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The Rise of Deep Learning in Radiology: An Overview of Recent Research

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Abstract: This is a consolidated look at the applications of various deep learning techniques in the field of radiology. For the past few years, deep learning has pervaded every field and the deep learning revolution has opened up new frontiers in artificial intelligence. From healthcare to art or from education to business - it has been applied successfully in a range of different domains to attain state-of-the-art, often reporting near human-level performance. Hence, in the field of radiology too, especially for image interpretation tasks, deep learning techniques are being increasingly used in recent times to optimize the medical workflow and to achieve better patient care and efficient medical surveillance. Convolutional neural networks (CNNs) are mostly dominant in the case of image interpretation applications in radiology, because of their unprecedented success in image-related applications in other domains such as computer vision. However, other deep learning techniques like recurrent neural networks (RNNs) and generative adversarial networks (GANs) are also being used in recent research for various image-related tasks in radiology like classification, segmentation and detection. In this paper, the imaging modalities associated with this field and the application of different deep learning techniques to these have been discussed at length. Moreover, deep learning can also be applied to radiology use cases other than image interpretation, such as patient scheduling or the processing of free-text radiology reports to improve healthcare surveillance. Finally, in this study, the practical challenges as well as the future research directions of this domain have been discussed. Some challenges include dearth of annotated data, the fear of AI unseating radiologist professionals, legal and ethical issues, black box behaviour of neural networks and adversarial fooling of deep learning algorithms by reverse engineering. To counter some of these problems, a few trends in applying deep learning to radiology in the future may include improved visualisation techniques, integration of the entire workflow for practical usability, unsupervised methods of deep learning like auto-encoders and improving research on GANs in radiology. This study may prove useful for researchers applying deep learning to various radiology use cases by providing a detailed overview of the state-of-the-art research in the field.
Keywords: Deep learning, radiology, neural networks, medical artificial intelligence, machine learning

I. INTRODUCTION

A. Radiology

Radiology has been defined as the science of utilizing high-energy radiation to obtain clinical images of the human body, with an aim to diagnose medical conditions and diseases, particularly cancer. These images are acquired by the help of special equipment from the patient's body by trained professionals called radiographers, while the results of these imaging exams are interpreted by trained medical specialists called radiologists [1]. A related term is radiomics, which refers to the study of feature extraction through suitable algorithms from medical images, to aid diagnosis.

Radiology is extremely important to the medical and healthcare workflow, as it is often the primary tool in the diagnosis of disease. With the research community actively studying how to enhance healthcare and clinical surveillance, it is only fitting that the interest in radiology research is high. On the other hand, artificial intelligence remains the most important and most-researched topic in present times— from self-driving cars to automated machine translation, to even drug discovery for cancer. Hence, implementation of artificial intelligence techniques, like deep learning, to the radiology domain, is very relevant in the present time, to achieve new dimensions in healthcare and disease surveillance.

It is interesting to note that the idea of leveraging artificial intelligence in radiology can be traced back to this prediction by Lee B. Lusted that Jha and Topol [2] alludes to : "an electronic scanner-computer to examine chest photo fluorograms, to separate the clearly normal chest films from the abnormal chest films...the abnormal chest films would be marked for later study by the radiologists." Today, radiology research and deep learning have made that possible, but there are many more strides to be taken in the future.

B. The Need of Deep learning in Radiology

Radiology, as is evident, concerns the extraction and study of radiology images of anatomical structures of the human body and make clinical decisions (e.g., disease diagnosis) by interpreting them. These medical images are extremely complex, and not at all similar to images that we encounter in image interpretation tasks in other domains. Given that data, especially image data forms the crux of radiology, it is evident that image processing, with a focus on complex preprocessing tasks, and image interpretation is essential in this field . Recently, the advent of deep learning and its massive success, especially in tasks related to computer vision and image classification has motivated researchers to apply deep learning to the medical field and use it to interpret complex clinical images for improved disease surveillance.

According to Jha and Topol [2], “Deep learning is an autodidact: like an outstanding radiology resident, the more images it analyzes, the better it gets.” Though there have been problems with acquiring large amounts of labeled data for the medical field, researchers have experimented with several techniques to overcome these hurdles. Hence, a study of deep learning in radiology is interesting from both perspectives - on the one hand, how it produces massively accurate results and facilitates medical diagnosis, and on the other hand, how the process also involves substantial challenges and the research being done to evade them.

Deep learning in radiology (and more generally, in medical imaging and healthcare informatics) have already been explored in several studies [3-6]. However, in this paper, we focus on the most recent research in using deep learning in radiology tasks, and the challenges therein.

C. Outline of this Study

The remaining of this survey is structured as follows. Section II looks at deep learning and radiology side-by-side, exploring the different imaging modalities and the tasks in radiology, as well as the use cases where deep learning are applied to. Section III details the different deep learning techniques and reviews recent research that has used deep learning in radiology. In Section IV, we outline the challenges in the field and Section V points at possible research directions in future. Finally, Section VI concludes the article.

II. DEEP LEARNING AND RADIOLOGY

A. Types of Imaging Modalities in Radiology

Common medical imaging modalities in radiology include the conventional method of X-rays, as well as CT (Computed Tomography) scan, MRI (Magnetic Resonance Imaging) and ultrasound scan. However, radiology also involves a broad spectrum of other diagnostic tests including PET (Positron Emission Tomography), fusion imaging, bone mineral densitometry, fluoroscopy, mammography and nuclear medicine [7].

B. Tasks in Radiology

Tasks in radiology are mostly either classification, detection or segmentation.

Classification tasks are mainly aimed at predicting a single output from two (say, yes or no) or more categories from a dataset of images indicating, for example, the presence/absence of a specific disease or abnormality or whether an abnormality (say, a tumor) is malignant or benign. Convolutional neural networks are the standard technique in classification tasks in radiology, and many variants of the basic technique have been studied to suit latest research.

Coming to segmentation, it is one of the most widely applied tasks and also one that has the most variety, according to Litjens et al. [8]. Segmentation aims to identify the parts (set of pixels/voxels) of the image that correspond to a specific organ/anatomical structure or substructure, commonly referred to as a target class, such as prostate for radiology relating to prostate cancer [8]. Lesion segmentation is also a related segmentation task, but it is related more to the object/lesion detection task than segmentation [9]. The U-net [10], a version of the CNN originally designed for segmentation of biomedical images, has been proved to be hugely successful in image segmentation and other related tasks thereafter, and is often cited as the state-of- the-art method [11]. Recently, GANs have been used in segmentation and for various related applications in cancer surveillance.

Lastly, detection refers to predicting the location of nodules/lesions in a radiology image, such as lung nodules in chest CT scans. Normally, such detection tasks are carried out pixel or voxel-wise, and a challenge is the class imbalance faced because the lesion-size often being insignificantly small compared to the entire image, most pixels/voxels correspond to non-target/non-diseased class [8]. In such tasks, it is important to take into account the three-dimensionality of the input image(since the nodule is 3D) and tweak the algorithm likewise by adding contextual perspective to it [8]. The detection visualization is often done by rectangular bounding boxes,or points. ROC (receiver operating characteristic) curve [9] and AUC (area under the curve) are commonly used as an evaluation metric in detection tasks.

C. Applications of Deep Learning in Radiology

1) *Image Interpretation*: Mazurowski et al. [12] have identified use cases in radiology image interpretation using deep learning which are not the regular practice for radiologists, e.g., radiogenomics or using results from other image interpretations in understanding cancer. The various image interpretation applications like classification, detection, segmentation, etc. have already been discussed in another subsection. However, other than image interpretation applications where deep learning has been applied successfully, Lakhani et al [13] have identified other less-discussed use cases where deep learning (and machine learning as well) could transform radiology.
2) *Advancement of the Radiology Workflow*: In some specific types of radiology, acquisition time is too long in emergency cases like stroke where immediate care is required. Deep learning can be used in such emergency scenarios to reconstruct the images from raw data and cut down on the acquisition time. Moreover, preliminary interpretation [14] of radiology images using AI even before a radiologist reads it could be useful in this regard. A related idea is cost optimization: as we know, radiology equipment are quite expensive, and deep learning techniques have been shown to be able to optimize equipment utilization and save costs substantially. Thus, deep learning techniques are able to better different steps of radiology workflow by inducing several minor changes to it, e.g., staff optimization and scheduling of patient screening, and even pre-analyzing some cases to prevent "observer fatigue" in the case of large number of screenings [15] but which could, taken altogether, bring about a substantial change in the workflow.
3) *Data Augmentation through Image Generation and Enhancement*: Coming to image enhancement, resolution of a radiology image or its signal-to-noise ratio could affect its quality and ultimately affect the performance of the algorithm [12]. One of the possible solutions is decreasing the dose of radiation in the radiology equipment; decreasing the dose leads to an increase in image noise, but using deep learning along with image reconstruction and recreation techniques can handle the problem [16]. Decreasing the noise or enhancing the image quality in general, are easily achievable, e.g., a trained convolutional autoencoder could learn to map from a noisy or a low quality input image and output one of much higher quality and without the noise [17]. Obtaining higher resolution images in this way, called super-resolution, can also lead to improvement in the performance of image processing tasks done on the radiology images, especially in cases of the imaging of the lung and the heart [12]. Moreover, certain unnecessary anatomical structures(or metal artifacts like prosthetics) have been successfully suppressed by DL techniques [18] to improve performance and accuracy. Moreover, generative adversarial networks, a deep learning technique involving a discriminator network which strives to detect fake images generated by a generator network, are often used for data augmentation when there is a dearth of data because the fake images are often very close to the real images [19]. Research is also being done on correlating radiology reports and radiology images, and exploring the semantic similarities. Deep learning has been used to automatically annotate radiology images [20], taking cues from its considerable success in automatic image captioning and labeling; and also precision medicine based on big data [20].
4) *Deep Learning and Information Retrieval Techniques on Radiology Reports*: Radiology reports have been an important source of research interest, and information retrieval (IR) methods have been applied to free-text reports relating to text classification. Mostly such clinical IR systems have utilized natural language processing (NLP); however, recently, with the advent of deep learning, advanced techniques related to it are increasingly being used to extract crucial clinical information from unstructured radiology reports and also to automate diagnosis by classifying clinical codes mentioned therein. Karimi et al. [21] used CNNs (CNNs, normally used massively in image-related tasks, were studied with respect to text classification by Kim [22] and also by Kalchbrennner [23]) and pre-trained word embeddings (Word2Vec [24]) for automated encoding of radiology reports, specifically to extract clinical ICD (International Classification of Diseases) codes. Chen et al. [25] also used CNN and pre-trained word vectors for extracting information from thoracic CT reports. The performance of this model compared with the open-source application "PeFinder", and it was found to surpass the latter, which is based upon traditional NLP techniques.

III. ALGORITHMS USED FOR DEEP LEARNING IN RADIOLOGY IMAGE INTERPRETATION

A. Convolutional Neural Networks (CNNs)

With regard to the various deep learning algorithms available, CNNs are the dominant approach in radiology, especially since image interpretation forms a major part of the use cases, and CNNs have been proved to exhibit massive success in this area. Common techniques that are used in this case are fine tuning and transfer learning. The latter is about pre-training a deep learning model on such a task that has sufficiently large amount of data to train on (most commonly, the ImageNet dataset). This is essential especially in the medical domain, as there is a substantial dearth of unlabeled data and deep learning algorithms are infamously known to be "data-hungry".

1) *Some Applications of CNNs*: Chung et al. explored how CNNs achieve high performance in detecting proximal humerus fractures and in classifying 4 types of fractures based on the widely used *Neer classification* [26]. An interesting observation was that CNN performed better and more accurately in complex fracture cases, which are normally difficult for humans, i.e. medical professionals, to process. However, the authors only considered a single radiograph per patient, which is often an inadequate method for inaccurate classification. Chest X-ray abnormalities were detected using pre-trained CNNs by training on a huge dataset by Putha et al. [27]. Ensemble learning was also implemented. Moreover, the authors made use of NLP methods to retrieve relevant clinical information from the reports. Rajpurkar et al. [28] developed the noted "CheXNet" algorithm based on pre-trained CNNs to successfully predict the presence or absence of pneumonia from chest X-rays, surpassing radiologist performance. Yan et al. [29] applied weakly supervised methods for classification as well as localization tasks to predict thoracic disease on un-annotated data. Yasaka et al. [30] [31] performed classification of liver fibrosis stages from CT scans of the liver using CNNs. Further improvement could be achieved, especially by way of incorporating more features of the liver or more relevant patient information. Desai et al. [32] successfully applied popular CNN architectures, namely the AlexNet [33] and GoogLeNet [34], for identification of basal ganglia hemorrhage on head CT scans, although it remains to be seen if the high accuracy could be replicated for small haemorrhages. Lee et al. [35] used pre-trained CNN to detect bones and tissues as well as to segment the wrist/hand in radiographs of the hand and ultimately performed bone age assessment (BAA) on the data. The visualizations were done via attention maps. Larson et al. [36] similarly performed BAA in pediatric hand radiographs using CNN, inferring that deep learning models are able to produce accurate estimates of skeletal maturity as well as or even with higher accuracy than trained radiologist experts. Becker et al. [37] used deep neural networks on chest X-ray photographs to detect tuberculosis patterns and localize pathological areas. Future improvement on the study could be by incorporating RNNs to study the course and progress of disease. Roth et al. [38] studied hierarchical segmentation of the pancreas in abdominal CT using CNNs to classify superpixel regions (local image regions) generated by feature extraction and random forest classifiers. Roth et al. [39] applied CNNs on 2D image patches in CT scans for detection of bone lesions, inferring that deep learning techniques could ef- fectively lead to false positive reduction in otherwise-used conventional CAD systems. High scores via AUC metric were recorded in this study. Anavi et al. [40] used pre-trained CNNs in retrieval and ranking of most similar X- ray images, given a query image. High recall estimates were obtained. The authors compared descriptor-based retrieval algorithms that utilize distance metrics with standard classification-based algorithms, and it was found that the latter method performed better. The highlight of the work done by Bar et al. [41] on pathology-condition detection from chest X-rays was that the CNN used by them was pre-trained on a dataset that did not consist of medical images. Pre-trained CNNs along with standard descriptors were used. It was also observed that using fused descriptors and applying a combination of a deep learning algorithm with them performs better than using single descriptors. The primary inference from this study was that it is indeed feasible to use deep learning techniques trained on non-medical data in medical tasks — which is important, given the relative lack of suitable large medical datasets for such studies. Lakhani and Sundaram [42] applied CNNs to detect tuberculosis from chest radiographs. Ensemble methods were successfully used in this study. Both pre-trained and untrained networks were used in experiments, and the architectures used were AlexNet and GoogLeNet. It was seen that ensemble methods performed better. A challenge in the study was that pathological conditions having almost similar appearance to that of the TB conditions (e.g., lung cancer and bacterial pneumonia) are often mistakenly classified as tuberculosis. To address the problem of 3D radiology images on 2D CNNs, Ciompi et al. [43] proposed multi-stream and multi-scale CNNs for nodule classification related to lung cancer that are able to extract several 2D views from a single nodule. Gjesteby et al. [18] used deep learning in addition to standard NMAR (Normalization-based Metal Artifact Reduction) techniques to rectify metal streaks in CT images. In this study, CNNs involving image reconstruction and super resolution were applied. This application has huge potential, especially in the case of more precise estimation of tumor volumes for proton therapy planning in cancer surveillance.

B. *Recurrent Neural Networks (RNNs)*

RNNs, known for their success in temporal data related applications and tasks that involve sequences, and hence massively successful in text-related and other sequence-related applications, have also been used sometimes, e.g., in organ segmentation, though not as widely as CNNs.

1) *Some Applications of RNNs*: Xie et al. [44] used spatial "clockwork" RNN for medical segmentation in histopathology images. Zheng and Yi [45] tweaked the traditional "vanilla RNN" architecture by adding a "competitive layer model" to produce accurate results in brain MRI segmentation. Xu et al. [46] applied a novel dual-channel preprocessing (composed of original CT

image as well as an enhanced density map) method as well as a CRF-RNN (CRF stands for Conditional Random Fields) model combined with CNN to extract maximal performance for bladder segmentation from CT images. The hybrid deep learning model was better than using only CNNs, because some limitations of the CNN, as mentioned above, were rectified by combining the CRF-RNN model. The authors achieved high segmentation accuracy with this method.

C. Generative Adversarial Networks (GANs)

GANs have been used increasingly in recent times for segmentation, though they have been mostly used in data augmentation. GANs involve a discriminator and a generator network that behave adversarially with respect to each other, which forces the discriminator to get better at recognizing real data from the fake data created by the generator.

1) *Some Applications of GANs*: Xue et al. [11] have tweaked the original GAN architecture and designed a CNN as the segmentor, with an adversarial critic network. This model was shown to have better performance than the U-net, which is a variant of the CNN as mentioned above.

D. Hybrid and Other Techniques

Hybrid techniques combining several of the above techniques have also been used, to extract maximal performance. Ensemble learning is a noted research trend that has earned sufficient traction in present times. On the other hand, unsupervised learning techniques work without the need of labeled data and that is significant in the medical domain where lack of labeled data is a huge problem.

1) *Some Applications*: Hua et al. [47] applied Deep Belief Networks or DBNs (pre-trained in an unsupervised manner with Restricted Boltzmann Machines or RBM) as well as CNN to the problem of nodule classification for lung cancer, and compared their performance with standard baseline methods and geometric descriptors. The authors inferred that although CNNs are the dominant approach in similar and related tasks, DBN, however, has more freedom due to undirected weights between network layers, and therefore achieves better performance. Cheng et al. [48] applied unsupervised methods like stacked denoising autoencoder (AE) on breast ultrasound lesions and lung CT nodules, exploiting the noise-tolerant features of the technique on noisy and highly variant medical images. The results were compared to that of conventional CAD systems and standard machine learning classifiers like SVM, and the technique performed favorably. Chilamkurthy et al. [49] applied deep learning techniques in the scope of identification and classification of critical conditions from CT scans of the head. A challenge in this study was to classify 3D CT images, while most studies have used 2D images for applying deep learning to segmentation and classification. The authors used the popular ResNet [50] architecture and its slight variations.

E. Discussion and Comparison of Deep Learning Techniques: Pros and Cons

From the papers surveyed as well as from a general overview of the field in general, we infer that CNNs are the dominant approach regarding deep learning applied to radiology. Ravi et al. [51], however, identifies a few challenges in using CNNs for radiology applications: most importantly, the fact that most radiology images are 3D while CNNs have been basically designed for 2D images.

Moreover, CNNs are traditionally invariant to rotation or scale; how they understand the position or orientation of objects is also confusing. Due to this invariance property, CNNs may often overlook detailed insights about the image, which is when sequence models like RNN or probabilistic models like conditional random fields (CRF) can prove to be better [52]. The most important reason why we use RNNs is when there is a temporal or sequence-related aspect to the task, which RNNs can perform well in because of their architecture that comprises feedback connections. Moreover, vanilla RNNs even have a few shortcomings, most notably the problem of exploding gradients, hence often RNN-LSTM architecture is used together. Coming to GANs, it is a relatively newer research area but one that has seen massive success in very recent times. A number of studies have utilized GANs for medical image segmentation and related tasks, but often the downside of this method is that with its discriminator and generator architecture, it is often too data-hungry and too complex for the task. Unsupervised methods like auto-encoders, etc. have seen some amount of success. It can be said that if unsupervised methods are experimented with in more studies, it may prove to be quite important in this field, given the dearth of labeled medical data which is essential for supervised learning algorithms.

Thus, it is evident that there is no single algorithm that can always prove successful or can always be the go-to method in certain situations. Different deep learning techniques exist to suit different needs of varying use cases and it is important to know the advantages and disadvantages as well as applications in the literature for every algorithm or method to be able to use it aptly.

IV. CHALLENGES IN USING DEEP LEARNING FOR RADIOLOGY

According to Thrall et al. [15], "Biology is far more complex than chess or Jeopardy! or Go." It is important to understand that training a classifier on, say, complex X-ray images is naturally more difficult than on typical images, e.g., ImageNet data, in which the typical location of the object of interest is mostly in the centre. Hence the challenges in using deep learning for radiology are quite daunting. Annotations made by radiologists (including style of reporting and use of language) are often not consistent, and expertise in the related medical domain, which is required to annotate radiology images [53], is very costly. Hence, in many cases, such annotated data is hard to find. Moreover, free-text radiology reports are often sources of essential data, but they require sophisticated text-mining methods to be processed in an automated way [8]. Besides, the raw medical data obtained cannot often be directly used for modeling by deep learning techniques. In this regard, deciding correct and suitable preprocessing technique and also choosing the hyperparameters and tuning them are extremely important parts of the task and also focal points of research. [51]. A challenge in this regard is that the hyperparameters vary from situation to situation and can never be predetermined [54].

There is a serious lack of collaboration between deep learning specialists and radiology specialists, which leads to miscommunication in leveraging deep learning to radiology use cases. Moreover, Mcbee et al. [55] warns that reverse engineering [56] may enable miscreant or adversarial systems to change the input data slightly, e.g., adding imperceptible noise to an image so that the algorithm outputs wrong results. This issue has also been raised by Kalra (Ge et al.) [57] that "fooling of neural networks" by adversarial examples results in the deep learning technique to misclassify. However, a point that is relevant in this case is that almost all machine learning algorithms and not just deep learning algorithms are susceptible to such issues [51].

Summers [58] reviewed the challenges in using such intelligent techniques in radiology and radiomics with a special focus on abdominal oncology imaging, like, the lack of expert annotations, and the high cost associated with it, as mentioned above — which could be solved by crowdsourcing and proper guided methods of data collection and data labeling.

Another challenge is that many radiology researchers use the same techniques to address different clinical problems. It is important to understand that medical problems are highly variant, and different issues need different handling. Many studies and reviews have reported that improvements in performance have stopped, false positive rates remain higher than necessary, and evaluation metrics for the algorithms never reach standard high values, contrary to what are actually being reported in studies. There have been suspicions regarding whether deep learning may unseat professional radiologists, along with other medical image interpretation professionals such as pathologists [57]. However it is better not to dwell upon such perspective, rather direct our research energies towards whether a symbiosis can be achieved between artificial intelligence and medical specialists, e.g. radiologists [13].

Dearth of enough labeled medical datasets often due to patient confidentiality issues is by far the most important problem, given that deep learning algorithms are inherently data hungry. Crowdsourcing has been suggested as a possible solution [51]. Also, inconsistencies of data in medical datasets poses huge challenges [55] which is the reason to call for large, unified and integrated medical databases that would foster future research [9]. The dearth of integration between results of radiology and clinical, pathology and laboratory results from other databases [57] may lead to inconsistent results. Legal and ethical issues are also key challenges, if we are to develop further smart technologies for radiology and advance the field. Moreover, some reviews [59] point out that the majority of deep learning techniques developed to date are "unitaskers", i.e., they address single type of image or modality or single disease entity, e.g., lung cancer. However, looking at the larger picture, it is not pragmatic to have multiple independent schemes for decision making on the part of the radiologist. Future research needs to integrate these techniques in a better way. Lakhani et al. [13] also dwell upon the idea that modern deep learning applications in radiology are only limited to narrow specific tasks, i.e., they tend not to emphasize upon accurate symptoms of diseases but rather on low-level task-specific signs [57]. This can only represent "artificial narrow intelligence" and not the broader mission of "artificial general intelligence".

V. FUTURE DIRECTIONS AND RESEARCH TRENDS

Several studies have pointed to future directions that could improve the application of deep learning in radiology use cases. First, a detailed inspection and analysis of why and under what circumstances a certain deep learning algorithm fails [59] would be useful for researchers to pinpoint at the methods that could be used to further optimize their techniques, and also to understand the pros and cons of every technique that could help further deep learning research in radiology. Such analysis could be carried out through effective visualization techniques. Secondly, Krupinski [59] aptly identifies that future trends of research in this domain should point towards "practical usability". User-friendly systems need to be developed that could be easily handled by non-professionals as well. Proper medical workflow related to such systems is needed, and constructive integration of all the systems or use cases developed into this workflow is essential. Third, AI specialists could be introduced to the radiology domain to collaborate with radiology professionals [15] and to oversee the deep learning techniques being developed and assess whether they are suitable or not. Fourth, it is a known and a constant concern that deep learning techniques exhibit undetectable "black box" behaviour not only in radiology use cases but in all situations. Research is ongoing to visualize the inner workings of deep learning algorithms to understand better and avoid this problem [60]. Fifth, as also described in Section 4, initiatives must be taken to not highlight merely low-level applications such as recognizing lung nodules to diagnose lung cancer [47], a common use case of deep learning in radiology, but rather emphasize upon the several abnormalities related to real patients and relying on data obtained from multiple different types of equipment and sources [57]. Sixth, even though CNNs are the standard and most widely used approach in this domain, unsupervised methods have received renewed interest in present times [8], for example, auto-encoders, more specifically variational auto-encoders, and RBMs.This may be attributed to the fact that unsupervised methods, as the name suggests, do not require labeled training data and the lack of labeled medical data in such fields makes it very difficult to train supervised deep learning methods. Moreover, GANs have already been discussed in the sections above, and this technique has a huge potential in radiology. These techniques need more research to strengthen their potential in radiology domain. Seventh, the need of a standardized proforma for acquiring medical data and for maintaining consistency of annotations by different sets of expert radiologists is essential and research must be carried out in that direction to enforce it. Lastly, Van Tulder et al. [18] have studied how the benefits of generative techniques may be combined with that of discriminative techniques in a deep learning scenario using RBMs. Research could be carried out in future based on a combination of generative and discriminative methods, rather than purely discriminative or purely generative learning, which showed to obtain better results in the study.

VI. CONCLUSIONS

In this paper, we have provided a brief outline of deep learning techniques in radiology, with a focus on recent research in the field. First, we have described the motivation to leverage deep learning in radiology research, and then detailed the different types of deep learning techniques and also various image modalities in radiology. Thereafter, different tasks in radiology have been discussed, such as classification, detection and segmentation. We have reviewed the recent research using various techniques like CNN, RNN, GAN, auto-encoders, etc. in this field. However, we have also looked at how deep learning can transform the radiology workflow in all aspects and how DL techniques have been successfully used in a broad spectrum of applications other than the commonly discussed image interpretation tasks. Finally, we have identified the substantial challenges in the field such as black box behaviour of deep learning techniques and outlined potential research directions to help overcome them in future, such as focusing on practical usability, better visualization and unsupervised methods. Deep learning in radiology research is an exciting and extremely relevant field, and the right direction of research is required to successfully exploit deep learning techniques to enhance healthcare and medical surveillance.

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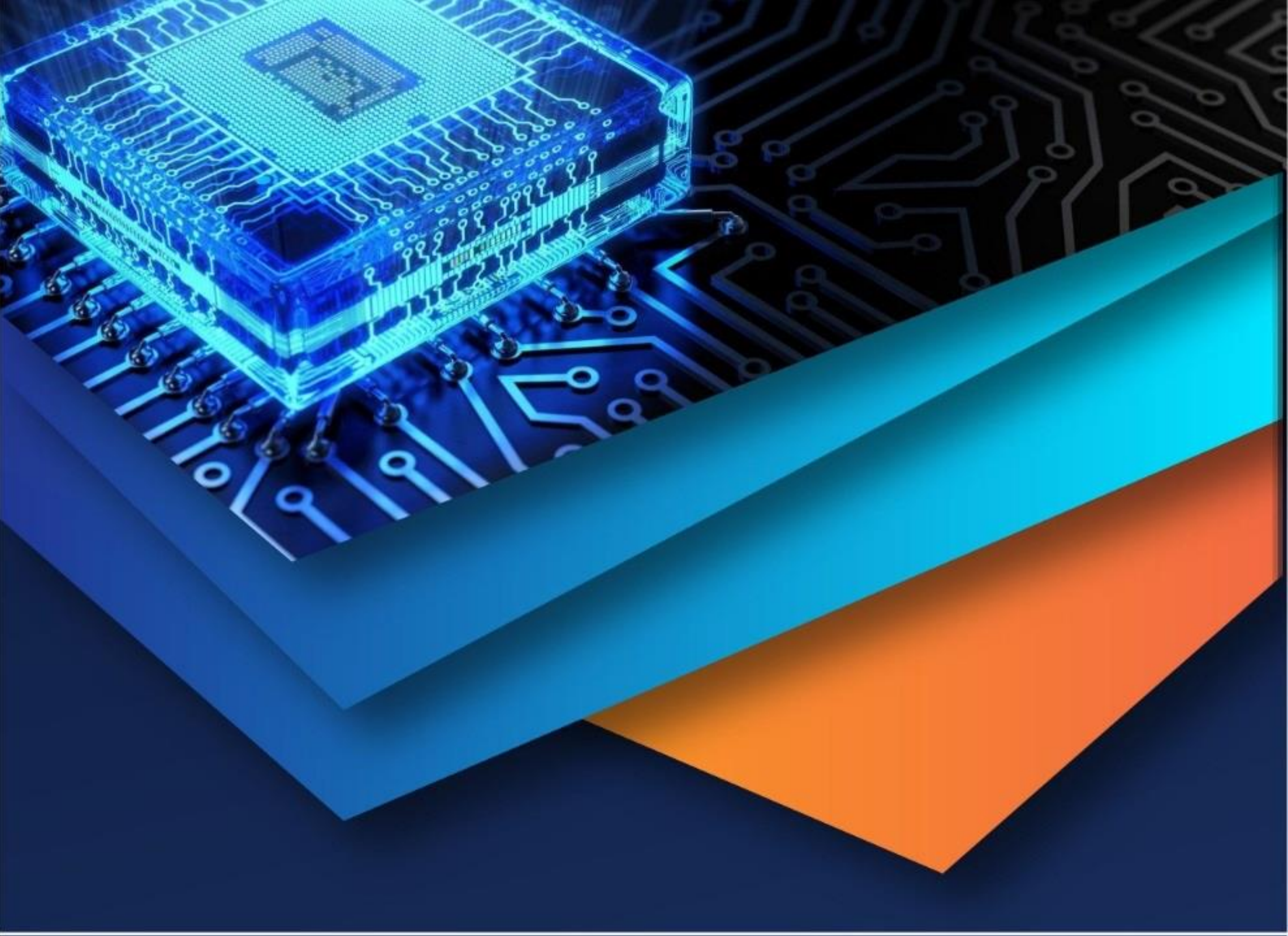

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