Predicting Tuberculosis from X-Rays By Using Deep Learning

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Introduction

Tuberculosis (TB) is a significant health issue for most countries across the world. According to Pasa, Golkov, Pfeiffer, Cremers, & Pfeiffer (2019), tuberculosis is the fifth leading cause of death across the globe, with 1.5 million annual deaths and 10 million new cases reported every year. Notably, it can be easily treated; therefore, the World Health Organization recommends broad and systematic screening to facilitate the management of the disease. The normal and tuberculosis chest X-ray samples can be seen in Figure-1 and Figure-2. The most common measure used for monitoring and diagnosing lung diseases such as tuberculosis is the chest X-ray (CXR), as they are affordable and easily accessible (Stirenko et al., 2018). The development and evolution of modern technologies such as deep learning modalities allow scientists to automatically detect the lung diseases from CXR images even for radiologists without certified expert knowledge on radiography. Deep learning is a branch of artificial intelligence with a network capable of learning unlabeled, unstructured, and unsupervised data. The NIH Chest X-rays images and text data can incorporate deep learning methods like Convolutional Neural Networks (CNN) and Recurrent Neural Network (RNN) to predict tuberculosis and thus enhance management and reduce deaths. This paper proposes a deep learning technique which is CNN and efficacy of using it in predicting tuberculosis using the National Institution of Health (NIH) chest X-ray images. The proposed model achieved %98 validation accuracy scores which is over state-of-art models.

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Figure-1 Tuberculosis chest X-ray sample

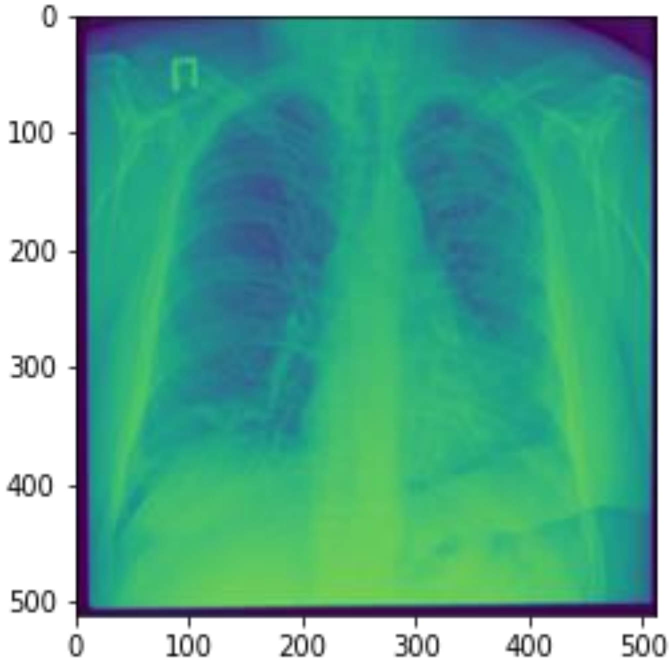
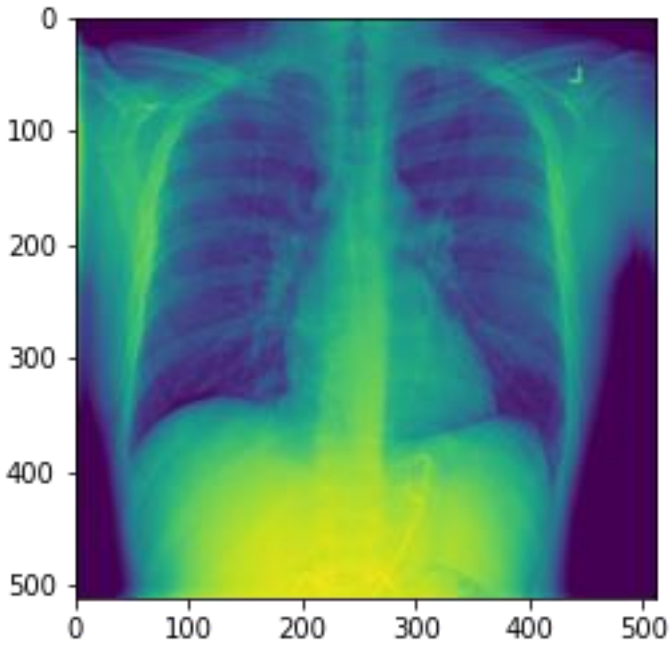


Figure-2 Normal chest X-ray sample



Significance of Deep Learning Techniques

The most common measure used in the screening of tuberculosis is CXR. However, the uses involve a long, complicated process. They require expert radiologists, yet most affected developing countries do not have enough radiologists with sufficient skills in interpreting results from the CXR (Stirenko et al., 2018). Similarly, Lakhani & Sundaram (2017) say that there is a lack of radiology expertise necessary for interpreting tuberculosis in many regions across the world, which consequently impairs work-up efforts and screening efforts. Deep learning technology describes artificial intelligence where computers can help human beings to perform tasks such as using existing data to examine relationships. Deep learning techniques thus provide an effective intervention as they increase accuracy in prediction tuberculosis.

Furthermore, identification of people with high risks of developing tuberculosis is a critical consideration of a need for imaging techniques that easy to use and accurate in making a prediction. Imaging is mainly a key screening measure for people suspected to have pulmonary tuberculosis among work-up patients (Lakhani & Sundaram, 2017). Therefore, deep learning techniques, which are cost-effective and efficacious automated methods, can help and facilitate screening and earlier detection of tuberculosis.

Convolutional Neural Networks (CNN)

According to Lopez-Garnier, Sheen, & Zimic (2019), CNNs, along with increasingly high medical datasets, have increased classification and detection capabilities. The CNNS are biologically inspired and use hierarchical methods to make assumptions about the location of images using pixels learned through information hierarchies. The layers are used to detect layers where the higher layers help in detecting sophisticated features. (World Health Organization, 2011) suggest that CNNs have abilities to outperform human experts in classification, recognition, and processing of images and texts, among other tasks. Lopez-Garnier, Sheen, & Zimic, (2019) designed and developed a trained CNN with abilities to identify *M. Tuberculosis* in a Microscopic Observed Drug Susceptibility (MODS) culture. CNN was trained on the 12510 MODS dataset and showed an accuracy of between 91% and 99% hence the efficacy of using deep learning in predicting tuberculosis using the NIH data.

DCNN (Deep CNN) is one supervised type of deep learning technology that incorporates multiple layers and has been successful in the classification of images (LeCun, Bengio, & Hinton, 2015). The abilities to present datasets like images at multiple levels are one significant advantage of deep learning. For instance, DCNN can whole objects in higher levels, parts of objects in intermediate level, and pixels with blobs, values, and edges at lower levels. The multiple layers make data analysis easy and increase the abilities to produce accurate results.

Deep learning techniques rely on big data sets to produce accurate and reliable results. Unfortunately, Wang, Peng, Lu, Lu, Bagheri, & Summers (2017), acknowledges that the incorporation of machine learning in CXR continues to be a challenge because of a lack of techniques that mimic high reasoning of human beings as well as a shortage of large-scale machine learning datasets.

Furthermore, the chest X-ray data set released by the National Institution of Health (NIH) with 100,000 anonymized CXR images form 32000 patients could be mislabeled as usual when they are not specific to TB (Wang et al., 2017). Additionally, Stirenko et al. (2018) assert that there is an increased belief that deep learning modalities are only valid when used with more massive datasets with more than 10,000 images and ineffective with smaller data sets of less than 1000 images as they are associated with lower accuracies and weak predictions. The small data on tuberculosis from NIH thus creates efficacy issues surrounding the use of deep learning in predicting tuberculosis. However, the embedding of texts and images, the use of pre-learning tools, augmentation of datasets, and ensembles help in countering the issues of small tuberculosis chest images available in NIH.

Most chest pathologies have large datasets that make a diagnosis using deep learning feasible. However, the use of deep learning in the diagnosis for some chest pathologies such as tuberculosis remains a challenge because of the available small dataset. For this reason, Lakhani & Sundaram (2017); Sivaramakrishnan et al. (2018) demonstrated that pre-trained architectures like ImageNet could effectively produce diagnosis results and detection of TB on small datasets. According to Lakhani & Sundaram (2017), training of ImageNet used in deep convolutional neural networks (DCNN) augments processing techniques, which consequently leads to increased accuracy in prediction of tuberculosis as opposed to the incorporation of untrained ImageNet. The pre-training ImageNet feature enables the DCNN to make accurate predictions even with small datasets. Besides, datasets can also be augmented by contrasting or rotating images. The augmentation features are essential to improving the performance of the deep learning technique.

Gozes & Greenspan (2019) found that deep learning modalities can be enhanced by incorporating learning image features that are specific to CXR using hospital scale datasets with metadata and pathology labels. Gozes & Greenspan (2019) proposed pre-training features, NIH Chest Xray14, and stated that metadata is an accurate and objective label for the element as it helps in countering the noise in the dataset. According to Gozes & Greenspan (2019), the MetachexNet feature is better than ImageNet in terms of predicting tuberculosis and the generalizability of results. Lakhani & Sundaram (2017); Sivaramakrishnan et al. (2018); Gozes & Greenspan (2019) all agree that deep learning can lead to the attainment of accurate results in predicting tuberculosis using CXR by adding learning features to the machine learning architecture. Small datasets are, therefore, not a limitation to the uses of deep learning for predicting tuberculosis.

The feature reduction is also an important part of deep learning models due to process time and eliminate overfitting. So there some approaches like principal component analysis, auto encoders to reduce features (Karim, A. M et al, 2019). However, auto encoder can be used as a model to data augmentation, reduction, and mapping input features to output features to reconstruct the image again (Karim, A. M et al, 2020).

The pertaining feature incorporation in deep learning architecture allows for random initialization so that the machine learning technology can relearn from the medical images provided. Another challenge with the use of deep learning is over-fitting, which occurs when trained models fit that dataset well but do not generalize unseen cases. However, measures such as model regularization or dropout can be used to overcome the challenge of over-fitting. In our model regularization and dropout parameters are used to fine tune the model.

Machine learning technologies in neural networks are nonlinear and can scale depending on the training data available. The stochastic training algorithm in deep leaning implies that they are specific to the different types of training, and the associated weights may give different predictions whenever the algorithm is run (Brownlee, 2019).

Method & Results

In the proposed model a custom CNN model is used to train and test NIH Chest X-ray dataset to predict an input image either indicates the tuberculosis or not. The dataset from Kaggle includes 4200 images consists of 3500 is normal and 700 tuberculosis. The test size is specified as 0.2 to train the model with 80% and test with 20% of the dataset. Images are resized to an 250x250 array. The convolution filters are used amount of 32, 64, 128 (3x3) and at the flattening layer 28800 features are handled. On the flatten layer the dense layers are added to reduce the features 128 and then the output layer gives the 2 values to classify the images is tuberculosis sample or not. Totally 6 convolutional, 2 dense and 4 maxpool layers are used to build the model. The optimizer has chosen as 'Adam' where the activation functions are set as 'relu' and at the output layer is used as 'softmax' to have best classification results. The batch value is provided as 32 and the epoch is 20 that gives the maximum accuracy value and does not improve after 20^{th} epoch. After the model successfully trained the test accuracy results for the classification hit the result over 98%. The confusion matrix, train and test accuracy and loss graphs can be seen in Figure-3, Figure-4 and Figure-5. The model evaluation is made on precision, recall, f-score values and the details are shown in the Table-1.

Figure-3 Loss graph for training and the test

Figure-4 Accuracy graph for training and test

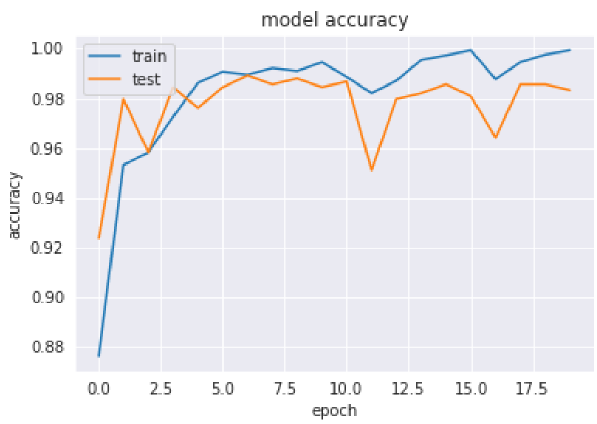


Figure-4 Confusion matrix for validation

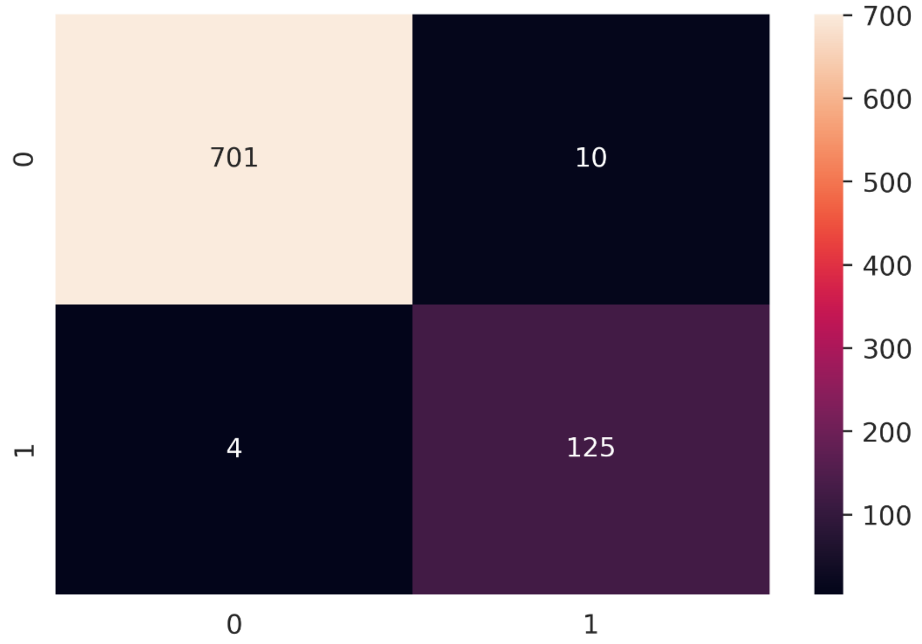


Table-1 The scores of model evaluation

	precision	recall	f1-score	support
Normal	0.993	0.996	0.994	679
Tuberculosis	0.981	0.969	0.975	161
Accuracy	0.990	0.990	0.990	0.990476
Macro Avg	0.987	0.982	0.985	840
Weighted Avg	0.990	0.990	0.990	840

Conclusion

There are wide ranges of deep learning technologies such as neural networks, CNN that can be used in predicting tuberculosis in chest x-ray images provided by NIH. With deep learning technologies, users can accurately predict the presence of tuberculosis, even with minimal expert knowledge. Therefore, deep learning has more advantages than the standard modality that involves the use of chest x-ray images that require significant specialist knowledge. As a result, clinicians will be better placed to reduce deaths and new cases of tuberculosis across the world. The tuberculosis datasets available are small, which undermines the use of machine learning technologies that rely on large amounts of data to make an accurate prediction.

Additionally, tuberculosis datasets are limited to the use of strategies such as crowd sourcing, as the data requires expert knowledge. However, the limitation of small data set can be countered by using pre-training learning features, augmentation of datasets. The training of images increases the abilities of the deep learning tools to make accurate predictions of the presence of tuberculosis. In the proposed model CNN architecture successfully helps to classify tuberculosis over chest X-ray image dataset which gives over 98% validation accuracy scores. The regularization parameters and dropout improve the model success and provide better classification results. For further improvements an optimization algorithm can be implement to find optimum parameters itself.

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