ARTIFICIAL INTELLIGENCE IN RADIOLOGICAL DIAGNOSIS: A REVIEW

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ABSTRACT: Data science and the employment of machine learning techniques in medical sciences have been on a constant rise. These methodologies are novel and have led to newer procedures and pipelines, which reduce cost-effectively and time consumption. These techniques have been applied on collections of datasets ranging across several domains spanning from the application of detection of road traffic in self-driving cars to the usages of financial prediction models. The uses of these statistical techniques are not unfamiliar with the medical datasets on which operations are performed, ranging from detection of none or any presence of abnormalities to the prediction of such anomalies. This review focuses on the various developments and uses of Artificial Intelligence in diagnosis methods regarding disease as Thoracic Imaging, Chest Radiograph Reading, and Volumetry. Here, the studies highlight the procedures for identifying various disease symptoms and signs that can be crucial for determining disease.

1. INTRODUCTION

As the years go by, newer and more disruptive technologies hit the market, including humanity, with several more unique techniques that become a new niche in the global spectrum. Hence, such is the case with Artificial Intelligence. Several computer systems have been developed or are in the phases of current development, which can help quickly that can diagnose diseases as breast cancer (Ng *et al*., 2002), as well as in the procedure and map planning in the synthesis of complex organic chemical compounds (Roch *et al*., 2020), solve equations in symbolic form, and to analyse electronic circuits. Some have reached levels of detection of human speech and natural language text and small bots capable of performing processes to meet formal specifications (Kepuska & Bohouta, 2018). Therefore, we can conclude by agreeing that these systems possess a form of artificial intelligence that may supersede human intelligence in the far future. There is also no doubt that these systems will inevitably be used on larger datasets & collections of medical samples for determining whether a prospective patient shall test positive regarding the disease they are being diagnosed with. Therefore, this review includes recent applications of artificial intelligence (AI) and other methodologies that have proven their capabilities if they apply to the field's detection and testing (Chassagnon *et al*., 2020, Soffer *et al*., 2019). Machine learning techniques have been in use since the dawn of the retrospective 1980s and 1990s. However, a practical approach and use only came about soon after the generation of increasing datasets and computing power of processors, which has become a boon to this field and has revived this field from the AI winter(Chassagnon *et al*., 2020).

2. APPLICATIONS IN THORACIC IMAGING

As of 2018, approximately 150 research articles are published in radiology with Artificial Intelligence applications, and their effects are denoted in radiological data analysis. One facet which had a great deal of growth from the AI revolution was the detection of images and segmentation of the data related to those images by use of "Deep learning techniques" whereby neural networks and several subtypes were trained in the process of identification of image characteristics (Chassagnon *et al*., 2020). This led to Radiomics, the study of radiometric data from medical reports to be visually identified by ML techniques and allowing a vast number of benefits to be reaped by their users. These techniques thus give us individuals a definitive answer towards a diagnosis of disease, e.g., Lung malignancies (Chassagnon *et al*., 2020). Techniques as random forest, clustering and dimensional analysis find those "Tell-Tell signs", which a professional medical staff would use to determine the condition of the patience (Chassagnon *et al*., 2020). This enables a significant improvement in detecting abnormalities in chest radiography or Chest X-Ray/ Chest film to detect the possible diagnosis of chest-related issues

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and diseases, short of CXR (Kligerman *et al*., 2013). However, since diagnosis might be difficult considering the overlaps in white and black images in bone and organs, AI powers implication. Hence, these methodologies are required for the masses since although these technologies are available for several individuals; there is a vacuum of expertise to diagnose this biofilm and to understand the technicalities behind these technologies; thus, the requirement of Computer-Aided Diagnosis again surpasses the need for accurate prediction in this field (Kligerman *et al*., 2013).

3. CHEST RADIOGRAPH READING (CXR)

The application of any artificial intelligent technique should be carried out, focusing clearly on making the workflow of diagnosis as optimised as possible, such as the advancement of CXR technologies by Kao *et al.* and co-authors, where the turnaround time-frequency for detection of anomalies in chest radiographic films was significantly decreased by 44 per cent (Kao *et al*., 2015). These advances also extend to several other areas of medical sciences as the detection of tuberculosis caused by *Mycobacterium tuberculosis* bacteria with symptoms inclusive of pain in the chest, swollen lymph nodes, painful breathing cycles, and presence of blood in phlegm (Hawn *et al*., 2014, C. Qin *et al*., 2018).

LUNG NODULES

One of the CAD tools' significant applications is detecting and characterising lung nodules on chest radiograph films. This includes CAD for detection (CADe) as well as for characterisation (CADx) (Chassagnon *et al*., 2020). These techniques help determine the frequencies of the probability of malignancy in these lung nodules or a combination of several characters, which may be indicators of a specific disease. In radiomics, CADx utilises deep learning or machine learning techniques, while the trend in developing CADe tools moves towards the employment of deep learning methodologies (Chassagnon *et al*., 2020).

The standard CAD systems usually include image preprocessing, lung nodule detection via various algorithms, followed by extraction of essential features, and categorising candidate nodules that may be affected. The selected features include shape, intensity, texture, size of the nodule, and the machine learning algorithm used for classification (Chassagnon *et al*., 2020). Depending on the CAD system, the classification may be carried out using the support vector machine (SVM) and Fisher linear discriminant. The aim focuses on developing adequate sensitivity with as low as possible false positives detections to improve the accuracy as high as possible (Chassagnon *et al*., 2020). The development of convolution neural networks requires massive annotated chest radiograph film datasets to avoid under and to fit, i.e. if Convolution neural network arrives at a character conclusion based on less dataset, it is considered underfitting as the characteristics are not taken up as features. If too many features are considered, noisy data prediction is created, or the network arrives at random inconclusive dummy data. Transfer learning hence is deemed applicable in such situations as it comprises a training algorithm with a collection of everyday images on an extensive data set and initialises the network with a smaller medical image dataset as its parameter (Chassagnon *et al*., 2020). Bush *et al*. and co-authors have already carried out this by using CNNs on chest image samples and has returned 86 and 92 per cent specificity and sensitivity, respectively, for the detection of lung nodules which is impressive (Jaffar *et al*., 2009). Similarly, Nam *et al*. and co-authors have created a deep learning algorithm to detect pulmonary nodule abnormalities in sample datasets of 43292 chest radiographs (Nam *et al*., 2019).

TUBERCULOSIS

The standard CAD systems are being used to detect potential Tuberculosis effects on the lungs' alveolus and better understand its damage. Its effects are seen to be commonplace in underdeveloped and developing countries where there is a significant lack of the presence of radiograph diagnostic specialists (Z. Z. Qin *et al*., 2019, Chassagnon *et al*., 2020). Techniques include machine learning modes where textures and patterns common in the affected lung of a patient having tuberculosis are understood and trained, making proficient in understanding the tell-tell features for diagnosis. Applying these same principles, Rohmah *et al*. have introduced the histographical detection of features common to tuberculosis, which has an efficient accuracy of up to 95.7 per cent (Chassagnon *et al*., 2020, C. Qin *et al*., 2018). Similar studies by Huang *et al*. used automated deep learning techniques, which ousted the performance of thoracic radiologists and their expertise with higher accuracy (Hwang, Park, Jin, Kim,

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Choi, Lee, Goo, Aum, Yim, Park, *et al*., 2019). Lakhani *et al*. explored the utilisation of pre-trained CNNs called Alexnet and GoogLenet, trained on radiograph films with positive and negative detection of Tuberculosis cases. Each later was combined to detect signatures indicative of damage caused in upper regions of the Lungs(Reinert & Rodgers, 2017). There are limitations to the uses of such algorithms to derive the identity of lung abnormalities caused by Tuberculosis symptoms since a flawed model can detect pathological signatures which have a similarity in features regards to that of Tuberculosis features, which hence may lead to a false diagnosis of the disease condition and therefore reduced accurate results are yielded as stated by these authors (Hwang, Park, Jin, Kim, Choi, Lee, Goo, Aum, Yim, Park, *et al*., 2019, Reinert & Rodgers, 2017, Chassagnon *et al*., 2020).

PNEUMONIA

The uses of AI techniques that go beyond usages such as detection of pneumonia have also been successful, as seen in the paper by Rajpukar *et al*., where the CheXNet deep learning algorithm outperformed 3 out of 4 radiologists(Rajpurkar *et al*., 2017). Their report concludes by introducing CheXNet based algorithms and improvements made by implementing automation techniques that would suffice the global lack of skilled radiologists to diagnose pneumonia in places where the skill vacuum existed (Rajpurkar *et al*., 2017).

ANOMALIES IN CHEST RADIOGRAM

The applications of AI methodologies are also implemented to detect anomalies or erroneous signatures, leading to misleading conclusions and results hampering diagnostic studies. However, even with well-trained datasets, deep learning algorithms will still struggle to detect such features as there may be a constant need to improve such methods by intense training on dataset collection sets since accuracy is the essential requirement of such studies, unlike case detection for disease scenarios (Chassagnon *et al*., 2020). As earlier mentioned, the plethora of datasets that might make the same algorithm predicts better results may be flawed if underfitting and overfitting conditions occur. A clearer idea is that if the results and predicted values produced by the algorithm are not satisfactory while training on validation and training datasets, this condition is called underfitting(Chassagnon *et al*., 2020). There is also a condition where if generalisation developed in an algorithm is low because of its performance and training in sample datasets gained from a typical vendor, to which it has a level of familiarity, then it might be inadequate and unacceptable. Hence, when unfamiliar cases are presented to that same algorithm trained with unknown datasets, it may not perform as well as one may expect (Chassagnon *et al*., 2020). Therefore, inherently, one of such flaws as mention may be avoided by starting with well-defined training and testing datasets, which enables annotation of sets of data with higher accuracy with lower and acceptable levels of ambiguity (Chassagnon *et al*., 2020). Still, if this annotation causes multiplicity in the generation of labels assigned to a signature/feature, it's called a weak annotation. Such training sets of extensive data for creating functioning projects can be gathered from databases affiliated with the National Institutes of Health as chest X-ray 8(Wang *et al*., 2019). This is a repository of 112,120 scans from 30,805 individuals with labels for eight diseases, which later added six more disease conditions, later called chest X-ray14 (Wang *et al*., 2019, Chassagnon *et al*., 2020). Some diseases included edema, lung nodules, fibrosis, and pneumonia (Wang *et al*., 2019). Rajpurkar *et al*.'s paper once again shows us that, compared to Chexnet's results trained on Chest-ray 14 dataset, the results obtained by 9 radiologists across a validation range of 420 samples as photographs with examples of pathology tags. The Radiologists received a significantly better AUC quality for cardiomegaly, emphysema, and hiatal hernia. In contrast, with other pathologies, The AUC reached with the algorithm had been higher the deep learning CheXNet outperformed when dealing with such pathologies(Rajpurkar *et al*., 2017, Chassagnon *et al*., 2020). Algorithms developed by Huang *et al*. also produced better results upon using training datasets of 54,221 collections from normal individuals with highlights on 35,613 anomalies in radiograph films provided with validation tests on 486 normal and 529 abnormal label datasets (Hwang, Park, Jin, Kim, Choi, Lee, Goo, Aum, Yim, Park, *et al*., 2019). Thus, to conclusively exclaim that the human error rate decreased to a massive amount which has brought back better result interpretation and results while tests are conducted upon chest radiographs (Hwang, Park, Jin, Kim, Choi, Lee, Goo, Aum, Yim, Cohen, *et al*., 2019, Chassagnon *et al*., 2020).

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4. CHEST COMPUTED TOMOGRAPHY

CAD is often used for artificial chest radiography. Identification by Computed tomography. Early approaches were established at the beginning of the 2000s on the foundation of mainstream machine learning models, including specific Support Vector Machines (SVM). Commercially produced computer-aided detection Packages were proposed by several companies like Siemens (Lung) Vcare), General electrical (Tomography ALA for helps in increased analysis), and R2 technology (Image Controller) (Chassagnon *et al*., 2020). Notably, although none of the two major experimental respiratory disease screening tests called NLST (National Test for Lung Cancer Screening)(Garc & Vaca-boh, 2014) and NELSON used CAD for diagnosis of lung nodules, an ancillary analysis from the NELSON group published a paper in 2012 regarding a CAD method where it was compared against the Double interpretation by radiologists in some sample collection of 400 CT scans at chance selected from the NELSON database(Y. R. Zhao *et al*., 2011, Y. Zhao *et al*., 2012). The lung CAD method was implemented from the software commercially provided by Siemens in 2006 (LungCAD VB10A) (Chassagnon *et al*., 2020). The test simulations performed on the lung nodule monitoring reached 78.1 per cent for the double readings and 96.7 per cent for CAD; the overall performance of 3.7 false-positive detections per test sample was obtained. Whether in non-solid or semi-solid, five subsolid nodules were detected in the 400 chosen CT scans. Still, two were not observed through CAD systems (Silva *et al*., 2018). Therefore, its need for visual confirmation is still considered important with CAD-based systems in Computed Tomography detection tests (Silva *et al*., 2018). However, the overall conclusive analysis shows that the usage of CAD techniques allowed for the pinpoint determination of lung nodules presence throughout thoracic patients and individuals with any malignant cases or abnormalities which allowed for enhanced identification of lung nodules with 11 per cent effective growth in guided readings and other consequent studies (Vassallo *et al*., 2019, Chassagnon *et al*., 2020).

VOLUMETRY

CAD is also used to evaluate device-detected nodule volumes found as results from the NELSON experiment, used to estimate the volume-based doubling time. This strategy has been adopted for the creation of a framework for the management of lung nodules as observed from the NELSON analysis with an overall volume of about 50mm^3 was considered as a negative screen with the detected lung nodules of sizes ranging from about 50 and 500 mm3 upon which volumetric based study concluded the doubling period greater than 400 days (Xu *et al*., 2006). This tactic was shown to reduce the false positives in particular since the ratio of positives screens (true and false positive) was at 6.6 per cent in NELSON analysis as opposed to 24.1 per cent in the NSLT where nodule diameters were observed by manual means and any nodule of at least four mm was considered as a successful screen (Chassagnon *et al*., 2020). Certain limitations are concerned with the calculation of nodule sizes, as there is a reader repetitiveness factor calculated to be 1.4 to 1.7, which does not allow us to measure the malevolent activities in nodules reliably, or even its size is about or less than 10 mm. The same applies to a volumetric analysis of nodules in the lungs by software since repetitions in volumetric data are possible (Revel *et al*., 2004). Plus, the doubling time for solid lung nodules for 500 days has about 98 per cent less prediction of values considering the detection of abnormalities and malignant features from the datasets (Revel *et al*., 2006). Therefore, these two mentioned reasons point out why the European stance on this topic recommends measuring volume doubling time and determining the volume sizes of such lung nodules as essential features for ease of management(Oudkerk *et al*., 2017). Therefore, we can conclusively say that the detection of subsolid lung nodules in the case by the usage of volumetric software is not any better as apparent discrepancies may be brought about in the long run, which is harmful considering human life is on the line(Chassagnon *et al*., 2020).

RADIOMICS APPROACH

Apart from volume-dependent doubling periodic time estimation, different approaches are needed to effectively define malignant tumours within or in lung nodules. One of such methodologies includes radiomics for the analysis of imaging capabilities derived from medical image analysis. Radiomics can interpret tumour progression, persistence, response to chemotherapy, and radiation treatments (Chassagnon *et al*., 2020, Coroller *et al*., 2017). The mentioned radiomics method allows us to uncover interesting facts about the biological processes of the tumour condition at hand. It can also forecast the diagnosis and treatment of reported lung cancers or assess the probability of metastatic disease

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progression and development into the distant future. Radiomics is also being used to estimate the histology history alongside mutative rates of malignancies within a specific lung tumour at hand. The employment of principal component analysis (PCA) successfully carries out this procedure, i.e. reproducible features can be easily identified and got. In contrast, the received radiomics signature can successfully discriminate between EGFR positive and EGFR negative cases (Paez *et al*., 2004). EGFR's role in cells and cell cycle regulation is essential as it controls the division and growth of cells. In situations where the EGFR gene becomes uncontrollable and is found to be trapped, "switch on" activity leads to critical damages in cells, as seen with positive non-small cell lung cancer (NSCLC), where mutation or damages are considered as "tell-tell" signatures or features of positive malignant activity. This leads to abnormal cell growth, which may remain benign or may become metastatic. EGFR's role in cancer detection is commonly observed, with lung cancer no exception (Paez *et al*., 2004). Among the major challenges of radiomics involve preserving its resiliency and universal applicability of the identified signatures realised through its usages and application (Robinson *et al*., 2019). The detection of any feature by the use of radiomics on images that are got under favourable conditions is not to be expected to be found in every scenario, which can be a flawed structure in the protocol for implementation with an eye for feature detection and its reproducibility under various circumstances is an essential requirement (Robinson *et al*., 2019, Chassagnon *et al*., 2020).

DEEP LEARNING APPROACH

Implementing Convoluted Neural Networks for Image data collected from Computed Tomography is far more nuanced than 2D torso images from simple X-rays because of the 3-dimensional nature of the image collection. Usually, these large numbers of images are sliced into a smaller and manageable sized dataset; this would prompt the creation of newer and radical methods, which may expand data collection methods under such scenarios. Certain studies have been used in Two-dimensional CNNs to overcome these issues for each slice, while others may choose to follow a patch-based strategy to decrease the loss of information. These techniques have proven their metal against the commonly used traditional machine learning techniques, which have yielded better results in the detection of malignancies, as showed by Zhao *et al*., where his deep learning techniques produced an AUC (Area under the ROC Curve) value of 0.758 for predicting EGFR mutations from sample sets (W. Zhao *et al*., 2019). AUC is a ranking system for determining the acceptability of the results produced by algorithms, in this case for deep learning for the receiver operating characteristic curve in diagnostic tests (Mandrekar, 2010). There are variations in these ranking values ranging from AUC of 0.5 suggesting no discriminatory values are detected (i.e., the capability to diagnose patients or individuals with and without the disease condition based on the test), 0.7 to 0.8 range is usually determined as acceptable, 0.8 to 0.9 range of values shows excellence, while over 0.9 is outstanding (Mandrekar, 2010). Ardila *et al*. recently equipped a deep learning algorithm for the NLST sample group collected from approximately 14,851 cases, out of which 578 developed lung cancer by the following year. They then tested the model for the first time on a dataset of 6716 incidents, which attained an AUC of 94.4 % (Ardila *et al*., 2019).

5. CONCLUSION

Artificial intelligence has already been part of the everyday lives of the radiologists and other faculties of medical sciences, which have a very optimistic approach involved in the betterment of ease of performing tasks effectively and at a faster pace. Several programs are currently being developed, which implement deep learning strategies that integrate several of the mentioned features essential in determining results and accurate precision; however, overdependence on these technologies should not cause lax in skill developed by individuals. Medical evaluations automatised by the single use of such techniques are far from their goals. Hence, more professional support and collaborative work need to be done in this field since it concerns the lack of adequate professional understanding about radiomics in several developing countries, the lives of many. These advances do not have to be viewed as a risk but more like an opportunity.

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