International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 369-377 www.ijaem.net ISSN: 2395-5252

Image Processing System for Abnormality detection for disease prediction (AI in Healthcare)

Dr Adilakshmamma T

Associate Professor, Silicon City College, Bengaluru, Karnataka

Submitted: 05-11-2021 Revised: 12-11-2021 Accepted: 15-11-2021

ABSTRACT: Artificial Intelligence (AI) is one of the emerging fields in healthcare. It is best fit for prediction modelling. In medical field one proverb is there, that prevention is better than cure, which can be best justified by the application of Artificial Intelligence. AI is basically a data driven model to converge to good results. Image processing is a well proven technique to identify different diseases for human. Different types of medical images from various sources are available. There exist strong image processing algorithms to identify diseases. Now, in the recent research AI is added with image processing and based on abnormality and existing database, prior hand disease can be detected. There are several tools as well as algorithms are available to process medical images and finally prediction model can be generated with the help of advanced AI model. The current work dealt with several medical image processing system for abnormality detection for disease prediction in association with artificial intelligence modelling.

Key Words: Artificial Intelligence, Image Processing, Disease prediction, Healthcare, Abnormality detection

I. INTRODUCTION

Artificial Intelligence have great impact on new medications as well as medical diagnosis process. Researchers have a foresight that artificial intelligencehave a massive impact by providing handy tools to the radiologists and doctors for faster and more accurate diagnosis with efficient treatment process. The combining trends of big data and artificial intelligence will improve the diagnosis process of the doctors and provide more advantages of handling and processing of huge amount of patient data in a fraction of second (Shen et. al. 2017). Previously, artificial intelligence has succeeded in solving image-based diseases like skin and organ specific diseases (Esteva et. al. 2017) any many more. Recently, scientists are expecting artificial intelligence-based virus disease detection as well as abnormality detection to predict new diseases.

Due to limited resources and technologies, prediction process is not up to the mark for various countries. Even though many developed countries are also facing difficulties to identify and track possible cases on time. Artificial Intelligence algorithms, and implementation of AI systems help with many concerns of healthcare, starting from CT-scans and X-rays for rapid processing and can identify the step-by-step improvement of the patient. AI algorithms are currently giving very good predictions and results for most advanced diseases like COVID 19, lungs shape analysis and severity of the disease. Similar diseases are well predicted by analysing CT scan images (Gozes et. al. 2020). The automation in healthcare industry is giving prior notification about infection (Alimadadi et. al. 2020).

In this connection, AI in medical industry is formed to accumulate multimodal data from different sources, sensor-based networks and other reliable sources, with an aim of efficient prediction of abnormality. The main objective to take this initiative is to help the developing countries with limited quality facility access people. As per sustainable development goal of the country, quality healthcare is mandatory for all, AI can provide cheap and best solution for the average income people. AI in healthcare introduce a revolution in the field of medical science.

Literature review can give insight about different segmentation methodologies. Segmentation is very much important part of image processing as t can localize the area of interest and apply technology on that to get good results. In order to identify good segmentation techniques, optimal solutions need to be searched, which will further give better results based on accuracy and

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efficiency. There are different sources of images also, which can be better diagnose by case wise.

The article is arranged as Section 2 covers a literature review covering the role of artificial intelligence in the field of health care system with the inclusion of emerging technologies in artificial intelligence and machine learning. Section 3 covers different methodologies explained in this new platform. Section 4 highlights the future workin the field of AI in healthcare. At the end, section 5 includes the other usage of the platform.

II. LITERATURE REVIEW

Literature review can give highlights on prior works in the same field. The much literature work can give much insight about the initial work in the same field. The works are related to application of artificial intelligence in the field of abnormality prediction in the field of health care.

2.1 Impact of Artificial Intelligence in Medical Imaging

Image classification is important to get good results based on input features. It includes inside computer vision. It includes other techniques like detection, segmentation, and localization. Deep learning is a new model which can solve image processing problems in better way with multiple hidden layers. It is applicable for linear as well as non linear knowledge processing. The transformation and extraction functions are use for proper pattern recognition (Rawat and Wang, 2017).

Computer based image processing is becoming more important in the area of healthcare. Most recent development in artificial intelligence, most specifically the advancement in the algorithm of deep learning opened a new door for recognition, classification and qualification of patterns in medical imaging (Shen et. al. 2017). Hierarchical function representation, feature selection and extraction process as well as domain specific classification made deep impact I the field of medical imaging. The introduction of deep learning opened a new era in the field of image processing, specifically medical image processing (Shen et. al. 2017).

The intervention of machine learning in image processing related to medical data enhances the quality and effectiveness of the output images in clinical treatment. Radiology image data quality enhances and can most precisely used by doctors and researchers. The quality of images also enhanced, so image analysis became much easier (Wu et. al. 2016).

Another new field of image processing explored known as computational medical image processing. It is the ability of Convolution neural network in medical images where images can be generated by various types of imaging techniques like X-ray, CT scan etc..The deep learning can be used for cell shape recognition, tissue and disease area segmentation etc (Shen et. al. 2017).

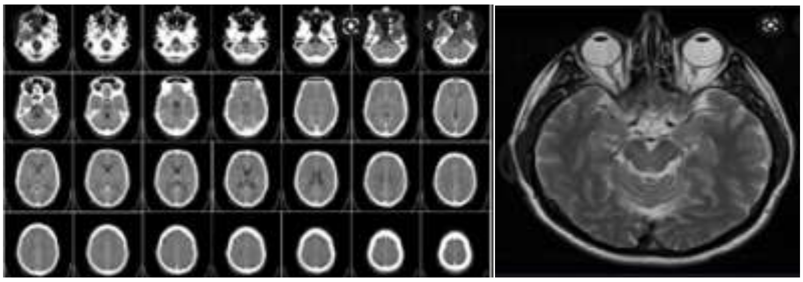

Fig. 1. CT and MRI Images

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Volume 3, Issue 11 Nov 2021, pp: 369-377 www.ijaem.net ISSN: 2395-5252

Fig. 2. PET and X-ray Images

Artificial neural Network is the mimic of Biological neural network. Brain function can be created artificially with the help of neural network.

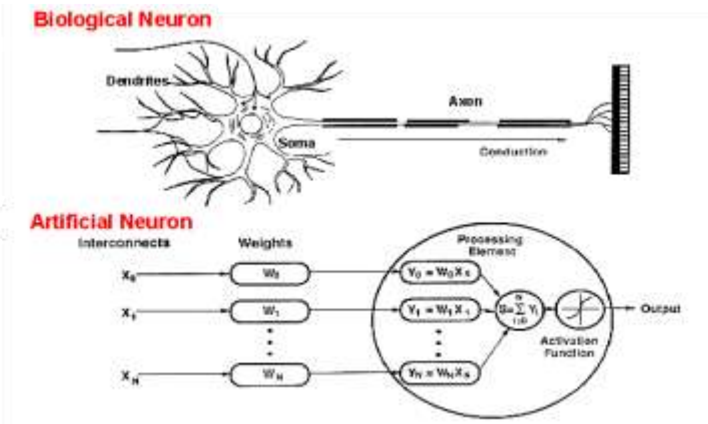

Fig. 3. Difference between Artificial Neural Network and Biological Neuron

The first and very simple model invented in the field of Artificial Neural network is perceptron model with single hidden layer, input and output layer, but due to its linear nature it was unable to solve more complex problems. Then modified or multilayer perceptron came into the picture to solve complex problems with different activation functions. The number of input and output layer neurons can be decided y number of features and required output classes respectively. More advanced algorithms present in artificial neural network are back propagation network, radial basis neural network, complex domain neural network and many more (Chen et. al. 1995). In case of Deep neural network, which is dedicatedly used for image related problems is dealing with multiple hidden layers (Bengio, 2009). The working principle of artificial neural network is training, validation and testing. Normally 70% of the data are used for training, 25% of the data for testing and 10% can be used for validation. Real time as well as processed data can be used for analysis purpose (Schwarz, 1978).

2.2 AI for Infection Detection

Now a days, virus infection related diseases are very high. The monitoring and progression are very much important in such cases. It must be real time and based on symptoms prediction of disease is also very much important. In this kind of crisis time technology only can help more to control the situation. The number of true positive and true negative need to be concentrate more to get low error (Haleem et. al. 2020). Confusion matrix is a kind of matrix which can give ideal diagnosis report based on available data in the matrix. The main purpose of AI in virus related infection is prediction and early detection of infection. It can work in a cost-effective way and can take help of many decision-making algorithms. Various diseases can be detected and cured soon. CT, MRI give valuable input to the AI algorithms

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which in turn enhance the accuracy and efficiency of the result.

Fig. 4 Image Detection and Segmentation

Segmentation is the basic image processing technique for viral infection detection. The region of Interest in various sectors of images play a major role for image analysis. The most popular networking is used for deep learning is U-Net. Proposed U-net can give better result for segmented data to identify different body parts related issues. Any segmentation can be classified into two groups. First one is need to identify the organ and the main effected area and in the second step damage area of the organ which is known as region of interest can be detected and analysed. U-Net ++ is the advanced version of U-Net used for more advanced segmentation purpose. Convolution Neural network is another method to segment and classify complex images more effectively. Higher dimension U net can work for 3d modelling. Another version of effective network model is V-net which can work with residual model of the network. VB net is another example which deals with more effective segmentation. Image pre-processing is another major step if dealing with real time data. There are two categories of image pre-processing, namely, restoration and reconstruction (Suzuki et. al. 2002)

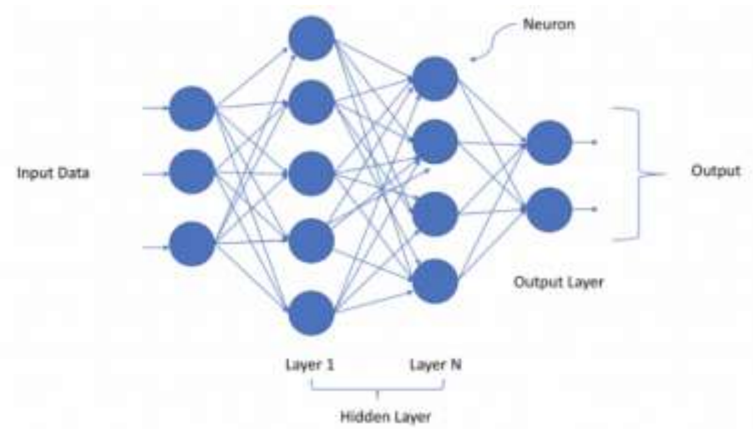

Fig.5. Deep Neural Network

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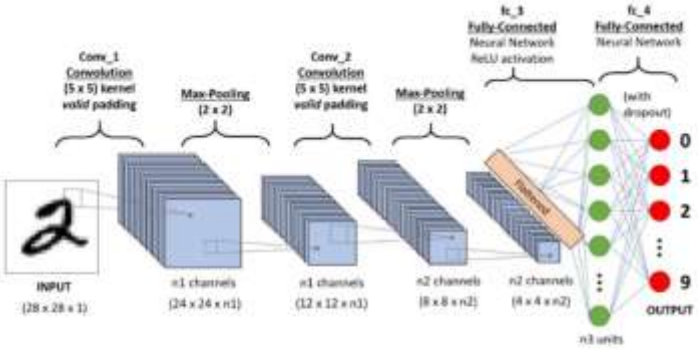

Fig.6. Convolution Neural Network

III ABNORMALITY RECOGNITION SYSTEM

This section deals with the adopted methodology. It can explain architecture, function and evolution in detail.

3.1 Architecture of the network

One of the major challenges in the area of medical imaging is lack of resources. The lack of quality data can reduce the reliability of the system. The study required large data set to get precise result.

AI based image processing can integrate AI and image processing hub in the same roof.

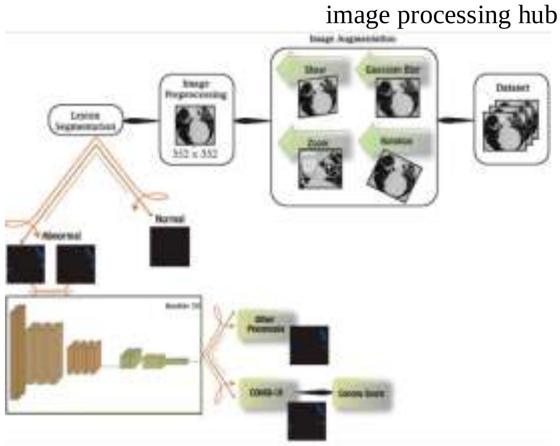

Fig. 7. Imaging Architecture

In this architecture it is seen that how image data set can be generated with the help of image augmentation, annotation and labelling.

3.2 Image Augmentation

It is a method to generate more data with the help of some original data set. The main goal of data augmentation is to get good result. There are several methods of augmentation are available like horizontal shift, vertical shift, rotation, zooming etc.

3.3 Image Processing

There are several steps in image processing like image standardization, image normalization, and many more pre processing techniques through which standardise data can be generated and can be used for classification purpose.

3.4 Leison's Segmentation

InfNet architecture is used for this architecture. The processed CT images can be trained with 80% and 20% model of training and testing respectively.

3.5 REsNet50 Deep Network

It is a well-known convolution neural network. ImageNet architecture is used for this and based on initial weight assignment to the network, gradient problem can be solved. Residual Neural Network can be used.

3.6 Evaluation Metrics

Accuracy can quantify the competency of the data.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

TP: True Positive

TN: True Negative

FP: False Positive

FN: False Negative

Recall is the sensitivity of the result.

Recall=TP/(TP+FN)

Precision is the understanding of positive data existence.

Precision=TP/(TP+FP)

Specificity is the negative prediction of the data.

Specificity=TN/(TN+FP)

F1-Score is responsible for quality detection.

F1-Score=2*(Precision*Recall)/(Precision+Recall)

IV DISCUSSIONS

The data can be obtained either from the existing data set or can be created from original image with the help of augmentation. GPU system can be used to analyse the data to get good result. In literature several algorithms are used for abnormality of the disease prediction. The feature sets and initialisation parameters are the deciding factor foe the outcome of the network. segmentation and ResNet deep network are two phases of AI system. The first and second phase can respectively identify the abnormalities in the medical images.Two different accuracies were generated as 95.54% and 96.5% respectively for the ResNet50 block. The final accuracy score is 95%.

FURURE SCOPE

This work is based on recent research trend. It is focused on AI based image processing techniques which can solve many medical imaging complex problem in a simple way. The introduction of big data analysis also can make doctors to handle multiple plenty of data and big data-based system can predict output more efficient way. This system can benefit prevention more than cure so that patients can be up to date about their health system before getting any complex disease. In future more advanced network and algorithms can be used to enhance the efficiency and the accuracy of the system.

CONCLUSION

In this work different deep learning and convolution neural network architecture are discussed. The feature sets and initialisation parameters are the deciding factor foe the outcome of the network. segmentation and ResNet deep network are two phases of AI system. The first and second phase can respectively identify the abnormalities in the medical images. Two different accuracies were generated as 95.54% and 96.5% respectively for the ResNet50 block. The final accuracy score is 95%.

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