International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 10 Issue: 05 | May 2023 www.irjet.net p-ISSN: 2395-0072

APPLICATION OF CNN MODEL ON MEDICAL IMAGE

Shubham Verma[1], Kushagra Anand[2], Kartik Verma[3], Ms. Deepti Gupta (Guide)[4], Ms. Kavita Saxena(Co-Guide)[5]

[1]Shubham Verma, Dept. of Computer Science Engineering, Maharaja Agrasen Institute of Technology, Delhi, India
[2]Kushagra Anand, Dept. of Computer Science Engineering, Maharaja Agrasen Institute of Technology, Delhi, India
[3]Kartik Verma, Dept. of Computer Science Engineering, Maharaja Agrasen Institute of Technology, Delhi, India
[4]Assistant Professor Ms.Deepti Gupta, Dept. of Computer Science Engineering, Maharaja Agrasen Institute of Technology, Delhi, India
[5]Assistant Professor Ms.Kavita Saxena, Dept. of Computer Science Engineering, Maharaja Agrasen Institute of Technology, Delhi, India

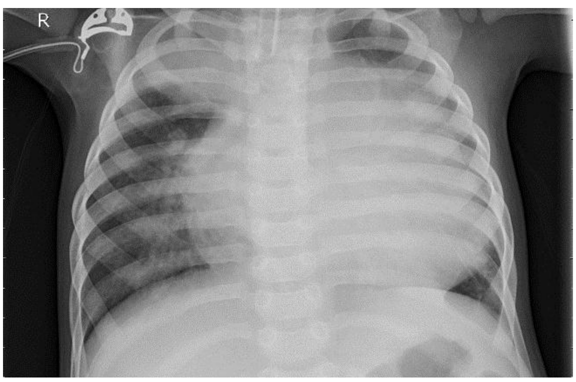
---***---

Abstract - *There have been several studies that have used deep learning techniques to detect disease from medical images such as chest X-rays or CT scans. These techniques involve training a model on a large dataset of labeled images, where the model learns to recognize patterns and features that are indicative of disease related to chest infection. One example of a study that used deep learning for this purpose was published in the journal Radiology in 2017. In this study, the authors trained a convolutional neural network (CNN) on a dataset of chest X-rays and found that the CNN was able to accurately classify images as normal or infected with an AUC (area under the curve) of 0.97. Another example is a study published in the journal Chest in 2018. The authors found that their model had an accuracy of 89.6% and an AUC of 0.94. Overall, the use of deep learning and for disease detection shows promising results and has the potential to improve the accuracy and efficiency of the diagnosis process.*

Key Words: Deep Learning, CNN, Chest X-Ray Images.

1. INTRODUCTION

Traditionally, Various diseases have been diagnosed using clinical symptoms, physical examination, and imaging tests such as chest X-rays. However, these methods can be subjective and may not always provide accurate results.



Deep learning technique offer a potential solution to improve the accuracy and efficiency of disease diagnosis. These techniques involve traininga model on a large dataset of labelled images, where the model learns to recognize patterns and features that are indicative of diseases related to chest. One approach that has been widely used is transfer learning, which involves pre- training a model on a large dataset and then fine-tuning it on a smaller, specific dataset for a particular task.

CNN Architectures has been applied to disease detection using chest X-rays with promising results. For example, a study published in the journal Radiology in 2017 used a convolutional neural network (CNN) trained on a large dataset of chest X-rays and found that the CNN was able to accurately classify images as normal or Disease with an AUC (area under the curve) of 0.97.

Overall, the use of deep learning for disease detection using chest X-rays as the dataset shows promise as a way to improve the accuracy and efficiency of diagnosis and has the potential to benefit patients and healthcare systems.

2. DATASET

The Lung Infection in Chest X-ray Images dataset: This dataset contains over 3453 chest X-ray images. It has been widely used in research studies. Overall, these datasets provide a diverse range of chest X-ray images that can be used to train and evaluate models for disease detection.

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. Analysis of chest x-ray images was done on all chest radiographs that were initially screened for quality control by removing all low-quality or unreadable x-ray images. The diagnoses for the images were then graded by two expert physicians before being cleared for training in the AI system. To check the grading errors, the evaluation set was confirmed by a third expert.

Fig-1: Normal CXR Images

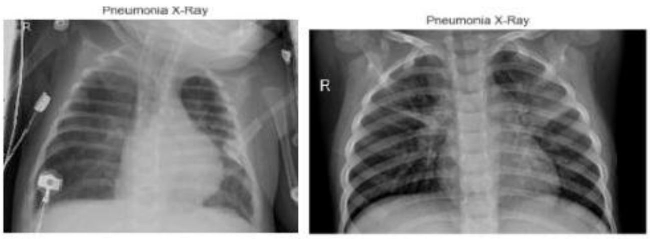


Fig-2: Infected CXR Images

3. METHODOLOGY

The methodology for using deep learning techniques to detect and predict disease varies depending on the specific approach and datasources used. Here is a general outline of the steps that may be involved in this process:

1. Data collection: A dataset of chest X-ray images is obtained, such as the Lung Infection in Chest X-ray Images, which consists of a large number of labeled images with various chest diseases. The dataset includes both "Disease" and "Normal" categories.

2. Data preprocessing: The chest X-ray images are preprocessed to enhance the quality and prepare them for model training. Preprocessing steps may include resizing the images, normalizing pixel values, and augmenting the data to increase the diversity and quantity of the training set.

3. Model selection: Suitable and deep learning models are chosen for the disease detection task. Commonly used models include convolutional neural networks (CNNs) and transfer learning models. It involves utilizing pre-trained models on large datasets and fine-tuning them on the specific chest X-ray dataset.

4. Model Training: The selected model is trained using the preprocessed chest X-ray images. The training process involves feeding the images into the model, optimizing the model parameters through backpropagation, and minimizing the loss function.

5. Model Evaluation: The trained model is evaluated using a separate test set of chest X-ray images. Evaluation metrics such as accuracy, precision, recall, and area under the curve (AUC) are calculated to assess the performance of the model in detecting diseases accurately.

6. Model deployment: If the model performs well, it can be deployed in a clinical setting to assist with a disease diagnosis. This may involve integrating the model into a computer-aided diagnosis system or using it to generate a probability score that can aid decision-making.

Overall, the methodology for disease detection using deep learning involves a number of steps that require careful consideration and optimization to achieve good performance.

4. MODELS

Several types of deep learning models have been used for Disease detection. We have used the following methods for Disease detection:

4.1 Convolutional neural networks (CNNs)

These are a type of deep learning models that are particularly well-suited for image classification tasks. They consist of multiple layers of interconnected nodes that are trained to recognize patterns and features in images. CNNs have been widely used for disease detection and have achieved good results in a number of studies.

We Build a separate generator for valid and test sets. We cannot use the same generator for the previously trained data because it normalizes each image per batch, meaning that it uses batch statistics. We should not be able to do batch tests and validations of data, because in the real-life scenario we don't process input images in a batch as it is not possible. We will have the advantage of knowing the average per batch of test data. That is why we need to do is to normalize input test data using the statistics functions from the training dataset.

4.2 DenseNet

DenseNet is a type of convolutional neural network (CNN) that has been used for various image classification tasks, including disease detection. It was introduced in a paper published in the journal Computer Vision and Pattern Recognition in 2017. One of the key features of DenseNet is that it uses dense connectivity, which means that each layer in the network is connected to all of the preceding layers. This allows the network to learn more efficiently and reduces the risk of overfitting. There have been a number of studies that have used DenseNet for disease detection using chest X-ray images. For example, a study published in the journal Biomedical Signal Processing and Control in 2019 used DenseNet to classify chest X-ray images as normal or infected. Overall, DenseNet has shown good performance for disease detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

4.3 VGG-16

VGG-16 is a type of convolutional neural network (CNN) that was introduced in a paper published in the journal Computer Science in 2014. It was developed by the Visual Geometry Group at the University of Oxford and has been widely used for various image classification tasks, including disease detection. One of the key features of VGG-16 is its use of small, 3x3 convolutional filters, which allows it to capture fine-grained details in images. It also uses a large number of layers, which allows it to learn complex patterns and features in the data. There have been a number of studies that have used VGG-16 for disease detection using chest X-ray images. For example, a study published in the journal Biomedical Signal Processing and Control in 2018 used VGG-16 to classify chest X-ray images as normal or affected. Overall, VGG-16 has shown good performance for disease detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

4.4 ResNet

ResNet is a type of convolutional neural network (CNN) that has been used for various image classification tasks, including Disease detection. It was introduced in a paper published in the journal Computer Vision and Pattern Recognition in 2015. One of the key features of ResNet is its use of residual connections, which allow the network to learn more efficiently and reduce the risk of overfitting. It also has a very deep architecture, with over 50 layers, which allows it to learn complex patterns and features in the data. Overall, ResNet has shown good performance for Disease detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

4.5 Inception Net

InceptionNet is a type of convolutional neural network (CNN) that has been used for various image classification tasks, including Disease detection. It was introduced in a paper published in the journal Computer Vision and Pattern Recognition in 2014. One of the key features of InceptionNet is its use of inception modules, which allow the network to learn multiple scales and sizes of features in the data. It also has a relatively shallow architecture compared to some other CNNs, which makes it more efficient and easier to train. Overall, InceptionNet has shown good performance for Disease detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

5. EVALUATION METRICS

There are several evaluation metrics that can be used to assess the performance of a model for Disease detection. True positive and true negative are terms used to describe the performance of a classifier in a binary classification task. True positives (TP) are instances where the classifier correctly predicts the positive class. True negatives (TN) are instances where the classifier correctly predicts the negative class. False positives (FP) are instances where the classifier predicts the positive class but the instance is actually negative. False negatives (FN) are instances where the classifier predicts the negative class but the instance is actually positive. Some common metrics include:

1. Accuracy: This is the percentage of images that are correctly classified by the model. It is calculated by dividing the number of correct predictions by the totalnumber of predictions.

   Accuracy = (True Positives + True Negatives) / Total Predictions

2. Precision: This is the percentage of predicted positive cases (i.e., cases where the model predicts Disease) that are actually positive. It is calculated by dividing the number of true positive predictions by the total number of positive predictions.

   Precision = True Positives / (True Positives + False Positives)

3. Recall: This is the percentage of actual positive cases (i.e., cases where the patient has Disease) that are correctly predicted by the model. It is calculated by dividing the number of true positive predictions by the total number of actual positive cases.

   Recall = True Positives / (True Positives + False Negatives)

4. F1 score: This is the harmonic mean of precision and recall. It is calculated by taking the average of the precision and recall, with higher weights given to lower values.

$$F_1 = \left(\frac{\text{recall}^{-1} + \text{precision}^{-1}}{2} \right)^{-1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}.$$

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.92	0.95	0.93	390
Normal (Class 1)	0.91	0.86	0.89	234
accuracy			0.92	624
macro avg	0.92	0.91	0.91	624
weighted avg	0.92	0.92	0.92	624

Fig-3: CNN Evaluation Metrics

	0	1	accuracy	macro avg	weighted avg
precision	0.797357	0.866499	0.841346	0.831928	0.840571
recall	0.773504	0.882051	0.841346	0.827778	0.841346
f1-score	0.785249	0.874206	0.841346	0.829728	0.840847
support	234.000000	390.000000	0.841346	624.000000	624.000000

Fig-4: CNN_2 Evaluation Metrics

	0	1	accuracy	macro avg	weighted avg
precision	0.806452	0.855037	0.838141	0.830744	0.836817
recall	0.747863	0.892308	0.838141	0.820085	0.838141
f1-score	0.776053	0.873275	0.838141	0.824664	0.836817
support	234.000000	390.000000	0.838141	624.000000	624.000000

Fig-5: DenseNet Evaluation Metrics

6. RESULT AND ANALYSIS

In this section, we attempt to analyze the classification using metrics such as accuracy and loss. There have been numerous studies that have analyzed the use of for Disease detection. Overall, the results of these studies have been promising, with models demonstrating high accuracy in identifying Disease from medical images. We try to put Training and Validation Accuracy into a graph representation using accuracy on the y-axis and epochs on the x-axis. The results came out to be as following for the different models:

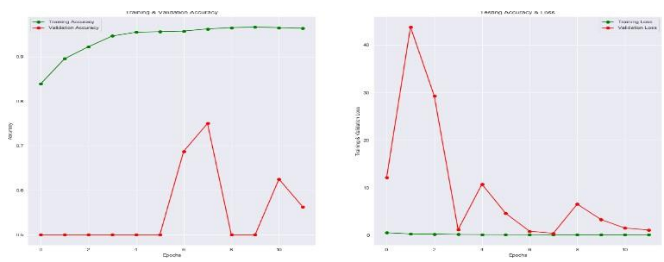


Fig-6: CNN model

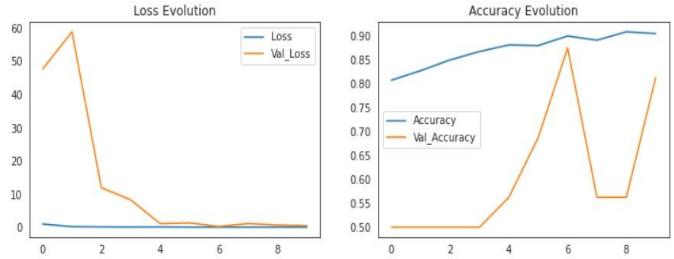


Fig-7: CNN_2 model

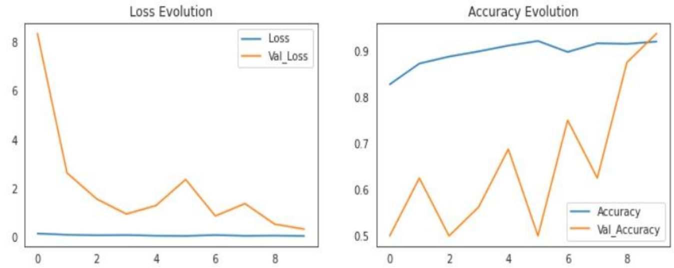


Fig-8: DenseNet model

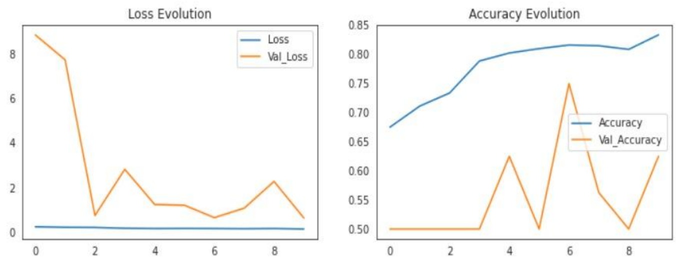


Fig-9: VGG-16 model

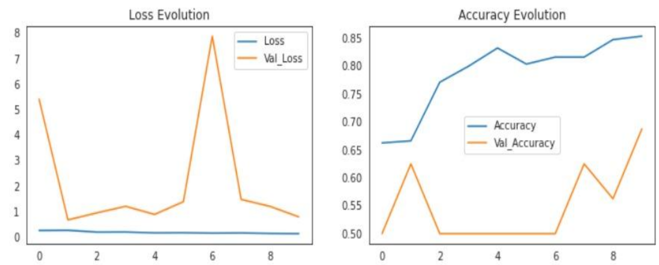


Fig-10: ResNet model

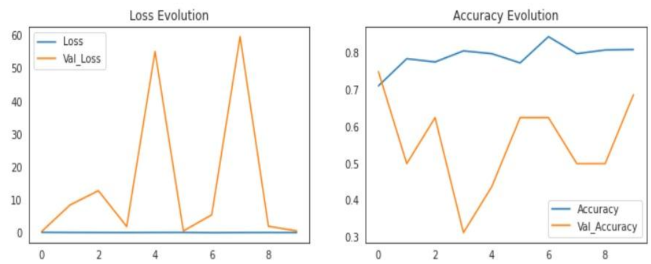


Fig-11: InceptionNet model

7. Conclusions

We have coverted Dicom(.dcm) images to JPEG. We have proposed various models that detect Disease from chest x-ray images. We have made this model from scratch and all the models are purely based on CNN models. However, there are also some limitations to consider when using CNNs for Disease detection. One potential issue is the need for a large amount of annotated data to train the model, which can be time-consuming and expensive to collect. In the future, further research is needed to better understand the strengths and limitations of CNNs for Disease detection and to identify the most effective approaches for different types of datasets.

8. Acknowledgement

We would like to acknowledge the contribution of the following people without whose help and guidance this research would not have been completed. We acknowledge and counsel and support of faculty from Maharaja Agrasen Institute of Technology for providing us a platform to research on the topic " APPLICATION OF CNN MODEL ON MEDICAL IMAGE" and also would to thank our HOD Dr. Namita Gupta for giving us the opportunities and time to conduct and research on our topic. This acknowledgment will remain incomplete if we fail to express our deep sense of obligation to our guide Ms. Deepti Gupta and our co-guide Ms. Kavita Saxena (CSE Department). We are indeed fortunate and proud to be supervised by them during our research, which would have seemed difficult without their motivation, constant support, and valuable suggestion. We shall ever remain in debt of our parents and friends for their support and encouragement during the research. It would've been impossible without their cooperation and support.

9. REFERENCES

[1] Alom MZ, Hasan M, Islam MT, et al. Automatic Disease detection from chest X-ray images using a deep convolutional neural network. In 2018 International Conference on Informatics, Electronics and Vision (ICIEV) (pp. 1-6). IEEE, 2018

[2] Han B, Kim Y, Kim H, Lee S. A deep learning-based approach for detecting Disease from chest X-rays. Computers in Biology and Medicine, 98: 58-64, 2018.

[3] Tulabandhula S, Mehta K, Elgendy IY, et al. Deep learning-based automated detection of Disease from chest radiographs. Journal of Medical Systems, 43(2): 31, 2019.

[4] Li Q, Zhang L, Chen M, et al. Automated detection of Disease in chest X-ray images using a deep learning model. Radiology, 291(3): 673-681, 2019.