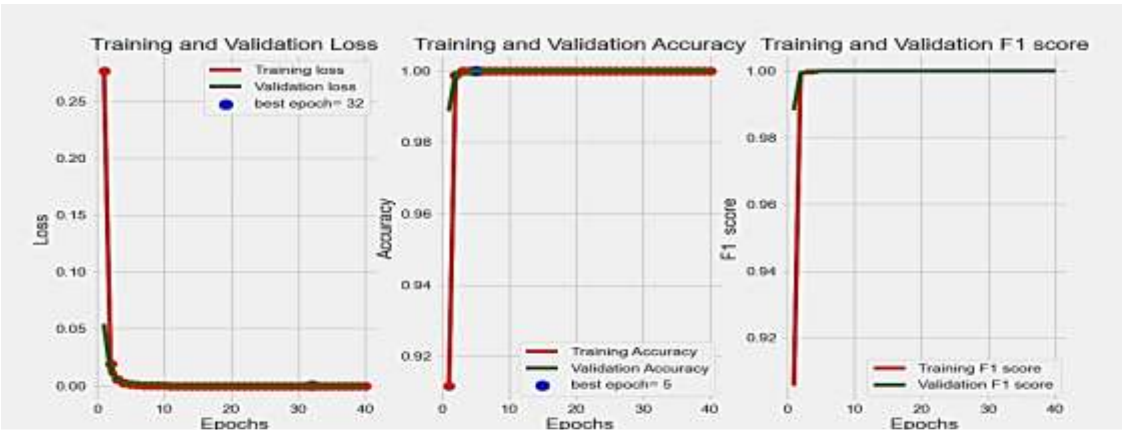

Figure 4 –the training and validation loss - the training and validation accuracy - the training and validation F1 score

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The confusion matrix below illustrates the global result of the classification task. It shows the high performance of the model into classifying each class.

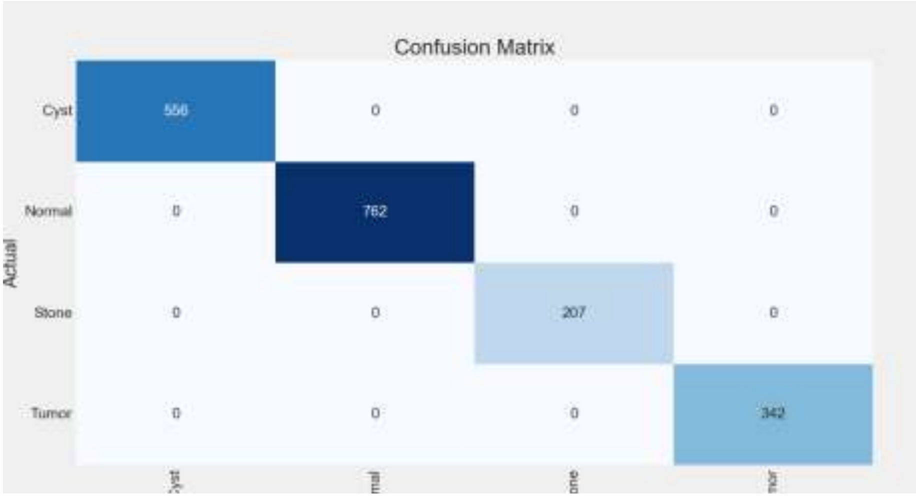

Figure 5 – Confusion Matrix

V. CONCLUSION

This study presents a kidney stone classification using transfer-learning based model. We have demonstrated our efforts to implement various techniques in order to have a lightweight model and the optimal results. Our results show that the presented model provides the highest values in all metrics and outperforms the state-of-the art recorded in this domain. Otherwise, the proposed system is more effective for classifying kidney stone images dataset. According to its nature, our model could be deployed on a lightweight mobile device such as smartphone. In fact, it could be also filled the gap of lack medical infrastructures within the hospitals in the developing country like Madagascar.

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