Medical Imaging in Artificial Intelligence: a Literature Survey

Jayprakash Upadhyay and Ayushi Jaiswal

February 26, 2023

MEDICAL IMAGING IN ARTIFICIAL INTELLIGENCE: A LITERATURE SURVEY

Jayprakash Upadhyay[1], Ayushi Jaiswal[2]

[1, 2] Department of ECE, Asst Prof., SRIST, Jabalpur, Madhya Pradesh, India

ABSTRACT: The increase of human population and the number of diseases each day causes the need for a fast and accurate diagnosis. In recent years, artificial intelligence (AI) technologies have greatly advanced and become a reality in many areas of our daily lives. In the health care field, numerous efforts are being made to implement the AI technology for practical medical treatments. With the rapid developments in machine learning algorithms and improvements in hardware performances, the AI technology is expected to play an important role. Artificial intelligence in medical diagnosis helps with medical decision making, management, automation, admin, and workflows. It can be used to diagnose cancer, triage critical findings in medical imaging, flag acute abnormalities, provide radiologists with help in prioritizing life threatening cases and help with the management of chronic diseases. Autonomous diagnosis is one of the popular research areas, which reduces the workload of the health workers and gives them the opportunity to spend more time on taking care of their patients while using the help of these systems for a fast and accurate diagnosis. But no matter if the diagnosis is done manually or by an autonomous system, image enhancement is very important since it directly affects the result of the diagnosis in both cases. This chapter includes recent studies which are related to image enhancement in healthcare applications.

Keyword: Artificial Intelligence, CT, MRI, Deep learning, CLAHE.

1. INTRODUCTION

Artificial Intelligence (AI) is a branch of science that simulates human intelligence in computer like machines that are programmed to think like humans and exhibit traits like learning and problem-solving. AI uses different digital inputs to gather multiple arrays of data. The data is then processed by AI analytical models for fast and effective output of information with human-like intelligence. Data processing is usually executed with the assistance of two sophisticated technological subsets of AI, which are Deep Learning and Machine Learning that help the machines to constantly learn and develop its knowledge.

Accurate and early diagnosis and prognosis are essential in many fields of healthcare. Artificial Intelligence (AI) applied to medical images allows for automated disease detection, characterization of histology, stage, or subtype, and patient classification according to therapy outcome or prognosis. It also permits outlining particular regions in the images, quantifying organ volumes, and extracting features from the images which, combined with machine learning algorithms, leads to quantification of image properties or image classification. In recent years an unprecedented amount of digital imaging data has become available in medicine thanks to digitalization, affordable data storage, and improved imaging techniques [2].

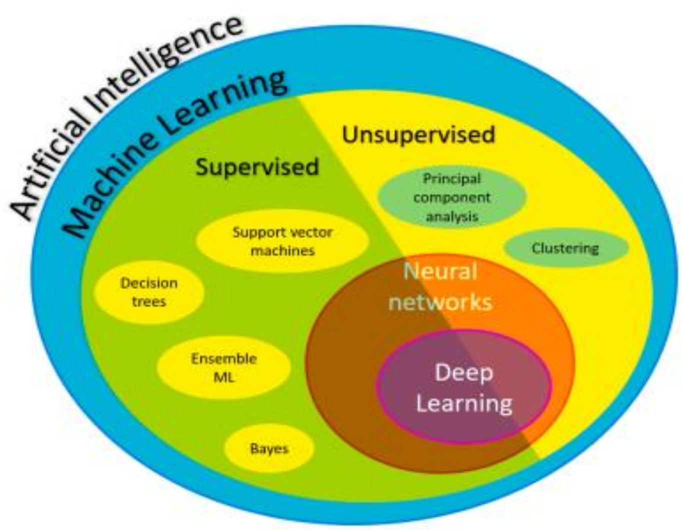

Figure 1: Definition of Artificial Intelligence used in the Review

Medical Imaging has been pivotal in diagnosis and monitoring different types of critical diseases in Hospitals. Medical imaging is the generation of images of various body parts and tissues. For example, if a person is diagnosed with problems is lungs, X-rays are used to monitor lungs which will give the part of lungs that might be affected. If the image is not clear enough to come to any conclusion, CT scans are used to have a better view of the part of lungs. Every year, Hospitals generates huge image data. These images can be used to implement deep convolution neural networks which can help in finding different patterns in the images. Artificial Intelligence will help in analysis of these images and it will further help in diagnosis and provide tools for Doctors to make life saving decisions. Medical Imaging refers to the different types of technologies that are used to view human body for the purpose of Diagnose, medical conditions or to monitor certain part. Different types of Medical Imaging are CT scan, X-Rays, MRI etc [5].

2. LITERATURE REVIEW

Pathology is finally profiting from the recent development of promising novel imaging techniques, as well as exploration of computational methods for extracting increased information from existing slides and conventional microscopy. Application of novel slide-free histology using stimulated Raman microscopy for intra operative guidance during brain cancer surgery is presented remarkably; this method includes AI classification tools (cancer/not cancer) that surgeons can rely on directly [1].

Deep learning is presently a dynamic research zone in machine learning and pattern recognition society and demonstrates that a variation of the stacked-inadequate denoising auto encoder can figure out how to adaptively improve and denoise from artificially obscured and disruption included preparing cases [3]. Deep learning is coming to play a key role in providing big data predictive analytics solutions. In this provide a brief overview of deep learning, and highlight current research efforts and the challenges to big data, as well as the future trends [8].

In surveillance, monitoring and tactical reconnaissance, gathering visual information from a dynamic environment and accurately processing such data are essential to making informed decisions and ensuring the success of a mission. Camera sensors are often cost-limited to capture clear images or videos taken in a poorly-lit environment. Many applications aim to enhance brightness, contrast and reduce noise content from the images in an on-board real-time manner. Results show significant credibility of the approach both visually and by quantitative comparison with various image enhancement techniques [9].

Automated analytical systems have begun to emerge as a database system that enables the scanning of medical images to be performed on computers and the construction of big data. Deep-learning artificial intelligence (AI) architectures have been developed and applied to medical images, making high-precision diagnosis possible [11].

There are a number of areas that need to be supplemented within the current health care system for the AI to be utilized more effectively and frequently in health care. In addition, the number of medical practitioners and public that accept AI in the health care is still low; moreover, there are various concerns regarding the safety and reliability of AI technology implementations [12].

AI methods excel at automatically recognizing complex patterns in imaging data and providing quantitative, rather than qualitative, assessments of radiographic characteristics. In this authors establish a general understanding of AI methods, particularly those pertaining to image-based tasks and explore how these methods could impact multiple facets of radiology, with a general focus on applications in oncology, and demonstrate ways in which these methods are advancing the field [13].

Proposed framework, adopt the concept of transfer learning and uses several pre-trained deep convolutional neural networks to extract deep features from brain magnetic resonance (MR) images. The extracted deep features are then evaluated by several machine learning classifiers. The top three deep features which perform well on several machine learning classifiers are selected and concatenated as an ensemble of deep features which is then fed into several machine learning classifiers to predict the final output. To evaluate the different kinds of pre-trained models as a deep feature extractor, machine learning classifiers, and the effectiveness of an ensemble of deep feature for brain tumor classification [14].

A method to improve the visibility and contrast of color images author proposed a method of joint technique scheme of Color Adaptive Histogram Equalization (CAHE) and interpolation method. CAHE is an effective algorithm for image contrast enhancement, and interpolation method enhances the image by increasing the number of pixels without missing any intermediate component of image [15].

Authors provides a survey of medical imaging in the machine and deep learning methods to analyze distinctive diseases. It carries consideration concerning the suite of these algorithms which can be used for the investigation of diseases and automatic decision making [16, 17].

3. AI IN MEDICAL IMAGING

The primary driver behind the emergence of AI in medical imaging has been the desire for greater efficacy and efficiency in clinical care. Machine learning, as a subset of AI, also called the traditional AI, was applied on diagnostic imaging started 1980's. Users first predefine explicit parameters and features of the imaging based on expert knowledge. Figure 2 shows the different medical image diagnosis method using artificial intelligence.

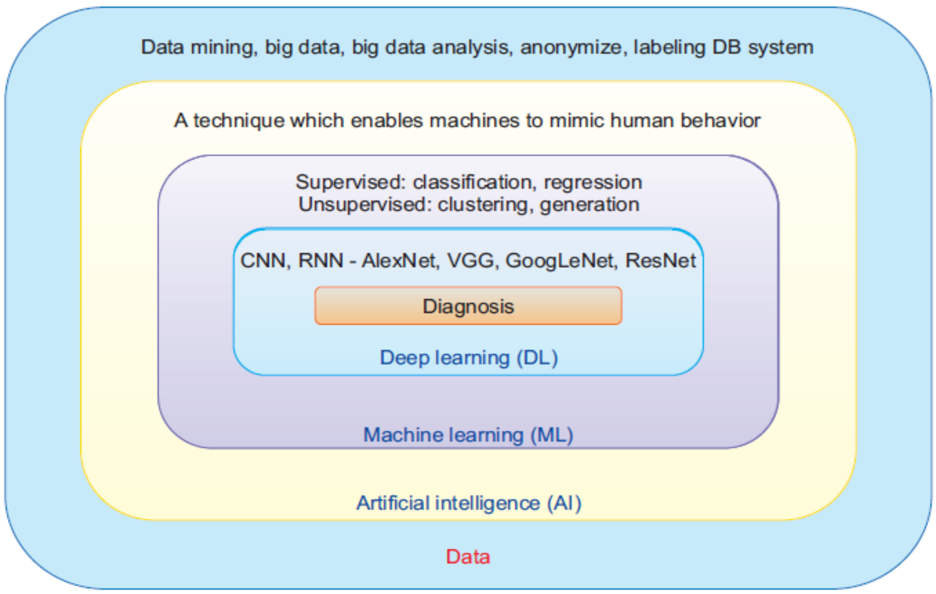

Figure 2: Medical image diagnosis method using artificial intelligence (AI)

One of the problems of machine learning is that users need to select the features which define the class of the image it belongs to. However, this might miss some contributing factors. For instance, lung tumor diagnosis requires user to segment the tumor region as structure features. Due to the patient and user variation, the consistency of the manual feature selection has always been a challenge. Deep learning, however, does not require explicit user input of the features. As its name suggests, deep learning learns from significantly more amount of data. It uses models of deep artificial neural networks. Deep learning uses multiple layers to progressively extract higher level features from raw image input. It helps to disentangle the abstractions and picks out the features that can improve performance. The concept of deep learning was proposed decades ago. Only till recent decade, the application of deep learning became feasible due to enormous number of medical images being produced and advancements in the development of hardware, like graphics processing units (GPU). However, with machine learning gaining its relevance and importance every day, even GPU became somewhat lacking.

To combat this situation, Google developed an AI accelerator integrated circuit which would be used by its Tensor Flow AI framework—tensor processing unit (TPU). TPU is designed specifically for neural network machine learning and would have potential to be applied on medical imaging research as well.

The main research area in diagnostic imaging is detection. Researchers started developing computer-aided detection (CAD) systems in the 1980s. Traditional machine learning algorithms were applied on image modalities like CT, MRI, and mammography. Despite a lot of effort made in the research area, the real clinical applications were not promising. Several large trials came to the conclusion that CAD has at best delivered no benefit and at worst has actually reduced radiology accuracy, resulting in higher recall and biopsy rates [7].

Medical Imaging refers to the different types of technologies that are used to view human body for the purpose of Diagnose, medical conditions or to monitor certain part. Different types of Medical Imaging are CT scan, X-Rays, MRI etc.

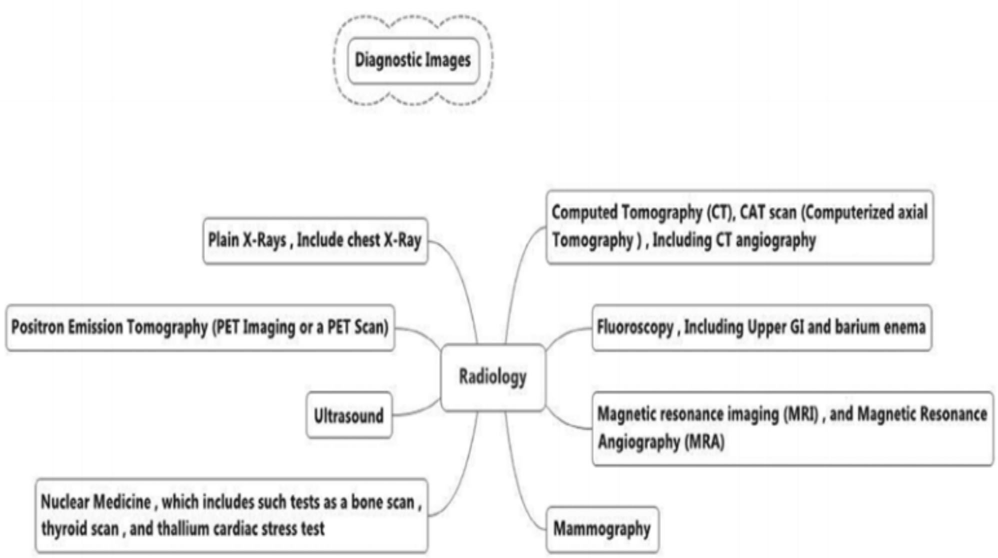

Figure 3: Different types of medical images

In fact, deep learning algorithms have become a methodology of choice for radiology imaging analysis. This includes different image modalities like CT, MRI, PET, ultrasonography etc and different tasks like tumor detection, segmentation, disease prediction etc. Researchers have shown that AI/deep learning-based methods have substantial performance improvements over the conventional machine learning algorithms. Similar to human learning, deep learning learns from enormous amount of image examples. However, it might take much less time, as it solely depends on curated data and the corresponding metadata rather than the domain expertise, which usually takes years to develop. As the traditional AI requires predefined features and have shown plateauing performance over recent years, and with the current success of AI/deep learning in image research, it is expected that AI will further dominate the image research in radiology.

In order to generate an effective AI algorithm, computer systems are first fed data which is typically structured, meaning that each data point has a label or annotation that is recognizable to the algorithm (Figure 4). After the algorithm is exposed to enough sets of data points and their labels, the performance is analyzed to ensure accuracy, just like exams are given to students. These algorithm “exams” generally involve the input of test data to which programmers already know the answers, allowing them to assess the algorithms ability to determine the correct answer. Based on the testing results, the algorithm can be modified, fed more data, or rolled out to help make decisions for the person who wrote the algorithm [5].

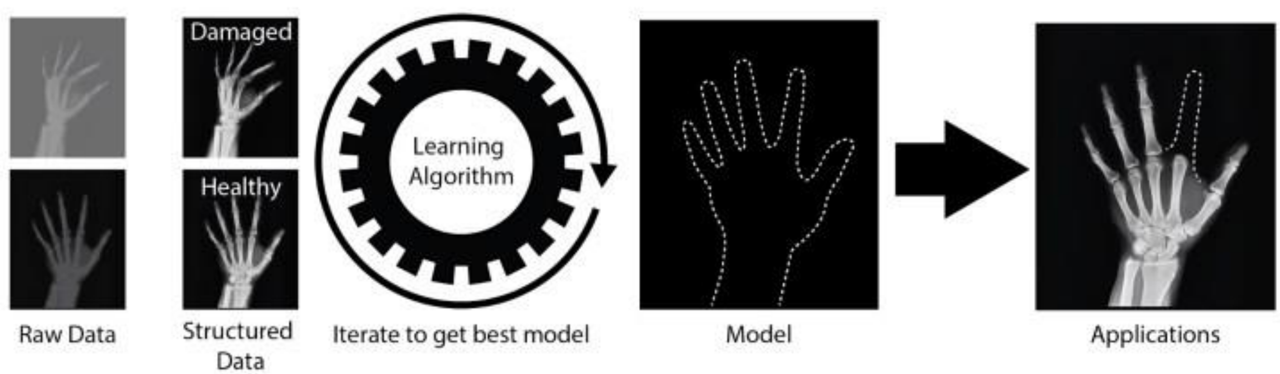

Figure 4: AI algorithms

The above image shows an example of an algorithm that learns the basic anatomy of a hand and can recreate where a missing digit should be. The input is a variety of hand x-rays, and the output is a trace of where missing parts of the hand should be. The model, in this case, is the hand outline that can be generated and applied to other images. This could allow for physicians to see the proper place to reconstruct a limb, or put a prosthetic.

Deep Learning in Image Processing In image processing, deep learning is often used for image classification [4] but has also been used for image filtering. One of the biggest issues in applying deep learning to image processing is how to input the image data into the neural network. A simple approach would be to have each pixel being an input to the neural network. However, with a standard photograph size of 5”x7”, a typical resolution is 630x450 pixels [6]. If the image is in RGB form as opposed to grayscale, this value gets multiplied by 3. This requires a neural network with 850,500 input notes, which can rapidly increase the size of the network if multiple hidden layers are used, dramatically increasing the required computation time for the network to be trained. To combat this issue, convolutional neural networks (CNNs) were created and will be used as the foundation of this project. These are a type of neural network which is designed specifically to be used with images, and differ slightly from traditional neural network structure. Each layer in a CNN is a 3D structure of nodes, as opposed to a 1D structure in regular neural networks. This can be seen more clearly in Figure 5.

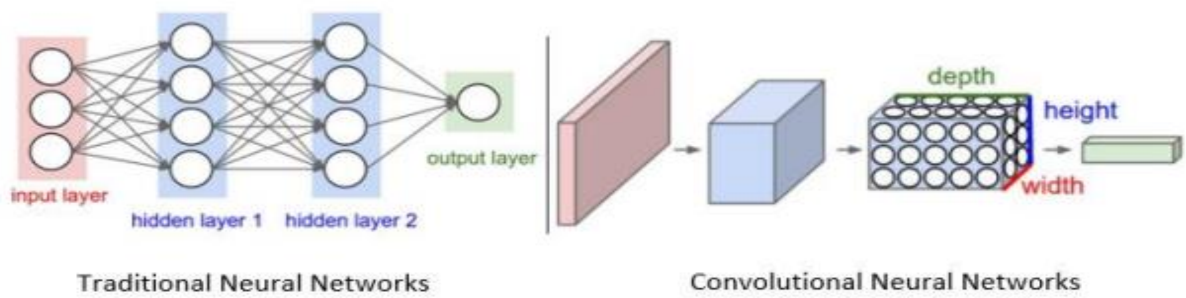

Figure 5: Traditional v/s convolutional neural networks

Another key property of CNNs is that they are not fully connected, where every node in a layer is connected to every node in the previous layer. There are three main elements to a CNN:

• Convolutional layer

• Pooling layer

• Fully connected layer.

These will be discussed in the following sections.

Convolutional Layer: The convolutional layer is a layer (or series of layers) that consists of a sequence of filters. The nature of these filters is trained by the neural network. The image gets convolved by each one of these filters, with the output being stored in an n by n-dimensional "slice" of the next layer, the blue cuboid shown in Figure 5. An example of this can be seen in Figure 6, with the blue matrix being the input image, and the green layer being the output. It's the convolutional layers which process the image, resulting in a filtered output from the network.

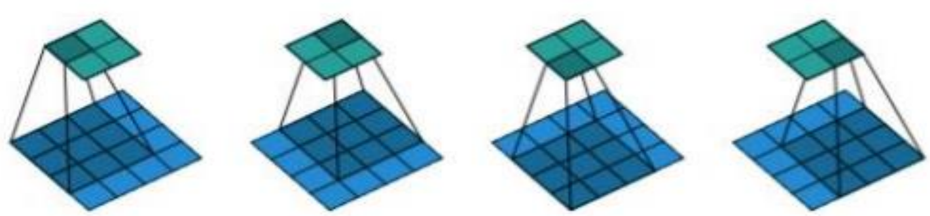

Figure 6: convolutional layer example

Pooling Layer : The pooling layer is simply there to reduce the dimensionality of the previous layer so it is a more appropriate size for the next layer of the network. Typically this is done with max-pooling, which takes the maximum value of the window the filter is looking at, convolved across the image. A CNN can have any number of convolutional and pooling layers, in any order, with the only limitations being computation power and time, and the risk of over fitting [7].

Fully-Connected Layer: The fully connected layer is a regular neural network and is typically used as the final step in a convolutional neural network being used for image classification, where the desired output is an m element array containing probabilities of the image being of a particular category. Deep Learning in Image Filtering In image filtering applications such as this, both the input and output of the CNN should be an image [12]. This can be seen more clearly in Figure 7, where an example CNN structure for image filtering is shown.

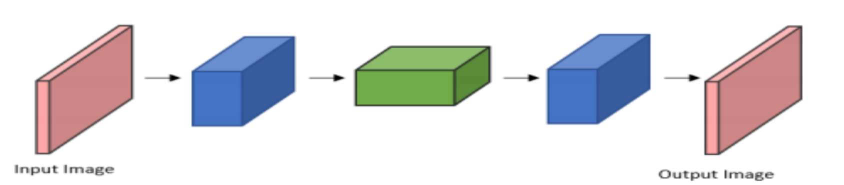

Figure 7: Image Filtering CNN

4. WHAT ARE THE PROBLEMS IN HEALTHCARE?

One major trend in the medical sector is increased usage of imaging techniques, leading to large amounts of complex data in the form of, e.g., X-rays, CAT scans, and MRIs. While imaging as a technique in medical practice is increasing, and consequently the workload associated with the analysis of this data, the number of trained radiologists stays more or less constant. With CT and MRI utilization significantly increasing in recent years, more work must be done by roughly the same number of radiologists; also the risk of increased errors or low quality image due to overworked medical professionals. Furthermore, it is important to remember that a radiologist's profession extends beyond image analysis, and with the workload within one task increasing, other responsibilities become harder to dedicate time to.

Why is AI the solution?

AI is valuable in supporting processes that are repetitive but based on complex data in varying conditions. DL algorithms excel at automatically recognizing complex patterns in unstructured data. For medical imaging, deep learning is therefore particularly interesting.

To show how far the value of this technology extends beyond one application, we will start by looking at how DL can be applied to the entire MRI processing chain in more detail by means of these examples.

i. Accelerating MRI through deep learning image restoration

Penetration of DL techniques into lower levels of MRI includes applications in MR signal processing, denoising and super-resolution, or image synthesis. One issue of MRI applications is the long scanning time, which is linked to elevated motion artifact perturbing image quality, as well as higher medical cost. One approach attempting to accelerate MRI scans is the development of signal processing-based methods. This describes efforts to explore and use prior information on MR images, to reconstruct undersampled k-space measurements (k-space = an array of numbers representing spatial frequencies in the MR image). Previous attempts were only able to use prior information from the image to be reconstructed (a very limited source of information) or from very few reference images, that information would then be manually integrated. Due to the anatomical similarities between individuals, and the large amounts of existing MR images, this research group had the idea of training a neural network on an extensive set of reference images, in order to reconstruct a new image in more detail. The algorithmic architecture of interest is the convolutional neural network, or CNN. One advantage of using CNNs is their strong ability to capture image structures due to their loosely inspired biological structure. The CNN was trained to learn an end-to-end mapping between zero-filled and fully sampled MR images. By training the deep neural network on high-quality MR images, the group developed a model capable of restoring details and fine structures [20].

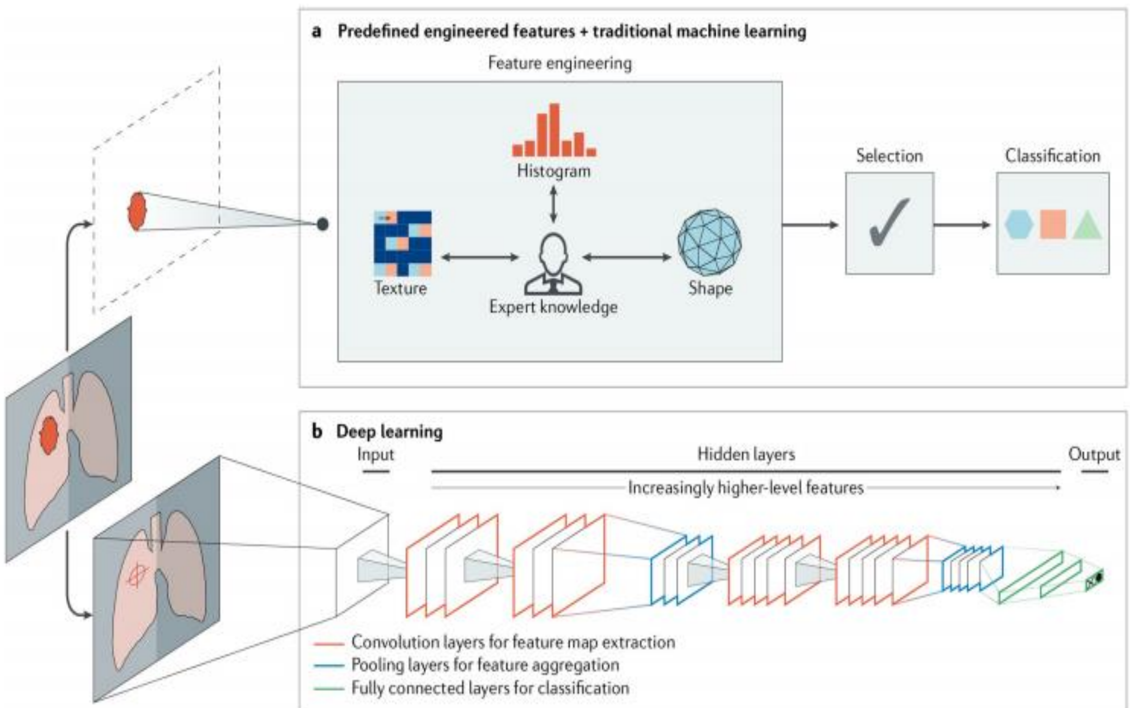

Figure 8: Artificial intelligence methods in medical imaging.

This schematic outlines two artificial intelligence (AI) methods for a representative classification task, such as the diagnosis of a suspicious object as either benign or malignant.

a. The first method relies on engineered features extracted from regions of interest on the basis of expert knowledge. Examples of these features in cancer characterization include tumour volume, shape, texture, intensity and location. The most robust features are selected and fed into machine learning classifiers.
b. The second method uses deep learning and does not require region annotation — rather, localization is usually sufficient. It comprises several layers where feature extraction,

selection and ultimate classification are performed simultaneously during training. As layers learn increasingly higher-level features (Box 1), earlier layers might learn abstract shapes such as lines and shadows, while other deeper layers might learn entire organs or objects. Both methods fall under radiomics, the datacentric, radiology-based research field.

There are two classes of AI methods that are in wide use today (Box 1; Figure 8). The first uses handcrafted engineered features that are defined in terms of mathematical equations (such as tumour texture) and can thus be quantified using computer programs. These features are used as inputs to state-of the-art machine learning models that are trained to classify patients in ways that can support clinical decision making. Although such features are perceived to be discriminative, they rely on expert definition and hence do not necessarily represent the most optimal feature quantification approach for the discrimination task at hand. Moreover, predefined features are often unable to adapt to variations in imaging modalities, such as computed tomography (CT), positron emission tomography (PET) and magnetic resonance imaging (MRI), and their associated signal-to-noise characteristics [11].

The second method, deep learning, has gained considerable attention in recent years. Deep learning algorithms can automatically learn feature representations from data without the need for prior definition by human experts. This data-driven approach allows for more abstract feature definitions, making it more informative and generalizable. Deep learning can thus automatically quantify phenotypic characteristics of human tissues32, promising substantial improvements in diagnosis and clinical care. Deep learning has the added benefit of reducing the need for manual preprocessing steps. For example, to extract predefined features, accurate segmentation of diseased tissues by experts is often needed33. Because deep learning is data driven (Box 1), with enough example data, it can automatically identify diseased tissues and hence avoid the need for expert-defined segmentations. Given its ability to learn complex data representations, deep learning is also often robust against undesired variation, such as the inter-reader variability, and can hence be applied to a large variety of clinical conditions and parameters. In many ways, deep learning can mirror what trained radiologists do, that is, identify image parameters but also weigh up the importance of these parameters on the basis of other factors to arrive at a clinical decision. Given the growing number of applications of deep learning in medical imaging, several efforts have compared deep learning methods with their predefined feature-based counterparts and have reported substantial performance improvements with deep learning. Studies have also shown that deep learning technologies are on par with radiologists' performance for both detection and segmentation tasks in ultrasonography and MRI, respectively.

ii. Artificial intelligence impact areas within oncology imaging

AI is expected to impact other image-based tasks within the clinical radiology workflow. These include the preprocessing steps following image acquisition as well as subsequent reporting and integrated diagnostics (Figure 9a). After carrying out various clinical tasks and generating radiology reports (Figure 9a), Al-based integrated diagnostics could potentially enable health-care-wide assimilation of data from multiple streams, thus capitalizing on all data types pertaining to a particular patient. In addition to radiology reports describing findings from medical images and their associated metadata, other data could be sourced from the clinic or from pathology or genomics testing.

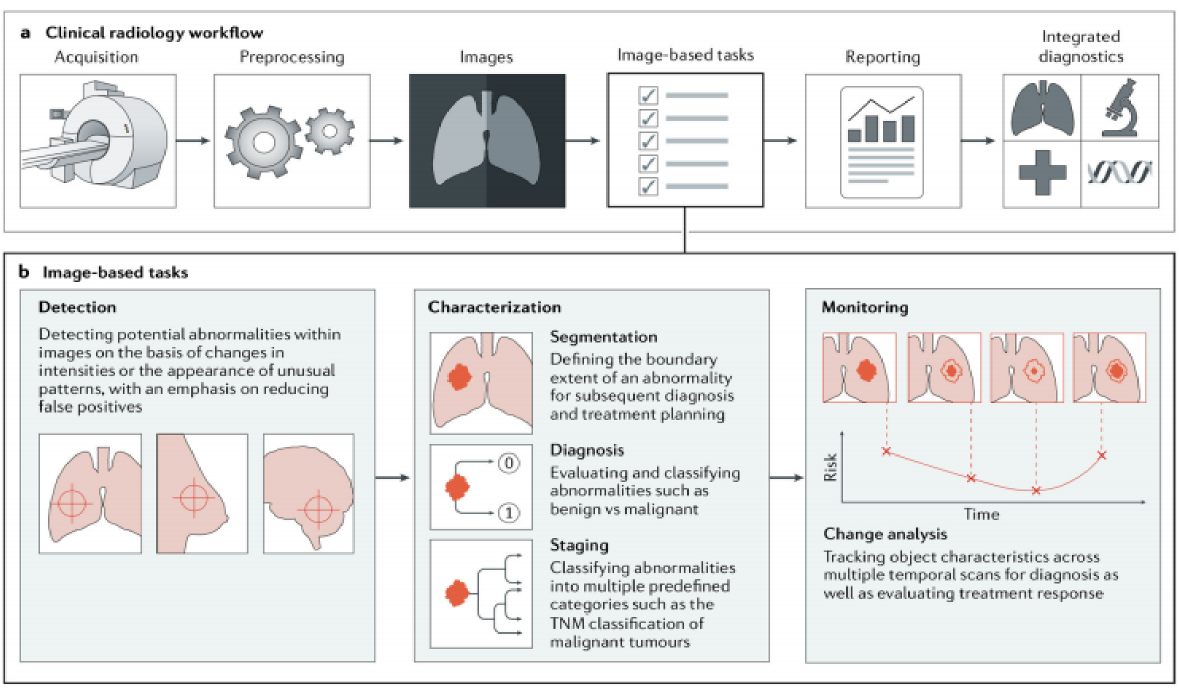

Figure 9: Artificial intelligence impact areas within oncology imaging.

This schematic outlines the various tasks within radiology where artificial intelligence (AI) implementation is likely to have a large impact.

a. The workflow comprises the following steps: preprocessing of images after acquisition, image-based clinical tasks (which usually involve the quantification of features either using engineered features with traditional machine learning or deep learning), reporting results through the generation of textual radiology reports and, finally, the integration of patient information from multiple data sources.
b. AI is expected to impact image-based clinical tasks, including the detection of abnormalities; the characterization of objects in images using segmentation, diagnosis and staging; and the monitoring of objects for diagnosis and assessment of treatment response. TNM, tumour–node–metastasis.

5. IMAGE ENHANCEMENT

Image enhancement is the way toward altering computerized images with the goal that the outcomes are more reasonable for show or further image investigation. Image enhancement should be possible by evacuating noise, image sharpening, or lighting up an image, making it less demanding to distinguish. Image enhancement algorithms include deblurring, filtering, and contrast methods. Deep learning utilizes neural systems to learn helpful portrayals of highlights straightforwardly from image information. Neural systems are pretrained to distinguish and remove different sorts of disruption from images and improve the images [8].

5.1 Methods in image enhancement: There are certain methods for Image Enhancement some of them are listed below [9]

1. **Histogram matching:** Histogram matching is the change of a images with the goal that its histogram coordinates a predefined histogram. The surely understood histogram equalization strategy is an exceptional case in which the predetermined histogram is consistently appropriated.

2. **Contrast-limited adaptive histogram equalization (CLAHE):** It is used to enhance the contrast of the grayscale image assumed as I by transforming. CLAHE works on small regions in the image called tiles, rather than the whole images [9]. Contrast of every tile is enhanced,

therefore, the histogram of the output region approximately matches the histogram predefined the „Distribution" parameter.

3. Wiener filter: Wiener filter is a filter used to create a gauge of a coveted or target arbitrary process by linear time-invariant (LTI) filtering of an observed noisy process, accepting known stationary signal and noise spectra, and added substance noise. The Wiener filter limits the mean square error between the evaluated random process and the desired procedure. Median filter: The median filter is a nonlinear computerized filtering method, regularly used to expel noise from a image. Such noise reduction is a common pre-processing step to enhance the results of later processing for example, edge recognition on an image. Median filtering is broadly utilized as a part of digital image processing in light of the fact that, under specific conditions, it preserves edges while removing noise.

4. Linear contrast adjustment: In this the contrast adjustment block changes the contrast of an image by linearly scaling the pixel values amongst lower and upper limits. Pixel values that are below or above this range are saturated to the lower or upper limit value, individually.

5. Unsharp mask filtering: Unsharp masking (USM) is an image sharpening method, frequently accessible in digital image processing software. The "unsharp" of the name gets from the way that the procedure utilizes an obscured, or "unsharp", negative image to make a mask of the original image. The unsharped mask is then joined with the positive (original) image, constructing an image that is less blurred than the original. The subsequent image, in spite of the fact that clearer, might be a less precise portrayal of the image's subject.

6. Deep neural network: Execute image processing undertakings, for example, removing noise from images and constructing high-resolution images from low-resolutions images, utilizing convolutional neural networks. Deep learning utilizes neural networks to learn valuable portrayals of highlights straightforwardly from information. For instance, you can utilize a pertained neural network to recognize the images and remove various type of noise from images.

7. CAHE (Color adaptive histogram equalization) algorithm: In this color image adaptive histogram equalization algorithm first to transform the color image to an alternative, perceptual colormodel such as HSV, in which the luminance component (intensity V) is decoupled from the chromatics (H & S) components which are responsible for the subjective impression of color. In order to perform such histogram equalization operation on color images 3 such steps is follow:(a) Transform the RGB component image to the HSV representation(hue, saturation, and variance).(b) Apply the histogram operation to the intensity component.(c) Finally convert the result back to RGB color space as required[15].

6. APPLICATION OF AI MEDICAL IMAGE ANALYSIS

1. AI in Brain Imaging:

In brain research using AI, many studies have been conducted in the field of Alzheimer's disease classification, anatomical segmentation of brain regions, and tumor detection. Alzheimer's disease (AD)/mild cognitive impairment (MCI)/HC classification was successfully performed by using the Gaussian Restricted Boltzmann Machine (RBM) to find feature expressions in volume patches of MRI and PET images. The 3-D convolution neural network in AD classification is superior to other algorithm classifiers. Twenty-five deep-layers called the 'voxelwise residual network' (VoxResNet) were developed and successfully segmented automatically. To demonstrate end-to-end nonlinear mapping from MR images to CT images, a 3-D fully convolutional neural network (FCN) was employed and verified in a real pelvic CT/MRI data set. Input and output improved performance by using two volume CNNs, and excellent performance was observed by evaluating the input and output forms in the MRI and PET images of the Neuro imaging Initiative (ADNI).

2. AI in Chest Imaging

By introducing the multiple-instance learning (MIL) framework, a de-convolutional neural network is constructed to generate the heat map of suspicious regions. A unique set of radiologic datasets of publicly available chest X-rays and their reports were used to find and report unique patterns by applying CNN algorithms. A method for classifying frontal and lateral chest Xray images using deep-learning methods and automating metadata annotations has been reported. A new method of using a three-dimensional (3-D) CNN for false positive reduction in automatic pulmonary nodule detection in a Volumetric Computed Tomography (CT) scan has been proposed. 3-D CNN is able to enter more spatial information and extract more representative features through a hierarchical architecture, trained with 3-D samples. The proposed algorithm has achieved high CPM (Competition Metric) scores, has been extensively tested in the LUNA16 Challenge, and can be applied to 3-D PET images.

3. AI in Breast Imaging

Since most mammograms are 2-D and the number of data is large, AI images can be successfully analyzed using deep-learning in natural images. The discovery of breast cancer is the detection and classification of tumor lesions, the detection and classification of micro-calcifications, and risk-scoring work, which can be effectively analyzed by CNN or RBM methods. It has been reported that U-net is used for segmentation breast and fibro-glandular tissue (FGT) in MRI in a dataset and accurate breast density calculation results are observed.

4. AI in Cardiac Imaging

Cardiac artificial research fields include left ventricle segmentation, slice classification, image quality assessment, automated calcium scoring and coronary centerline tracking, and super-resolution. 2-D and 3-D CNN techniques are mainly used for classification, and deep-learning techniques such as U-net segmentation algorithm are used for segmentation. The high-resolution 3-D volume in the 2-D image stack has been reconstructed using a novel image super-resolution (SR) approach. The image quality is superior to the SR method because the CNN model is computationally efficient, but SR-CNN is advantageous in image segmentation and motion tracking.

5. AI in Musculo-skeletal Imaging

Musculo-skeletal images are analyzed by deep-learning algorithms for segmentation and identification of bone, joint, and associated soft tissue abnormalities. 3-D CNN architecture has been developed to automatically perform supervised segmentation of vertebral bodies (VBs) from 3-D magnetic resonance (MR) spine images, and a ‘Dice’ similarity coefficient of 93.4% has been reached. Automatic spine recognition, including spine location identification and multiple images naming, requires large amounts of image data and is difficult to recognize due to the variety of spine shapes and postures. By using a deep-learning architecture called Transformed Deep Convolution Network (TDCN), the posture of the spine was automatically corrected to process the image [11].

7. CONCLUSIONS

AI technologies are expected to bring innovations to the existing medical technologies and future health care. The currently available AI-based health care technologies have shown outstanding results in accurately diagnosing and classifying patient conditions and predicting the course of diseases by using the accumulated medical data. Accordingly, these technologies are expected to bring contributions in assisting the medical staff in the treatment decision-making and in the process improving the treatment results. However, AI-based health care technologies currently have various issues regarding privacy, reliability, safety, and liability. For the AI technologies to be more actively applied in health care, general public awareness of AI, establishment of standardized guidelines, and systematic improvements will be required in the future in addition to the technological advancements.

REFERENCES

1. Tanishq Abraham, Austin Todd, Daneil A, Orringermd: "In Book: Artificial Intelligence And Deep Learning In Pathology ,Chapter Applications Of Artificial Intelligence For Image Enhancement In Pathology 2021, Page No. 119-148.
2. Michele Avanzo , Massimiliano Porzio, Leda Lorenzon , Lisa Milan, Roberto Sghedoni, Giorgio Russo, Raffaella Massafra, Annarita Fanizzi , Andrea Barucci, Veronica Ardu, Marco Branchini, Marco Giannelli, Elena Gallio, Savino Cilla, Sabina Tangaro, Angela Lombardi, Giovanni Pirrone , Elena De Martin , Alessia Giuliano, Gina Belmonte, Serenella Russo , Osvaldo Rampado ,Giovanni Mettiviert "Artificial Intelligence Applications In Medical Imaging: A Review Of The Medical Physics Research In Italy" Physica Medica May 2021, vol 83, Page No. 221-241.
3. Amanjot Kaur, Gagandeep: "A Review on Image Enhancement with Deep Learning Approach" Accents Transactions on Image Processing And Computer Vision (TIPCV), Vol 4 Issue 11, Page No. 16-20.
4. L. P. Valem And D. C. G. Pedronette, "Selection And Combination Of Unsupervised Learning Methods For Image Retrieval," CBMI, Florence, 2017.
5. J. Blahtua, T. Soukip And J. Martinu, "An Expert System Based on Using Artificial Neural Network And Region-Based Image Processing To Recognition Substantia Nigra And Atherosclerotic Pleques In B-Images: A Prospective Study," Advances in Computational Intelligence, Pp. 236-245, 18 May 2017.
6. Walgreens Photo Help, "Image Resolution and Dpi Requirements," Walgreens, 24 July 2017. [Online]. Available: Http://Custhelp2.Walgreens.Com/Articles/Information/Image-Resolutionrequirements. [Accessed 24 March 2018].

7. Mathworks, “Improve Neural Network Generalization and Avoid Overfitting,” Mathworks, [Online]. Available: Https://Uk.Mathworks.Com/Help/Nnet/Ug/Improve-Neural-Networkgeneralization-And-Avoid-Overfitting.Html. [Accessed 24 March 2018].
8. Chen Xw, Lin X. Big Data Deep Learning: Challenges and Perspectives. IEEE Access. 2014; 2:514-25.
9. Lore Kg, Akintayo A, Sarkar S. Llnet: A Deep autoencoder Approach to Natural Low-Light Image Enhancement. Pattern Recognition. 2017; 61:650-62.
10. J. Rajeswari, M. Jagannath: “Advances in Biomedical Signal and Image Processing – A Systematic Review” Informatics in Medicine Unlocked 8 (2017) 13–19.
11. Hyun Jin Yoon, Young Jin Jeong, Hyun Kang, Ji Eun Jeong, Do-Young Kang : “Medical Image Analysis Using Artificial Intelligence “Progress In Medical Physics 30(2), June 2019 Page No. 50-59.
12. Chan-Woo Park , Sung Wook Seo ,Noeul Kang , Beomseok Ko, Byung Wook Choi, Chang Min Park, Dong Kyung Chang, Hwiuoung Kim, Hyunchul Kim, Hyunna Lee, Jinhee Jang , Jong Chul Ye, Jong Hong Jeon , Joon Beom Seo , Kwang Joon Kim, Kyu-Hwan Jung, Namkug Kim, Seungwook Paek, Soo-Yong Shin, Soyoung Yoo, Yoon Sup Choi , Youngjun Kim And Hyung-Jin Yoon: “ Artificial Intelligence in Health Care: Current Applications And Issues” J Korean Med Sci. 2020 Nov 2;35(42) Page No. 1-11.
13. Ahmed Hosny, Chintan Parmar, John Quackenbush, Lawrence H. Schwartz, And Hugo J. W. L. Aerts: “Artificial Intelligence In Radiology” Hhs Public Access, 2018 August; 18(8): 500–510.
14. Jaeyong Kang 1 , Zahid Ullah 1 And Jeonghwan Gwak: “Mri-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers” Mdpi, Sensors 2021 Page No. 1-21.
15. Jayprakash Upadhyay, Ayushi Jaiswal (2015), A Joint Implementation of Adaptive Histogram Equalization And Interpolation, Optik, 126 (24), Page No. 5936–5940.
16. Jahanzaib Latif, Chuangbai Xiao, Azhar Imran, Shanshan Tu: “Medical Imaging Using Machine Learning And Deep Learning Algorithms: A Review” 2019 International Conference On Computing, Mathematics And Engineering Technologies – Icomet 2019 Page No. 1-5.
17. Khairul Munadi (Member, IEEE), Kahlil Muchtar (Member, IEEE), Novi Maulina and Biswajeet Pradhan (Senior Member, IEEE): “Image Enhancement For Tuberculosis Detection Using Deep Learning” IEEE Access 2020, vol 8 Page No. 217897-217907.
18. A. Raj, N. Dheetsith, S. S. Nair, And D. Ghosh, “Auto Analysis Of ECG Signals Using Artificial Neural Network,” In Science Engineering And Management Research (ICSEMR), 2014 International Conference On IEEE, 2014 PP. 1–4.
19. Ferrari R, Mancini-Terracciano C, Voena C, Rengo M, Zerunian M, Ciardiello A, et al. ML-Based Artificial Intelligence Model To Assess Response To Therapy In Locally Advanced Rectal Cancer. Eur J Radiol 2019;118: page number 1–9.
20. R. Nawaratne, D. Alahakoon, D. D. Silva, And X. Yu, ``Spatiotemporal Anomaly Detection Using Deep Learning For Real-Time Video Surveillance," IEEE Trans. Ind. Informat., Vol. 16, No. 1, Pp. 393_402 Jan. 2020.