Applying Multi-CNNs model for detecting abnormal problem on chest x-ray images

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***Abstract*— Image diagnosis is the significant problem in medicine. Nowadays, with modern facilities that allow doctors to diagnose early and accurately disease, limiting unnecessary treatment procedures. By that way, the image diagnosis is at the forefront of the processing diagnosis and treatment of the disease. Heart and lung failure accounts for more than 500,000 deaths annually in the United States and is most commonly screened for using plain film chest X-Ray (CXR). With the growing number of patients, the doctors must overwork, so he cannot counsel and direct take care of his patient. So, a computer system that supports image classification is needed. In this paper, we propose a deep learning model to detect abnormal sentisy in chest x-ray images. The proposed model uses multiple Convolutional Neural Network to decide input image, this is called Multi-CNNs. Input data is the digital chest X-ray image dataset that was collected from 6/2017 to 3/2018 at An Binh Hospital, HCM, VN (AB-CXR-Database). Each component of the Multi-CNN is a convolutional neural network that is developed base on ConvnetJS library. The output of the proposed model is Normal/Abnormal density. In this paper, we also propose a method for synthesizing the results of the components of the model which we are called Fusion rules. The experimental results 96% in our x-rays image dataset showed the feasibility of a proposed Multi-CNNs model.**

Keywords*— *image classification, Chest x-ray image, Convolutional neural network (CNN), chest x-ray image classification using CNN)

I. INTRODUCTION

Heart and lung failure accounts for more than 500,000 deaths annually in the United States and is most commonly screened for using plain film chest X-Ray (CXR)[2]. In Vietnam and most of the countries in the world, x-ray and CT images are used much in the cancer sign diagnosis. Chest x-ray images, or radiographs, provide a single view of the chest cavity. CT scans can provide a complete view of the chest internals and can thus be used to more easily detect shape, size, location, and density of lung nodules [3]. However, CT scan technology is expensive and is often not available in smaller hospitals or rural areas. By contrast, basic chest radiographs are relatively cheap and fast and expose the patient too little radiation, so they are usually the first diagnostic step for detecting any chest abnormalities [3].

In recent years, machine learning has been used in the detection and classification of medical images to assist in the early detection of expression pathology. Especially, it's can help the radiologist reduce workload. There are many classification methods is proposed to solve this problem. At present, popular methods for solving image classification problems, such as K-Mean, K-NN, deep neural network, Support Vector Machine (SVM)… One of the popular approaches is used method of Artificial Neural Networks for pattern classification problem. Convolutional neural network (CNN)[1] is one of the deep learning models that has garnered much interest from researchers in recent years. It's used a lot of in image classification, image recognition, language translate, medical diagnostics, and many other domains, etc. and giving a result with high accuracy.

Therefore, in this paper, we propose a model called Multi-CNNs based on convolutional neural network. In this paper, we also propose a method for synthesizing the results of the components of the model which we are called Fusion rules. The experimental results 96% in our x-rays image dataset showed the feasibility of a proposed Multi-CNNs model.

II. BACKGROUND AND RELATED WORK

A. Background

Deep Learning is a new area of Machine Learning research. Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, and bioinformatics, etc [4], which give a result with high accuracy.

Convolutional neural networks (CNN) is a special architecture of artificial neural networks, proposed by Yann LeCun in 1988 that has been widely applied to a variety of pattern recognition problems, such as computer vision, speech recognition, image classification, image recognition, language translate, medical diagnostics, etc. A CNN is composed of layers that filters (convolve) the inputs to get useful information. These convolutional layers have parameters (kernel) that are learned so that these filters are adjusted automatically to extract the most useful information for the task at hand without feature selection. CNN is better to work with images. Normal Neural networks do not fit well with image classification problems.

ConvNetJS is an open JavaScript library for training Deep Learning models (Deep Neural Networks) entirely in your browser[5]. We used it to build an application for training and testing Multi-CNNs model which we proposed in this paper.

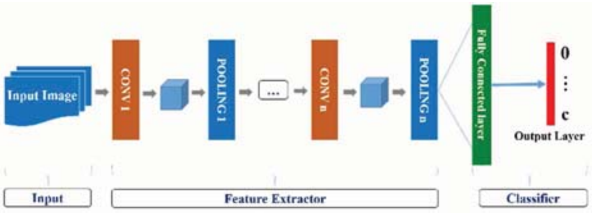


Figure 1: CNN Image Classifier Model

Figure 1: shows an overview of convolutional neural network architecture for image classification

B. *Related work*

The problem of detecting abnormal objects in medical imaging is a great practical problem to support physicians in diagnosing diseases in medicine, the more accurate the detection results, the more effective in the process of diagnosis and treatment of doctors. Using deep learning methods for detecting abnormal problem on medical images that has attracted many interests from researchers. In [2], developing a simple preprocessing pipeline using digital image processing techniques and expert radiologist advice; Create a pipeline that can apply three neural network architectures that have proven successful in classification tasks, GoogLeNet, InceptionNet, and ResNet, on our cohort of CXR images; Use neural network visualization techniques to understand what type of features our model weights most heavily. In [3], this study uses a revolutionary image recognition method, deep learning, for the classification of potentially malignant pulmonary nodules. They report results of their initial findings and compare performance of deep neural nets using a combination of different network topologies and optimization parameters. Classification accuracy, sensitivity and specificity of the network performance are assessed for each of the four topologies. In [6], they propose a novel work to first segment CT scan image to obtain all probable nodule candidates. Then they perform SVM based classification of the candidates based on image moments and texture features. Potential nodule candidates are marked, and other candidates are omitted. They perform the test on 50 images from Tata Cancer Research Centre CT images. Also compared the results of proposed technique with nearest neighbor classifier. It was evident that by taking statistical features from GLCM matrix, performance of the nearest neighbor classifier improved significantly. However SVM performance was observed to be consistent. Out of 50 images with nodules, their system detected all fifty nodules correctly whereas miss classifying 8 candidates in total. False positive was about 6% whereas false negative was zero. Involves matching these features to yield a result that is visually similar.

III. MULTI-CNNS MODEL FOR DETECTING ABNORMAL SENTISY IN CHEST X-RAY IMAGE

A. *Multi-CNNs model architecture*

As mentioned above, in this paper we propose a model that is called Multi-CNNs. This model consists of three components, each of which is a CNN (Figure 2). For each component, we call them the following: CNN-128F, CNN-64L, CNN-64R.

All CNN components were run on a PC with specification: Intel Core i7 - 7700, 8 GB RAM, Windows 10 pro 64bit, Google Chrome browser.

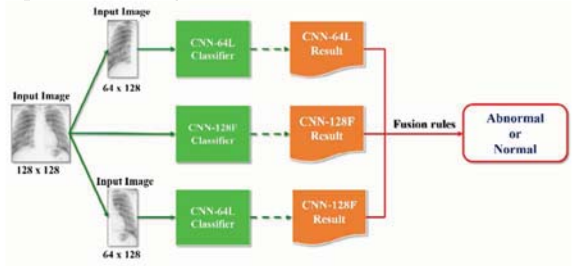


Figure 2: Multi-CNNs Model architecture

With each input image, the result of each CNN classifier of the model component is normal or abnormal and a probability value and then we use a rule to compute those results which we called Fusion Rule. It mentioned in the section III.C.

B. *CNN components of Multi-CNNs Model*

a) CNN-128F

CNN-128F, which has an architecture as Figure 3 used to train on 128 x 128 chest x-ray image dataset (Dataset 1). This dataset will mention in section IV.A.

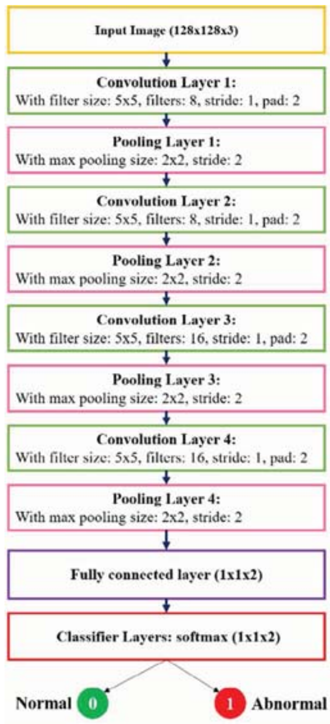


Figure 3: CNN-128F architecture

Figure 3: shows an overview architecture of the CNN-128F component which is part of the Multi-CNNs Model.

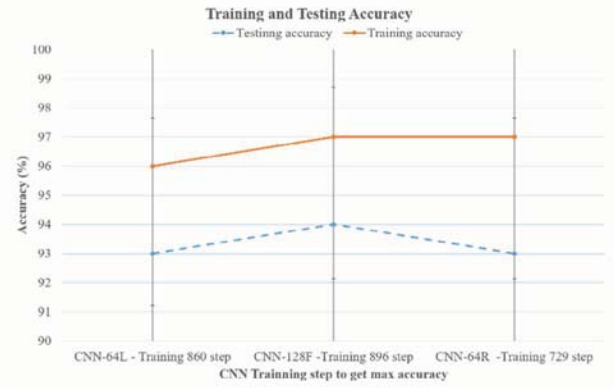


Figure 4: Testing accuracy and Training accuracy

b) CNN-64L and CNN-64R

CNN-64L and CNN-64R, which has an architecture as Figure 5 used to train on 64 x 128 left and right chest x-ray image dataset (Dataset 2, Dataset 3). Those datasets will mention in section IV.A.

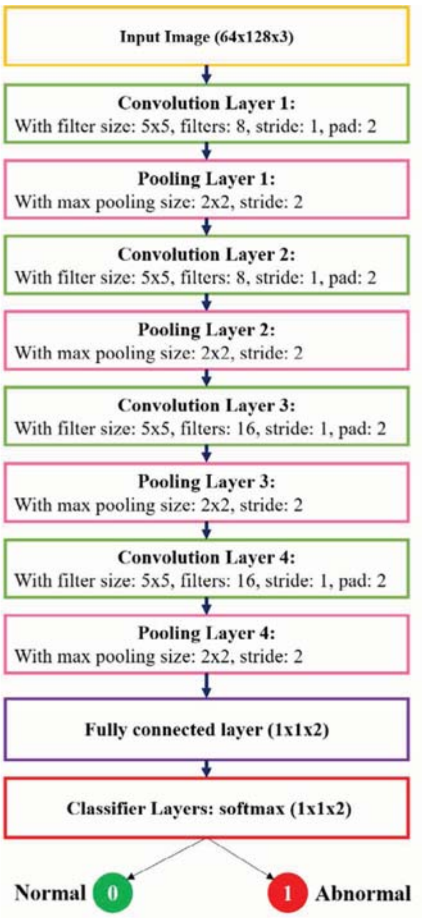


Figure 5: CNN-64L, CNN-64R architecture

Figure 5: shows an overview architecture of the CNN-64L and CNN-64R component which is part of the Multi-CNNs Model.

CNN-128F, CNN-64L, CNN-64R performance was assessed using a held-out test set with 100 independent images consist of 50 normal and 50 abnormal chest X-Ray images. Overfitting was assessed by comparing the training accuracy and testing accuracy that is showed as Figure 4.

c) CNN components accuracy evaluation

Assess the accuracy of the classification is very important, because it allows to predict the accuracy of the classification results of future data. Accuracy helps to compare different classifiers. With each CNN classifiers component of Multi-CNNs Model, we used Hold-out method for evaluating.

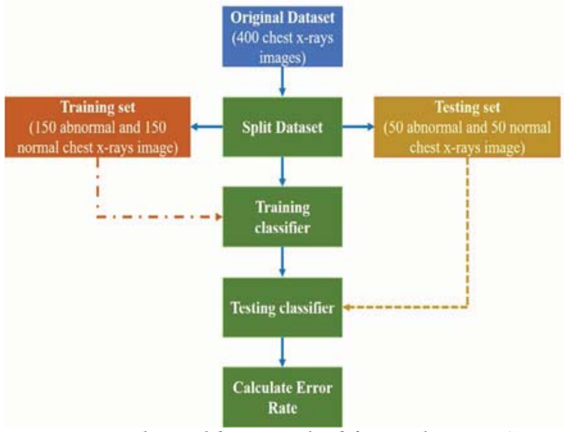


Figure 6: The Hold-out method for evaluating CNN component

Figure 6: shows an overview of the Hold-out method which we had used for evaluating the accuracy of CNN-128F, CNN-64L, CNN-64R components of Multi-CNNs Model

Table 1: Training and testing result for each CNN classifier component:

Network / Result	CNN-128F	CNN-64L	CNN-64R
Training time (minutes)	360	25	150
Max Accuracy on test set (%)	94	93	93
Classification loss (%)	1	10.5	4
L2 Weight loss (%)	1	1.8	2

C. Fusion rules base on Conclusion tree

As mentioned at section III.A, in Multi-CNNs model, we have used an association rule to compute these results which we called **Fusion Rule**. In this section, we describe detail about it.

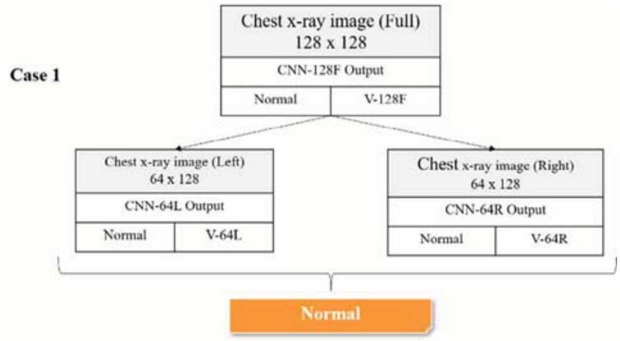
For each CNN output, we derive the result consist of two values, one of which is the input image of the class, and the probability value of that image belongs to. We call the probability value as follows:

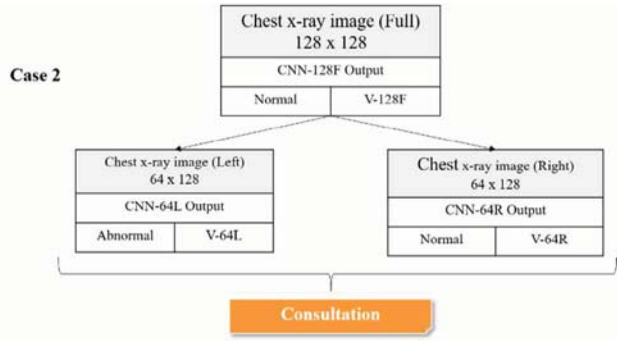
+ V-128F: This is the probability value after the calculation for the input image of CNN-128F.

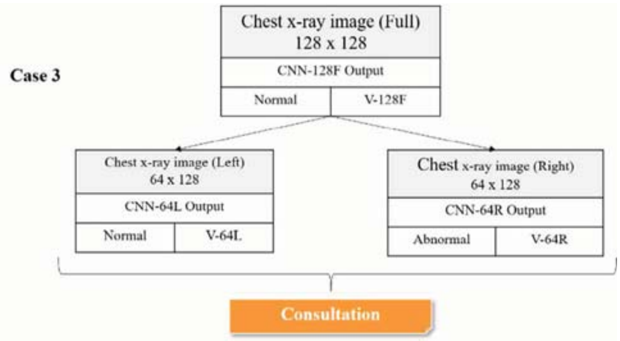
+ V-64L: This is the probability value after the calculation for the input image of CNN-64L.

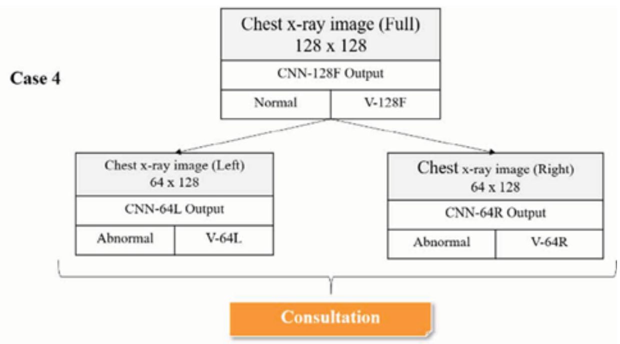
+ V-64R: This is the probability value after the calculation for the input image of CNN-64R.

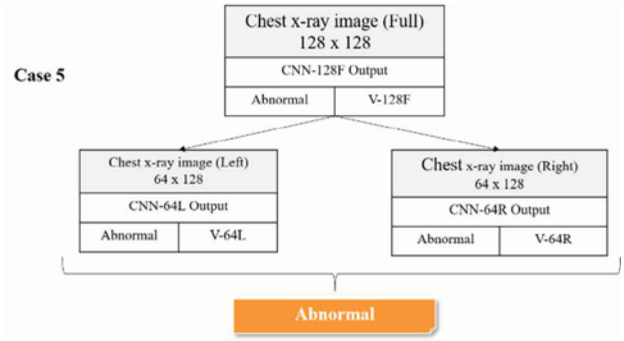
In this Fusion rule we divide into 8 cases as below to make the final conclusion of the classification model:

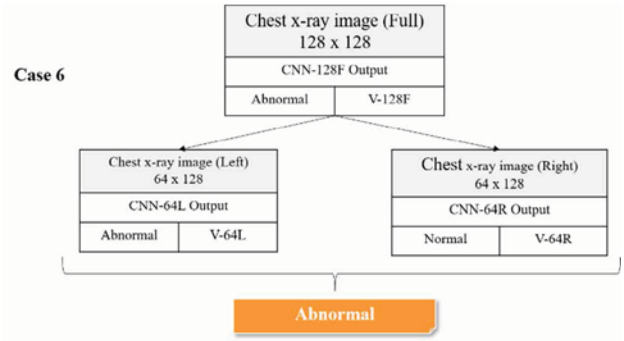


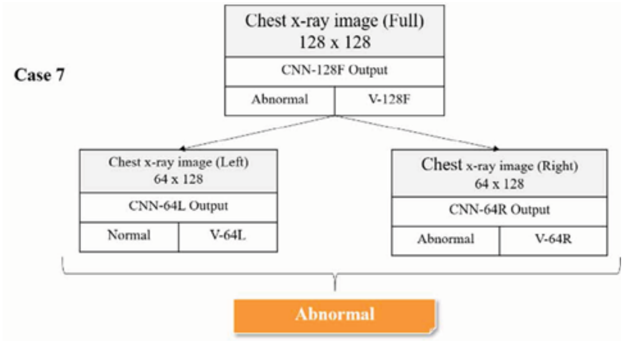


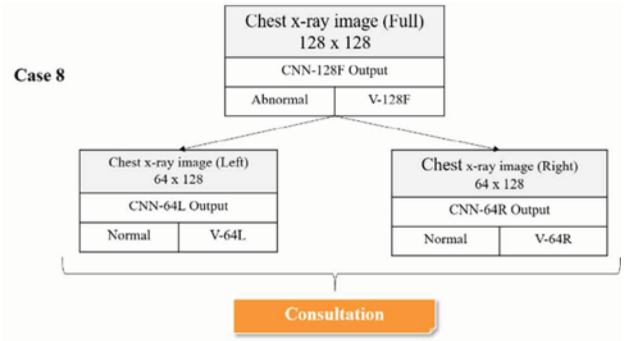












In the **Consultation cases** (case 2, case 3, case 4, and case 8), we use three methods to calculate and make the final conclusion abnormal or normal as below:

- **FR 1: Fusion rule based on Average**

Case	Probability value	Result
case 2	$V = \frac{V\text{-}128F + V\text{-}64R + (1 - V\text{-}64L)}{3}$	$V > 0.5 \rightarrow$ Normal $V <= 0.5 \rightarrow$ Abnormal

case 3	$V = \frac{V\text{-}128F + V\text{-}64L + (1 - V\text{-}64R)}{3}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 4	$V = \frac{V\text{-}128 + (1 - V\text{-}64R) + (1 - V\text{-}64L)}{3}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 8		V <= 0.5 ➔ Normal V >0.5 ➔ Abnormal

- **FR 2: Fusion rule based on overall**

Case	Probability value	Result
case 2	$V = \frac{V\text{-}128F + V\text{-}64R + (1 - V\text{-}64L)}{4}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 3	$V = \frac{V\text{-}128F + V\text{-}64L + (1 - V\text{-}64R)}{4}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 4	$V = \frac{V\text{-}128 + (1 - V\text{-}64R) + (1 - V\text{-}64L)}{4}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 8		V <= 0.5 ➔ Normal V >0.5 ➔ Abnormal

- **FR 3: Fusion rule based on conflict regions**

Case	Probability value	Result
case 2	$V = \frac{V\text{-}128F + (1 - V\text{-}64R)}{2}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 3	$V = \frac{V\text{-}128F + (1 - V\text{-}64L)}{2}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 4	$V = \frac{2 * V\text{-}128 + (1 - V\text{-}64L) + (1 - V\text{-}64R)}{4}$	V > 0.5 ➔ Normal V<=0.5 ➔ Abnormal
case 8		V <= 0.5 ➔ Normal V >0.5 ➔ Abnormal

For example:

Tested with image named abnormal_test_4_full.jpg:

+ CNN-128F: Normal V-128F = 0.98609

+ CNN-64L: Abnormal V-64L = 0.92142

+ CNN-64R: Abnormal V-64R = 0.99969

FR1: V= 0.354993333 ➔ Abnormal

FR2: V= 0.266245 ➔ Abnormal

FR3: V= 0.5127675 ➔ Normal

IV. EXPERIMENTS AND DISCUSSION

A. Dataset

For this project, our primary dataset is chest x-ray image of patients that was collected from 6/2017 to 3/2018 at An Binh Hospital, HCM, VN (AB-CXR-Database). The dataset contains 400 digital images were labelled, which we divide into a training set with 300 images, a testing set with 100 images. For each image, it was labelled 0 for normal, 1 for abnormal by an expert who has 15 years experience in the field of imaging diagnosis. We have build 03 datasets from images which collected:

- **Dataset 1**: Containing 400 chest x-ray images with dimension 128x128.

- **Dataset 2**: Containing 400 left chest x-ray images with dimension 64x128.

- **Dataset 3**: Containing 400 right chest x-ray images with dimension 64x128.

B. Methods

- Pre-processing image

With each original chest x-ray image has been labeled, we scaled it to 128 x 128 size. And then we divided it into two parts to get 3 input images including left chest x-ray, right chest x-ray and full chest x-ray image. From this, we have constructed three datasets as mentioned above.

- Training Multi-CNNs Model's

To train the model, we trained each CNN component of the model with the CNN architecture mentioned in Section III with the following parameters:

- Learning Rate: 0.01, Momentum: 0.9,

- Weight decay: 0.0001, Batch size: 1,

- Method for training is Adadelta.

- Multi-CNNs Model's accuracy evaluation

As mentioned above, assessing the accuracy of the classification model is very important. To evaluate the model that we have proposed, we have selected any 50 chest X-ray images *(consist of 25 labelled abnormal and 25 labelled normal images)* from [10, 11] for model testing which we proposed. The results of the 96% accuracy evaluation that we will present are detailed in the next section.

C. Results

a) The result of Multi - CNNs Model testing:

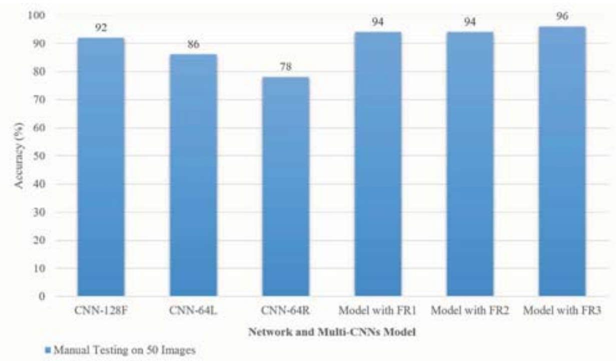


Figure 6: Result of testing on 50 chest X-Ray images

Table 2: Result of each CNN component of model on 50 chest x-ray images:

Network / Result	CNN-128F		CNN-64L		CNN-64R	
	Amount	(%)	Amount	(%)	Amount	(%)
True	46	92	43	86	39	78
False	4	8	7	14	11	22

Table 3: Result of Multi-CNN model with 3 methods computes:

Fursion rule / Result	Multi-CNNs Model results					
	G1		G2		G3	
	Amount	(%)	Amount	(%)	Amount	(%)
True	47	94	47	94	48	96
False	3	6	3	6	2	4

V. CONCLUSION

In this research, we proposed Multi-CNNs model and a method for synthesizing the results of the components of the model which we are called fusion rules.

The proposed Multi-CNNs model consists of three components: CNN 128F, CNN 64L, and CNN 64R. These components are developed based on CNN.

The proposed model used the association fusion rule in order to combine the results. The fusion rules process to integrate the results in 8 cases to make the final conclusion of the Multi-CNNs classification model. In 8 cases of this rule, we tested three combined methods for cases with unclear conclusions.

We tested Multi-CNNs model with Fusion rules to detect abnormal sentisy on 50 chest X-ray images *(consist of 25 labelled abnormal and 25 labelled normal images)* which were chose from [10, 11]. The accuracy results 96% showed the feasibility of the proposed model when it combines this rule.

VI. ACKNOWLEDGEMENT

We would like to thank doctor Chung Gia Vien for helping us with labelling chest X-ray images. We also thank the Diagnostic Department of An Binh Hospital, HCM has allowed us to use database chest X-ray image database of the hospital to perform this study.

VII. REFERENCES

[1] A. Krizhevsky, I. Sutskever and G.E. Hinton, "Imagenet classification with deep convolutional neural networks," Advances in neural information processing systems, pp. 1097-1105, 2012

[2] Tataru, Christine, et al. "Deep Learning for abnormality detection in Chest X-Ray images." (2017).

[3] Gruetzemacher, Richard, and Ashish Gupta. "Using deep learning for pulmonary nodule detection & diagnosis." (2016).

[4] Ghasemi, F.; Mehridehnavi, AR.; Fassihi, A.; Perez-Sanchez, H. (2017). "Deep Neural Network in Biological Activity Prediction using Deep Belief Network".

[5] A.Karpathy, "ConvNetJS: Deep learning in your browser," http://cs.stanford. edu/people/karpathy/convnetjs, 2014.

[6] Puranikmath. Veena, Y. S. Lalita, and Shivaganga Patil (2015). "Automated Lung Nodule Detection and Classification using Morphological Segmentation and Texture". International Journal of Ethics in Engineering & Management Education, ISSN: 2348-4748, Volume 2, Issue 5, May 2015.

[7] Yang, He, Hengyong Yu, and Ge Wang. "Deep learning for the classification of lung nodules." arXiv preprint arXiv:1611.06651 (2016).

[8] Bhandare, Ashwin, et al. "Applications of Convolutional Neural Networks." International Journal of Computer Science and Information Technologies (2016): 2206-2215.

[9] Vo, An Tien, Hai Son Tran, and Thai Hoang Le. "Advertisement image classification using convolutional neural network." Knowledge and Systems Engineering (KSE), 2017 9th International Conference on. IEEE, 2017.

[10] JSRT Database - http://db.jsrt.or.jp/eng.php - download date: 17.5.2018

[11] Dataset from Indiana University hospital network - https://openi.nlm.nih.gov/imgs/collections/NLMCXR_png.tgz - Download date: 17.5.2018

[12] Nhon Do, Hien Nguyen, A reasoning method on Computational Network and Its applications, 2011 International Multi Conference of Engineers and Computer Scientists, IMECS 2011, ISBN: 978-988-18210-3-4, pp. 137-141, Hongkong , March 2011

[13] Tran, Hai Son, Thai Hoang Le, and Thuy Thanh Nguyen. "The Degree of Skin Burns Images Recognition using Convolutional Neural Network." Indian Journal of Science and Technology9.45 (2016).

[14] Amato, Filippo, et al. "Artificial neural networks in medical diagnosis." (2013): 47-58.