JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Comparative Study on Challenges in Diagnosis of Paediatric Diseases Using Medical Images

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Abstract

Infection in the Lower Respiratory is the primary cause of paediatric death in recent decades. During the pandemic of Covid-19 the cases were increased and diagnosing the diseases becomes more challenging. The X-Ray based diagnose system may help to detect early and provide proper treatment at right time. But the availability of X-Ray samples is less, and they are limited to specific infection categories. In this review, we present Various methods that can be helpful for the detection of common respiratory infections like Croup Cough, bronchitis, Pneumonia, lobar pneumonia, and pneumothorax. This review addressing the limitations and appropriate techniques to handle the challenges.This article will guide the researchers to choose relevant model and approach for the paediatric medical image classification task.

I. Introduction

Medical Image Processing becomes the most important research field post pandemic. The researchers were working on new methods for increasing efficacy of the medical image classification system. Still the accuracy rate of the Automated computer aided system for medical image classification in few areas not achieved. Paediatric image classification is the one area were the researchers facing lot of challenges like lack of dataset, Adequate model for excellent accuracy. These challenges that experimented in machine learning face and methods to be discussed to overcome in real-time environments.

In addition to that, building new Convolution Neural Network (CNN) model with minimum amount of training datasets and the poor architecture model that forces to data leakage were the most faced challenges in most of the research work.The well-known Google's medical AI (Artificial Intelligence)has excellent accuracy in the Lab, but the practical implementation in all other Xray images for the disease like Croup Cough and Pneumoniaturned out to different, as it failed to give results at all when applied to real-life situations.

The pre-trained deep learning models always looking for large dataset for training phase. But the generation of large dataset we use tradition augmentation does not working well in many medical images. The expectation on CNN (Convolutional neural networks) model always high in term of accuracy. But it often faces few challenges like Dataset availability, Expertise models and its final production. These all depended on each other which affects the overall objective of the model.

So, this article summarizes the following as the primary challenges for applying Machine Intelligence to Pediatric Medical Imaging

- Unavailability of Dataset
- Choosing appropriate CNN Model.

The above-mentioned challenges to addressed with related works and adequate recommendation to be described in following sections.

II. Background

A. Data Acquisition

The primary challenge in dataset is collecting samples from appropriate department. The process starts from official approval from concern department. The data will be collected from the lab or hospital then it muststore in local device. Then the stored data need to evaluate the quality of the data to be ensured using proper methods. Finally, the labelling the data based on the categoriesthen thelabelled data samples grouped with different classes. Fig 1 shows the overall process of Data Collection.

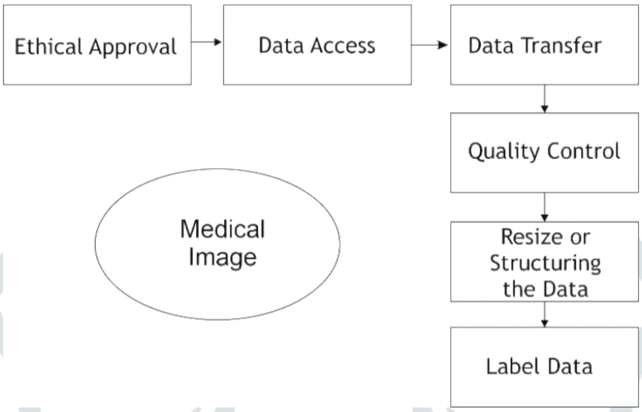

Fig 1: Fig 1. Data Acquisition Process

B. Data Collection for Rare Diseases

In recent years, 1 out of 1o people affected by few rare diseases.Especially the paediatricsare often affected by rare disease the diagnosis time for these cases will take long time to find the abnormalities through typical procedures. Most of the time these diseases can be identified using medical images such as X-Ray, CT and MRI. Diseases like Tumours,Respiratory infections are easily diagnosable using Medical Images. The Implementation of Computer Aided Diagnose system may help to detect the abnormalities using Machine Learning Techniques.

However, most of the successful machine learning model looking for larger dataset for training the model. So, the rare diseases data sample or image samples are very rarelyavailable. The number of the available dataset is not enough to conduct experiments. These challenges arise especially for the rare diseases like tumours and respiratory infection among kids.

In the article [1], Hasani N et all, Addressed the rare disease Positron Emission Tomography. Author suggests the national level repository for the rare disease data samples. The importance of technical assistance for the data augmentation is the key aspects of handlingthese shortcomings. Piñol M et al has created automated symptoms checkers for rare cases in the article [2]. They have introduced efficient diagnosis system that helps the physicals to diagnose the disease.

C. Role of Machine Intelligence in Medical Imaging

The significant prospects of Machine Learning in healthcare industries is enormous. The recent developments in healthcareequipment in diagnoses and management shows the consistent changes but the Machine learning based applications always looking for larger data samples for the training model. The primary shortcoming is whether the dataset is available for the rare disease. The accuracy of Deep Learning algorithm is highly correlated with size of Data Samples.

In the article [3] author addressed the limits on performance affected by dataset. After a series of experiments the performancecompletely relay on the quality and size of data samples. Further they demonstrated the robustness of the method to select the appropriate classifier and this limitation can be addressed by using the recommended models such as Transfer Learning algorithms with data Augmentation.

The medical images such as Xray, CT, PET, MRI in the training of Deep Learning algorithm seeks larger number of data samples from these rare diseases.

D. Data Augmentation

Data augmentation often used to address the problem in model training by adjusting the positions of the images. The common augmentations are scaling, rotation, flipping, and translation are being used in CNN model. These techniques applied to the dataset to increase the size of Data samples for training the model. The physicians always usemedical images like X-Ray and CT for finding the abnormalities in the respiratory way. Especially the disease like pneumonia, bronchitis, Chronic Cough, Croup cough and Asthma. The Radiologist will not share the medical image such X-Ray and CT due to the patient privacy concern. Accessing the data were already explained in previous sections. the data augmentation can be the possible solution for the dataset limitation. Fig 2 Show the Architecture of Generative Adversarial Network for the synthetic data generation. The GAN has two important network such as Discriminator and Generator.

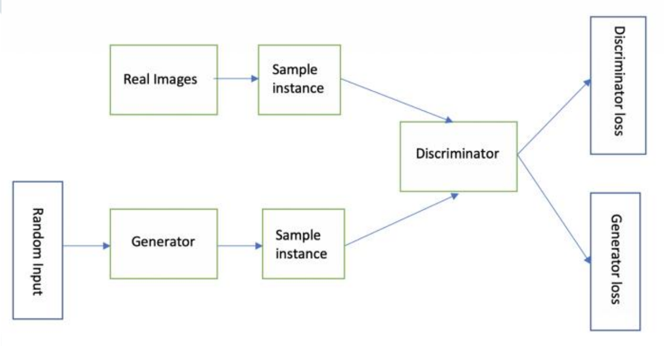

Fig 2 GAN Architecture

There are many inhereted versions of GANs such as Deep Convolutional Generative Adversarial Network (DCGAN),Conditional Gan (CGAN), Deep Convolutional GAN (DCGAN), CycleGAN and StyleGAN. In the article [4] SagarKoraVenu and Sridhar Ravulaused DCGAN for generating augmented x-Ray images for pneumonia classification. The architecture of DCGAN is depicted in Fig 3.

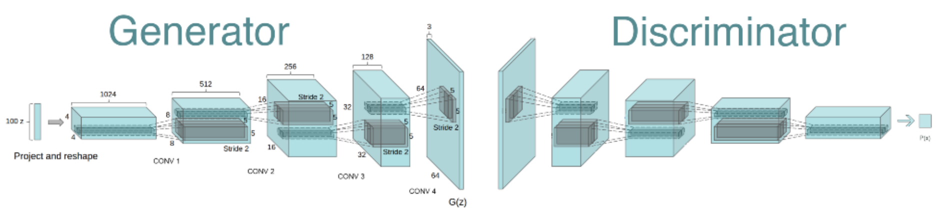

Fig 2 Data Augmentation using DCGAN

Author conducted the experiment with 1341 Normal chest X-ray, and they created artificial samples by retaining primary features to the original data with this technique. The results show excellent accuracy with augmented data.

The data augmentation is one of the major domains in recent research in medical images. The GANs method can be employed by many researchers to create a synthetic dataset. And Data augmentation being used toavoidoverfitting issue while training the Model. In the article [5] Yi et al surveyed the same on usage of GANs in Image Classification.Chuquicusma et al. [5] created realistic lung nodule samples using Deep

Convolutional Generative Adversarial Networks and they presents visual Turing test to ensure the quality of the model.

In the article [7] Salehinejad et al performed improved pathology classification using DCGAN by augmenting original dataset. Author suggested that DCGAN for generation of medical image dataset for the deep learning network. Some complex problems in medical images such as cardiac for finding abnormalitiesachieved by using GANs.Madani et al. [8] used DCGAN for classification of cardiac abnormalities in chest x-rays. cardiovascular abnormalities have been classified by using Convolution neural Network by Madani et al. [8]. In that experiment author have used DCGAN for generating chest X-Ray Images. The promising accuracy was obtainedfrom the CNN model. Lahari et al. [9] performed medical image segmentation and the generated Retinal Vesseldataset using DCGAN shows excellent resultscompared withfully supervised model.

Further, GANs used in 3D medical image Model imagesegmentation and the performance has been improved by comparing with other segmentation methods. In the article [10] Mondal et al.for 3D multi-modal medical image segmentation.

Rare diseases like liver lesion also addressed using DCGAN. In article [11] Frid-Adar et al. used augmented dataset of liver lesions images for binary classification. They used CNN network for the classification the accuracy also promising. Other rare organ image Brain MRI Images also generated by using GANs method. In the article [12] Bermudez et al used GANs for the T1 weighted MRI synthesis learning using 528 data samples.

II. Discussion

The Data Hungry deep learning model usually requires substantial number of datasets for training the model. The typically used method for handling this shortcoming by introducing Data augmentation technique. This technique used to generateenormous number of data samples from the original data sample. The medical images are always challenging the researchers to acquire the data from authorized organisations. Since the legal issue remains difficult to collect the data from patients' privacy concern.

In the study, we surveyed related articles that are addressing small dataset problem using GANs Method. The synthetic generation of medical images such as Xray, CT and MRI using deep convolutional generative adversarial networks. The resultfrom the study suggests the researcher especially working withpaediatric images and Rara disease medical images. Most of the models produced the promising results with augmented datasets.

Further, The model works with images augmented using DCGAN has produced good accuracy while compared with results other traditional methods. There by the DCGAN method can be used to two primary usage in medical image classification task

1. To generate synthetic Dataset
2. To reduce the overfitting.

III. Conclusion and Future Work

Data requirement for the deep learning model can be addressed by using Data Augmentation by increasing size of dataset. In the field of computer vision, since many methods were implemented to address the small dataset issue.Data Augmentation is using GANs method works promisingly to generate considerable number of high-qualitydatasets to address the challenge. The study results show the classifier performance with augmented data. Hence, DCGAN based Data generation gives better accuracy than the other existing traditional method. In addition, stillto improve the quality of the generated image we can use of Wasserstein loss with gradient penalty as loss function.

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