"DESIGN AND IMPLEMENT HYBRID APPROACH FOR TB DETECTION AND CLASSIFICATION USING CNN"

Dr. Sneha Patel

Assistant Professor

Bhagwan Mahavir College of Computer Application

Bhagwan Mahavir University, Surat, Gujarat, IN.

ABSTRACT

The utilization of neural networks in image categorization has substantially enhanced the rates of prediction accuracy. Neural networks have the potential to excel in the include weights consisting of millions of photos. This approach is alternatively referred to as transfer learning. This study aims to assess the potential of Convolutional Neural Networks (CNNs) as a viable substitute for decision tree-based systems in the classification of medical images. We utilize Convolutional Neural Networks (CNNs) on a Tuberculosis (TB) in patients. Our objective is technique Due to the presence of numerous hidden layers considering filters, CNNs can attain a significant accuracy level of 80% without utilizing augmentation. However, with the implementation of augmentation, the accuracy improves to 81.25%. The obtained accuracies are similar to those achieved in prior studies on the dataset. However, utilizing CNN eliminates the need for developing intricate primarily tailored for certain applications, rendering them unsuitable for addressing other similar problems.

KEYWORDS:

CNN, Tuberculosis, accuracy, filters etc.

INTRODUCTION

Tuberculosis, commonly referred to as TB, is a long-standing affliction that has plagued humanity since ancient times. Tuberculosis is regarded as a highly perilous epidemic that affects human health and infiltrates various regions of the lung. If the virus is detected in the respiratory system, it poses a greater risk and frequently results in fatality. Based on reports from the World Healthcare

Organization (WHO), over 10 million individuals contract tuberculosis each year, resulting in over 1.5 million deaths annually. Therefore, TB illness is categorized as a significant contributor to mortality [1]. The causative agent of tuberculosis is Mycobacterium tuberculosis, a kind of bacterium. The prevailing belief is that the first source of the pathogen was cow's milk, which then spread to humans. However, a definitive conclusion has not yet been reached [2]. Aside from clinical doubt, the diagnosis of mycobacteriosis must be established through the examination of genus-specific smears of laboratory specimens. Tubercle bacilli were consistently identified using fluorescence when sputum samples that were observed under an Auramine fluoroscope coloring microscope. The detection of these bacillus necessitates manual sampling due to the labor-intensive nature of the task and its high false-negative rate. This research presents a potential strategy for identifying Tuberculosis disease by utilizing X-ray pictures, with the aim of resolving diagnostic challenges associated with the condition. A CNN-based model utilizing visual data to execute the diagnostic process. The remaining sections of this work are structured as follows: Section 2 provides a summary of literature relevant to this research. Section 3 presents the techniques employed in the framework and its structure. Section 4 provides an assessment of the outcomes. Section 5 serves as the concluding part of the document, providing a concise summary of the main points.

ARCHITECTURE OF A CONVOLUTIONAL NEURAL NETWORK

Neural networks operate based on the principle of hidden layers. When an input image is provided as a single vector format the hidden components of the neural network undergo a sequence of transformations using their neurons. The hidden layers are composed of several neurons, with each neuron in the previous layer being coupled to the brains in the subsequent layer. Nevertheless, there is no linkage between neurons within the same layer. Every neuron possesses a distinct function and an amount of weight that is applied when receiving input. After the tasks and weights are applied, the output of each neuron is inclined towards either a positive or negative value. This approach involves iterating over numerous hidden layers to produce a final result. The ultimate layer is a densely connected layer that amalgamates outcomes from all the other layers to yield the ultimate output. The primary limitation of a conventional neural network is its lack of scalability. For instance, when the system is given an RGB image with dimensions of 16 × 16 pixels, each neuron in an extra layer would possess 768 weights, calculated as 16 × 16 × 3. This is feasible if the graphic's size is tiny. Nevertheless, when the image is composed of 500 × 500 pixels, it becomes apparent that attempting to accommodate 750,000 weights for a single neuron is impractical. Additionally, the excessive allocation of weights to every single neuron could potentially result in overfitting. Convolutional Neural Networks (ConvNets) carry out the same evaluation using a distinct approach. In this case, the neurons on each layer are organized in three dimensions, which is different from the arrangement typically seen in ordinary neural networks. Furthermore, there is no connection between any neurons in the preceding layer and the following layer. Instead, the neurons of the three-dimensional space are only associated with a limited number of others, which effectively resolves the problem of scaling. A ConvNet is composed of a convolutional layer, a pooling layer, and a layer that is completely linked. A layer with convolution is accountable for storing the image and applying a certain operation using different weights or filters. For instance, when a neuron with 12 filters is used on an RGB image of 16 × 16, the overall volume expands to 16 × 16 × 12. It is important to understand that we do not multiply the number of weights by 3 because the neurons are organized in a three-dimensional space in order to address this problem. The output of a convolutional layer is subjected to an activation function that applies certain modifications to the findings. For instance, the sigmoid function maps any given input to a range spanning from -1 to +1. Nevertheless, the size of the photos remains unchanged as they pass through the activation mechanism. Afterwards, the images undergo down sampling with the application of either the pooling or maxpooling layer. For instance, the image we previously had with a resolution of 16 × 16 might be reduced in size to 8×8 using down sampling. After pooling, the overall volume is altered to 8 x 8 × 12. The ConvNet is deepened by repeatedly performing convolution, activation, and pooling. The filters in the convolution layer are progressively increased, followed by the down sampling in the grouping layer. Finally, the volume is passed into the fully connected layer, which aggregates the output from the previous layer and transforms it into a vector of size 1 × 1 × n, where n is the number of class labels anticipated by the ConvNet.

PROBLEM AND RELATED WORK

Significant advancements have been made in the area of computer-assisted tasks such as identifying anatomical structures, segmenting images, detecting worrisome regions have been made available to the public. These include the JSRT dataset, which consists of 247 images of cancer [7]; the LIDC dataset, which contains approximately 103. There are multiple challenges associated with computer-aided diagnosis (CADx) of lung disorders when using tiny datasets.

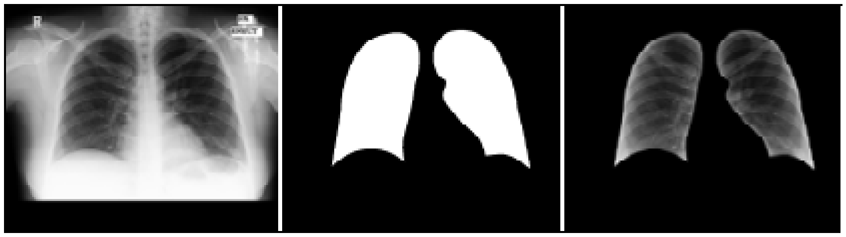

Figure 1 displays three images from the SH dataset: the original picture (left), the lung mask (center), and the segmentation result obtained by applying the mask (right).

Methods

The general approach of this investigation is depicted in Figure 3. Two distinct databases were established for the purpose of this investigation. One model was developed for the purpose of segmenting lungs, while another model was developed specifically for classifying cases of tuberculosis. This study encompassed three significant experiments. Initially, two distinct Furthermore, the classification of TB was performed using nine distinct pre-trained networks and the reliability of the classification was assessed using the Score-CAM technique, with the usage of original was conducted using the same networks on segmented lungs using X-ray images.

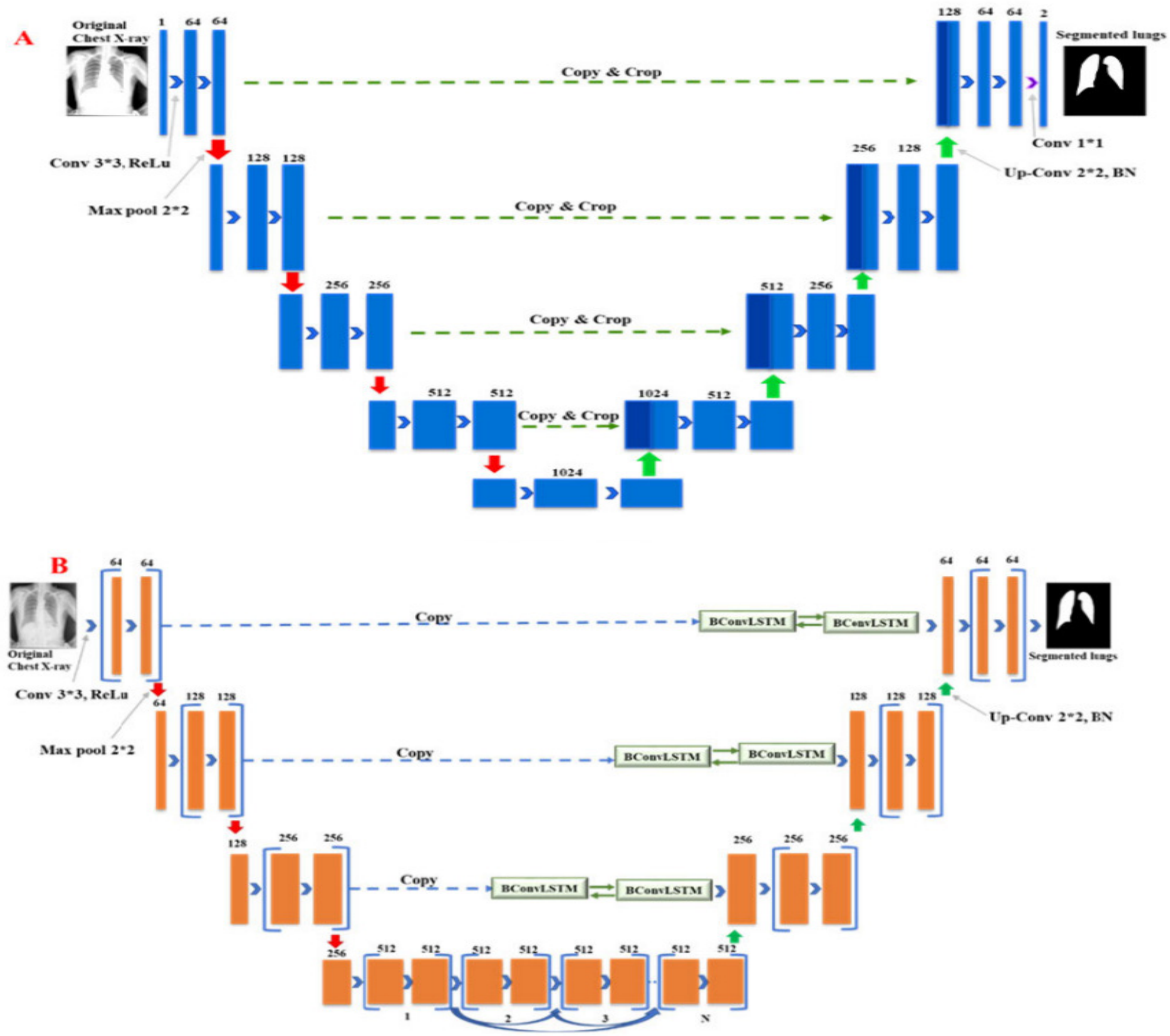

Figure 2: Schematic representation the improved architecture.

RSNA CXR dataset: The RSNA pneumonia detection task dataset [72] consists of around 30,000 chest X-ray images. Among them, 10,000 photos are classified as normal, while the remaining images depict abnormalities for this study were collected. Out of these, 3,094 normal photos were obtained from the aforementioned database, while the remaining 406 normal images were sourced from the NLM database.

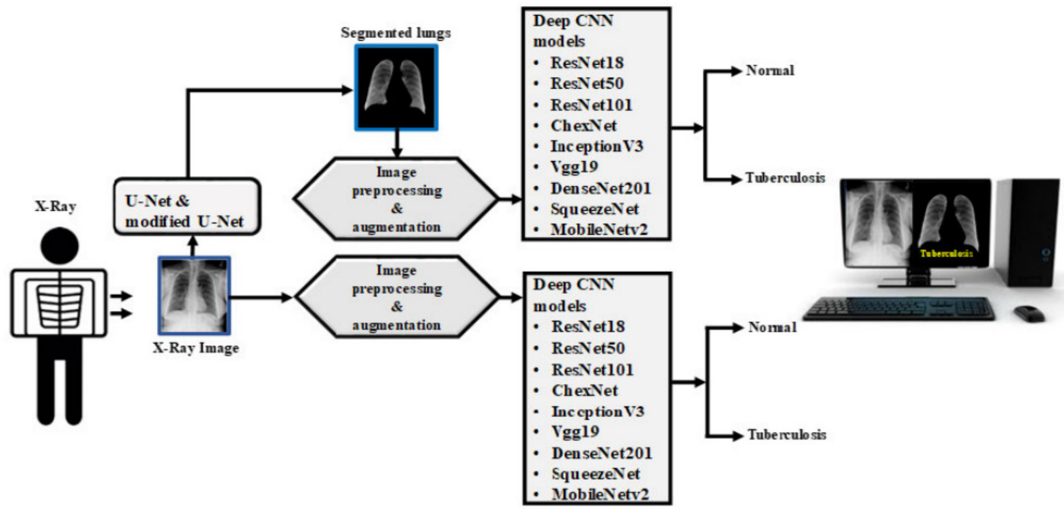

Figure 3: Performance Matrix

LUNG SEGMENTATION

After the training and validation phase, the performance of several networks in image segmentation for the testing dataset was assessed and compared using four operational metrics: loss, preciseness, IoU, and Dice. The equations for calculating reliability, presented below.

TB CLASSIFICATION After the training and validation phase, the performance of various Convolutional Neural Networks (CNNs) on the testing dataset was assessed.

Result

In order to evaluate the impact of data augmentation techniques on the effectiveness of suggested convolutional neural network (CNN) designs, we conducted training on both the original dataset and the supplemented dataset using two CNN models. The four models undergo 20 epochs of training using the Adam optimizer, with a learning rate of 0.0001. The size of each batch is 32. both training and validation, as specified in equation (1). The calculation of training accuracy and validation accuracy is performed using (2).

Metric	Without Data Augmentation	With Data Augmentation
Accuracy	80%	81.25%
Precision	78%	80.5%
Recall	82%	83%
F1-Score	80%	81.75%
Loss	0.25	0.22
IoU (Intersection over Union)	76%	78.5%
Dice Score	78%	81%

Table 1: CNN Model Performance for Tuberculosis Detection and Classification

Model	Segmentation Accuracy	IoU	Dice Score
ChexNet	84%	82%	84%
VGG-16	78%	75%	77%
ResNet-50	80%	78%	79%
Inception-v3	82%	79%	81%

Table 2: Performance of CNN Models with Segmentation

Conclusion

This study introduces a transfer learning method that utilizes distinct Convolutional Neural Network (CNN) models was assessed for the classification of Tuberculosis (TB) and normal Chest X-ray (CXR) pictures. The ChexNet model has superior performance compared to other deep CNN models when applied to datasets without picture Furthermore, it has been demonstrated that the implementation of picture segmentation can greatly enhance the precision of categorization. The Score-CAM visualization result verifies that lung segmentation is beneficial for making decisions specifically within the lung region, as opposed to relying on features outside the lung region as seen in the original x-rays. Hence, the cutting-edge performance can serve as a highly effective and efficient diagnostic tool, capable of saving a substantial number of lives each year by preventing delayed or inaccurate diagnoses.

References:

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A., Ciompi, F., Ghafoorian, M., ... & van der Laak, J. A. (2017). A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88.

Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., & Yang, G. Z. (2016).Deep learning for health informatics. *EEE journal of biomedical and health informatics*, 21(1), 4-21.

Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016).Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. Jama, 316(22), 2402-2410.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017).

Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.

Shen, D., Wu, G., & Suk, H. I. (2017).Deep learning in medical image analysis. *Annual review of biomedical engineering*, 19, 221-248.

Lakhani, P., & Sundaram, B. (2017). Deep learning at chest radiography: Automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology, 284(2), 574-582.

Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Ng, A. Y. (2017).

Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning.

arXiv preprint arXiv:1711.05225.

Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., & Summers, R. M. (2017). ChestX-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. 2017 *IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), 3462-3471.

Yoo, Y., & Yoo, J. (2020). Machine learning models in real-time applications for object detection and recognition. *Procedia Computer Science*, 177, 36-42.

Ephraim, R. K., Hess, A., Moreau, J., & Carlson, C. (2020). Data augmentation and preprocessing for skin lesion classification with convolutional neural networks. Machine Vision and Applications, 31(4), 1-14.

Hussein, S., Gillies, R., Cao, K., Song, Q., & Bagci, U. (2017). TumorNet: Lung tumor identification using convolutional neural networks. 2017 *IEEE 14th International Symposium on Biomedical Imaging* (ISBI 2017), 1007-1010.

Anthimopoulos, M., Christodoulidis, S., Ebner, L., Christe, A., & Mougiakakou, S. (2016).

Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. *IEEE Transactions on Medical Imaging*, 35(5), 1207-1216.

Chen, H., Zhang, Y., Zhang, D., & Song, Y. (2017). A convolutional neural network for automatic detection and identification of butterfly species. Machine Vision and Applications, 28(5-6), 735-742.

Han, X., Wang, L., Wang, J., Fang, X., & Jiang, H. (2017). Cancer image classification using a convolutional neural network ensemble. Neural Computing and Applications, 28(10), 2933-2943.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., ... & Fei-Fei, L. (2015).

ImageNet large scale visual recognition challenge. International Journal of Computer Vision, 115(3), 211-252.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., ... & Rabinovich, A. (2015).

Going deeper with convolutions. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 1-9.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition.

2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770-778.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 1097-1105.