A SURVEY ON ARTIFICIAL INTELLIGENCE IN RADIOLOGY

Abstract

Radiology plays a major role in initial stage by diagnosing the cause of symptoms in a patient. There are various techniques used in Radiology such as X-Rays, Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) scan, etc. One can use Artificial Intelligence (AI) algorithms such as Deep Learning, to enhance the outcome of the scan results. Deep Learning methods such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Auto-Encoder have found application in areas where medical images are involved. As compared to traditional methods where radiologist had to manually analyze the images to assist the doctors; AI has helped in automating these tasks. In this article, we have discussed various proposed Deep Learning techniques that are available and being used by radiology department to get accurate and enhanced results. We explore the positive impact and limitations of the existing systems. Finally, we conclude with discussion on further areas of improvement.

Keywords: Radiology, Artificial Intelligence (AI), Deep Learning (DL), Long Short-Term Memory (LSTM)

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I. INTRODUCTION

Field of Artificial Intelligence (AI) is ever evolving with the introduction of new techniques to tackle problems that require human intelligence. These advancements have helped various domain to leverage the performance of existing systems with the use of AI. Technique such as Deep Learning (DL), which is a subset of Machine Learning, that uses artificial neural networks that imitate working of human brain, now is majorly used for understanding the hidden information from the existing data in many domains. Radiology is one such domain which has seen many applications of AI. Deep Learning techniques are being used to analyze the digital images that are produced during CT-Scan and MRIs to extract knowledge. These techniques have outperformed human minds in task-specific applications.

Various startups and research institutes are coming up with techniques to improve the existing systems in Radiology by developing cost-efficient and accurate AI-tools. AI tools being used for purposes such as reasoning, prediction, perception of radiology methodologies, etc. AI in Radiology is majorly used in areas such as processing of quality images, report generation, administration. Due to the improved capabilities, there is a debate regarding the ownership of decisions and analysis done by AI and the various risks that are present with this kind of advancement.

II. LITERATURE

AI techniques are being used to solve various problems in Radiology. The applications include Chronic Myocardial Infarction detection, Brain Tumor detection and segmentation, Chest Imaging and analysis, Breast cancer detection, etc. We have discussed few of the current development in each of the above topics.

1. **Chronic myocardial infarction:** It has been observed that Renal impairment is one of the common symptoms in Chronic Myocardial Infarction (CMI). To verify this, various invasive tests are performed such as late gadolinium enhancement (LGE) imaging. Although LGE is effective there are few side effects to it such as intra-cranial deposition. To overcome this, DL method is introduced [1] to make use of MRI scans to classify whether a patient is affected with CMI.

   The authors have used various techniques such as CNN, RNN, Pixel Prediction for detecting Area of Interest (AOI), segmentation and classification respectively. The proposed model is able to detect the presence of CMI with accuracy close to LGE imaging. It is proved effective to use DL techniques where insight from the images is crucial.

2. **Brain tumor segmentation:** Many Machine Learning and DL techniques are been proposed in the subject of Brain Tumor. Various DL techniques that make use of CNN are proved to be effective in finding AOI for a given image. Various systems are already in use for detecting Brain Tumor. Many of these techniques make use of model cascading where we train models for detecting separate sections of brain such as normal tissues and cancerous tissues. After training individual model, they are combined to get the desired results.

Disadvantage of such a technique is that, if one model predicts the AOI incorrectly, the final result may contain huge error. To overcome this, [2] authors have proposed a model that does not require individual training and cascading. They trained the model to detect the AOI and segment the cancerous region in single pass of the input. The model had much less error rate compared to cascading model.

3. **Chest CT imaging:** Chest CT Imaging is the most researched area where DL is widely used. Here we can use DL to detect anomalies in Lungs that can be harmful if not diagnosed on time. DL is also used in checking progression of disease, severity and response of lungs to ongoing treatments. It is a challenging task to identify the cause in early stages to get complete recovery. Various ideas are proposed to tackle these challenges. Traditionally, CT-scan are analyzed by trained physicians to detect any Malignant clusters in lungs. If suspected, a needle biopsy is required. The [3] authors have devised a semi-supervised learning framework that can classify a nodule in given CT-scan as Benign or Malignant. The proposed framework has high accuracy as compared to the existing frameworks.

Another proposed idea in [4] aimed at predicting the mortality risk by giving a severity score. Authors have used CNN and LSTM network for generating the score from CT-scan image. They have built the framework based on the existing protocol of Fleischner system.

Similar study was done [9] where the author has segmented the mouse lung CT-scan images into various levels of fibrosis that are present. The author used U-net model, which follows autoencoder structure, to perform the classification task.

4. **Cancer detection:** DL techniques are also used to classify whether a cluster is cancerous or non-cancerous. They are also used in finding the impacted area so that incase of surgery, exact section can be removed without disturbing the healthy cells. The authors [5] have proposed a DL architecture that can detect the segment of Breast MRI that contains cancer clusters. The architecture follows U-net model to predict the region of cancer.

AI techniques are not only used in detection and classification problems, they are also used in processing the patients reports to structure them in understandable format. The authors [10] have proposed an NLP system that can convert the given report into a well-structured XML file that highlights the important points for the doctors to analyze.

5. **Other imaging areas:** There are various other areas of Radiology which are not fully explored yet. The author [6] has discussed how we can use the DL techniques to analyze the m Musculoskeletal images for analysis in Long-leg radiography. Similarly, authors [7] have discussed how we can fully automate the support system using AI for treating the patients with Long-Leg alignment problem.

Another paper [8] aimed at creating a architecture that could be used as a pre-trained model in various radiology applications. The authors used various datasets to support their argument. The model performed on-par with the existing systems that are developed for specific tasks.

III. RESEARCH ANALYSIS

Table 1: Summary of Research Analysis on Various Papers.

Paper Reference Number	Positive Impact	Criticism
[1]	1. Model has high Specificity score. 2. Proposed system gives high Specificity score in less training time. 3. The proposed method uses non-enhanced cardiac cine images, which is part of basic analysis.	1. The Sensitivity score of the model is not good. 2. They have used multiple models and cascaded them to achieve the results. Cascading model usually piles up the error rate of the task. If there is an error while finding the Region of Interest in first model, the Local motion feature and Global motion feature will produce incorrect results. 3. The Dice score that they achieved (86.1% 6 5.7) is less compared to other models in similar domain having score of around 88%. 4. The dataset had only 598 samples overall, so the model may not have learned all variations that may occur in real life scenario.
[2]	1. Proposed method can be used for segmenting the brain tumor in the given CT-scan.	1. The Dice score of the proposed model is less compared to other models the authors tested.
[3]	1. Proposed model can detect benign or malignant cluster from initial diagnosis i.e., CT-Scan Images. 2. Faster classification of cluster in chest CT-Scan than traditional method of detecting benign or malignant which are invasive in nature and are time-consuming.	1. As the dataset used was biased in nature, the initial figure of improved accuracy for semi-supervised learning vs supervised learning may be not correctly measures and could be some different value. 2. Rather than just classifying the cluster as benign or malignant, detection of exact position of the cluster would have been helpful to doctors for further diagnosis.
[4]	1. Proposed model can classify Emphysema Pattern in patients CT-Scan which is much faster than traditional approach. 2. The computation time for each patient is lower and has higher accuracy compared to existing systems.	1. The protocols used in CT-Scan varies from region to region. The author's had used Fleischner system which is not commonly used radiology protocols. Hence the hospitals may need to change their existing systems if they want to implement the model.

		2. The parameters for the model training vary based on the available data and how it is collected. 3. As LSM was used, there is a high chance that the model is over trained if not correctly trained. 4. Authors were unable to achieve the visual score they were trying to get.
[5]	1. Proposed model can reduce the workload of doctors to read the full report. The doctors can read the main tags to get a quick understanding of the situation. 2. The storage of reports is simplified and can be stored in structured manner.	1. Model cascading is used to get the desired results, cascading the models can lead to huge error if first model is not predicting the heading properly. 2. There is a chance of model not correctly identifying the label due to which the patient may be in influenced directly. 3. The BI-RADS protocol is not widely used in other regions, so the implementation is a challenging task.
[6]	1. Proposed a method uses radiographs to produce exact assessment of the hip, knee, ankle, and femoral anatomic mechanical angles using CNN.	1. Proposed model does not give the exact measurement of the angles. 2. Model has hardware dependencies.
[7]	1. Proposed a model can accurately analyze the Alignment in Long-Leg using CT-scans. 2. The model is accurate and fast compared to traditional methods.	1. Data is not diverse and may lead to overtraining of the model. 2. There is a bias in the dataset that is used for training purpose. This may cause incorrect predictions for excluded group.
[8]	1. Proposed can be used as pretrained model for various image analysis as pre-trained model.	1. The overall accuracy of the model with comparison to existing ones is still less.
[9]	1. Proposed model can accurately segment the lung fibrosis from given CT scan image.	1. The proposed method was unable to capture the higher dimension of data that can be extracted when comparing multiple sections.
[10]	1. Proposed system can segment the breast cancer from given MRI scan. 2. It automates the work of radiologist in identification and segmentation of cancerous cluster from MRI image and reporting it.	1. The dataset used to train the model was collected using older techniques. It may not be generalized across various institutes.

IV. CONCLUSION

Although the model proposed in [4] outperformed the existing models, it is not easily implementable as there is a dataset dependency. Also, the hyperparameters are not same for different are not generalized for different datasets that could be used. We can propose aN image data collection framework based on existing methods that could help in improving the implementation issue. Also, we can explore the hyperparameters that could be used for all images collected from the existing framework.

V. RESULTS

AI has been used in radiology domain to assist trained physicians to make decisions. AI techniques such as DL has helped in producing faster analysis results that can take days if performed using traditional methods. Although there are some concerns regarding the ethics and responsibilities involved in using results generated by a black-box like DL models. We can see there is still room for improvement we the existing DL models are not completely accurate.

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