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MEDICAL IMAGING ENHANCEMENT WITH AI MODELS FOR AUTOMATIC DISEASE DETECTION AND CLASSIFICATION BASED ON MEDICAL IMAGES

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Abstract - **The development of artificial intelligence (AI) in the healthcare industry has recently been of utmost importance. Early discovery, diagnosis, categorization, analysis, and treatment options are always positive medical breakthroughs. In making diagnoses and strategic decisions for healthcare, precise and consistent picture classification is essential. The semantic gap has emerged as the main problem with picture sorting. To bridge the gap, traditional machine learning techniques for classification mainly depend on low-level features rather than high-level ones, use some hand-crafted features, but compel intensive feature extraction and classification procedures. Deep convolution neural networks (CNNs), a potent technique that has significantly advanced in recent years, are successful in classifying images. A thorough assessment of pertinent studies is required to further assist readers in understanding the research and its main concepts captured. This study highlights the various AI models for automatic disease detection and classification based on medical images. This can include identifying tumors, lesions, fractures, or other abnormalities. The models discussed in this article include Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), One-Class Learning Models, Recurrent Neural Networks (RNNs), and 3D and Multimodal Models. Since these models work with various modalities, there are numerous instances where computed tomography (CT), positron emission computed tomography (PET), X-ray, magnetic resonance imaging (MRI), and ultrasound (US). Are mentioned to help complement the research.**

Keywords— **AI, Machine learning, Deep learning, CNNs**

I. INTRODUCTION

The future of healthcare is taking shape right before our eyes due to advancements in digital healthcare technologies like robotics, nanotechnology, 3D printing, and artificial intelligence (AI), among others. Healthcare digitization offers several potentials to decrease human error, enhance therapeutic results, and monitor data over an extended period [2]. Healthcare providers can benefit from artificial intelligence (AI) across various intelligent medical systems and patient care. Different artificial intelligence techniques and methods, ranging from deep learning and machine learning, are being applied in medicine to help develop new drugs, identify patient risk factors, and diagnose diseases [1, 2]. In using AI in the medical field, several data sources are needed to accurately identify illnesses, including mammography, magnetic resonance imaging, computed tomography scan, ultrasound, and many more. For instance, AI and deep learning technology are instrumental in cancer diagnosis and management. Artificial intelligence mainly improved hospital treatments and facilitated patients' transition to home-based rehabilitation [1, 2].

AI applies various models in detecting diseases like cancer and lesions. These models include Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), One-Class Learning Models, Recurrent Neural Networks (RNNs), and 3D and Multimodal Models. These techniques are accurate as they use actual electronic health data records collected data from patients [2,3]. This paper reviews various AI model technologies that can be used to identify multiple diseases, including tumors, fractures, lesions, and related abnormalities. This will incorporate multiple radiological images such as computed tomography (CT), positron emission computed tomography (PET), X-ray, magnetic resonance imaging (MRI), and ultrasound (US).

II. BACKGROUND AND BASICS – MACHINE LEARNING AND DEEP LEARNING

Artificial intelligence is based on various machine learning algorithm types. Ahsan et al. [4] note that 'Machine learning (ML) is an approach that analyzes data samples to create main conclusions using mathematical and statistical approaches, allowing machines to learn without programming.'

The fundamental idea behind ML is to use data to predict the future or make decisions based on a given objective [4]. ML algorithms fall into three categories: supervised, semi supervised, and unsupervised. However, there could be more algorithms, as shown in Figure 1 below.

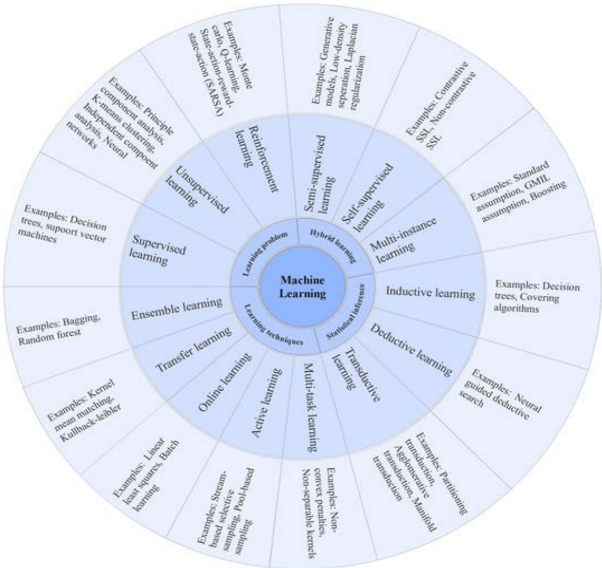

Fig. 1. Various Machine Learning Algorithms [4]

Furthermore, deep learning (DL) 'is a method for designing the ML algorithm in which simple concepts are built on top of each other to form a deep structure with numerous layers' [5]. DL is ML's evolution to analyze large amounts of data. Figure 2 below gives the relationship between AI, ML, and DL. It is crucial to note that AI is the 'mother' of the two subsets, ML and DL. The discipline of artificial intelligence (AI) spans several areas of mathematics and science [5]. A subset of AI would encompass all automatically performed tasks regarded as "intelligence" by machines.

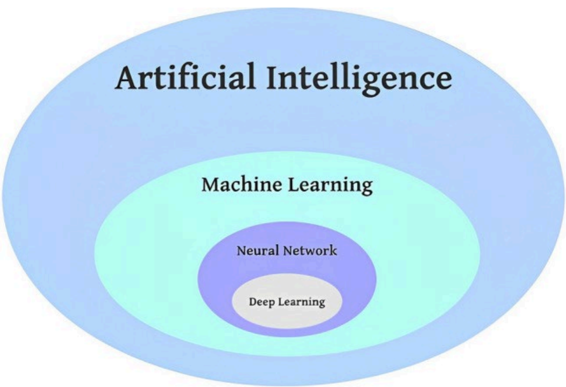

Fig. 2. The Relationship between AI, ML, and DL [5]

Numerous illnesses are predicted and diagnosed using artificial intelligence (AI) techniques, particularly those whose diagnosis is based on signaling or imaging analysis, such as DL and ML algorithms.

III. THE ROLE OF AI IN MEDICAL IMAGING

In AI, particularly deep learning, there is an excellent ability to analyze medical images. AI models can automate medical image interpretation, making these images more accessible and precise [6]. This has helped healthcare providers reduce misdiagnosis, improving the general healthcare quality of patients. AI models are developed to assist early detection and improve accuracy, consistency, and efficiency. For instance, early illness and abnormality detection made possible by artificial intelligence (AI) may result in more efficient treatment and improved patient outcomes.

Medical imaging uses AI models for autonomous illness diagnosis and categorization, including lesion detection, neuroimaging, tumor detection, fracture identification, and cardiovascular imaging. In tumor identification, oncologists may apply AI algorithms to detect tumors, involving MRIs, X-rays, and CT scans, assisting in early identification and planning for treatment [7]. The AI models are primarily used to design various medical equipment, including X-ray machines, CT scans, and MRI machines used in detecting, treating, and managing multiple diseases.

IV. AI MODELS FOR DISEASE DETECTION IN MEDICAL IMAGING

A. Convolutional Neural Network

Convolutional neural networks are a kind of deep neural network used most frequently to interpret visual data in deep learning. CNNs have four typical layers that are used in image detection. It has revolutionized the field of computer vision, enabling computers to read and interpret images efficiently. The four layers include input, convolutional, pooling, and fully connected layers. The input layer enters data into the model [8, 9]. Typically, CNN will accept one image or a series of photographs as input. This layer contains the image's unprocessed information. Besides, the convolutional layer automatically extracts and learns features from the input medical images. This is possible through convolutional filters known as kernels sliding over the image [8]. It is crucial to note that each kernel identifies a particular set of regional patterns or characteristics, including edges, textures, and more intricate structures. This is advantageous in identifying illnesses at different stages. The convolutional layers output is known as feature maps.

In the pool layers, feature maps are down-sampled to reduce the spatial dimensionality. Max-pooling is a widely used method that chooses the highest value from a particular area of the feature map. As a result, the computational complexity decreases, the model becomes more robust to input fluctuations, and the most critical aspects are brought into sharper focus [8]. After several pool and convolutional layers, the CNNs are comprised of one or several connected layers, which can be equivalent to the human biological neural system; this are the fully connected layers [8]. These layers enable the network to make predictions by mapping the high-level characteristics discovered by the convolutional layers to particular categories or classes. Throughout this procedure, convolutional and fully linked layer outputs are subjected to various activation functions, including the Rectified Linear Unit (ReLU). By introducing non-linearity through ReLU activation, the network can represent intricate connections between features and learn from and adapt to various visual data [8]. As a result, output originating from the connected layers is sent to a logistic function to classify each class as the output based on the probability score defining the outcome. The classification can be carried out by softmax or sigmoid within the logistic regression model.

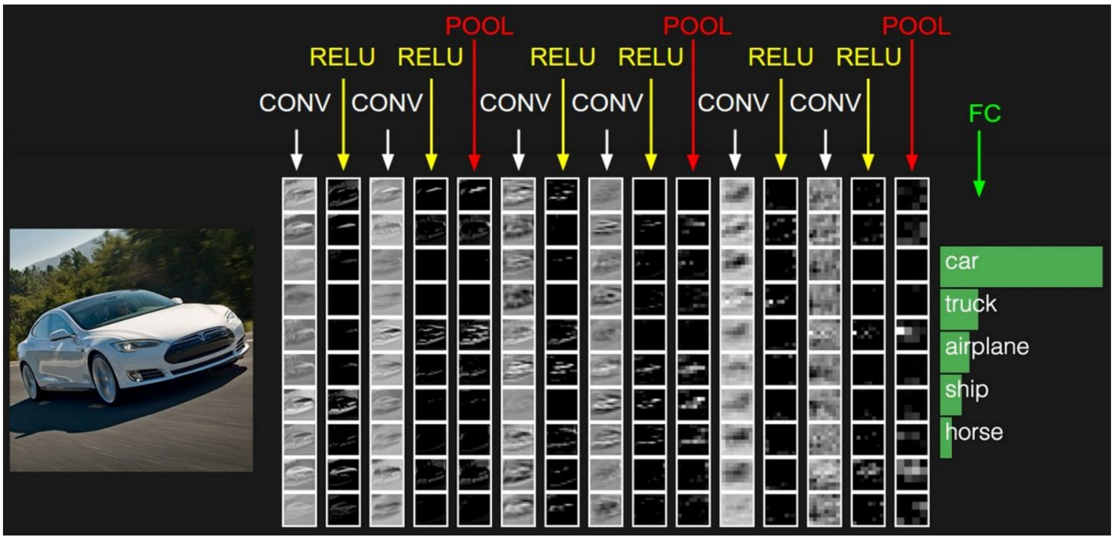

Fig. 3. A Sample of How the Convolutional Neural Networks work to idenify objects.

The image represents the various layers, and the Rectified Linear Unit activates every layer to ensure that the intended identification is reached; in this case, a car has a higher probability.

The capability of CNNs to capture hierarchical representations is its main benefit. Deeper layers recognize more complicated patterns, whereas lower levels may only detect simple elements like edges and corners. Because of their ability to comprehend low-level and high-level picture information, CNNs are incredibly successful at recognizing illnesses and anomalies. To detect malignancies, CNNs are used in radiology to evaluate pictures from imaging modalities, including X-rays, CT scans, and MRIs. They can determine whether tumors are present and to what extent. Dermatologists apply CNNs to identify skin lesions and categorize them as malignant or benign, thereby assisting in identifying diseases like melanoma earlier.

B. Generative Adversarial Networks (GANs)

A generator and a discriminator make up Generative Adversarial Networks (GANs), which compete with one another to make more accurate predictions using deep learning techniques. The discriminator and the generator are the two neural networks comprising a GAN. A deconvolutional neural network is the discriminator, while a convolutional neural network is the generator. The generator aims to provide outputs that may be mistaken for actual data. The discriminator's task is to determine whether the results it receives are artificially produced [10]. GANs are utilized in medical imaging to create artificial pictures that may be used for training, enhancing datasets, and performing image-to-image translation actions. GANs are helpful for data augmentation, particularly when assembling a sizable and varied dataset is difficult. They may create variants on synthetic pictures, increasing the robustness and generalizability of AI models. GANs, for instance, may produce artificial X-rays with varying degrees of disease, enabling AI models to learn from various conditions.

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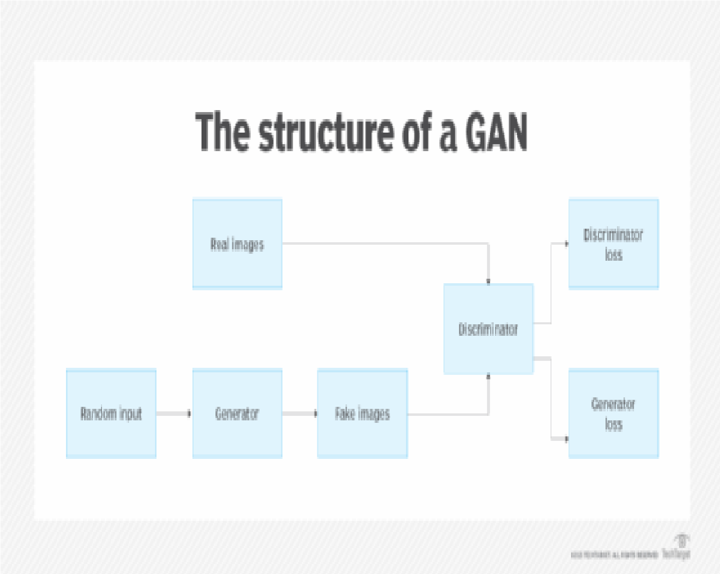

Fig. 4. The Structure of GAN [10].

The figure 4 above shows the structure of GAN. Authentic images from patients are fed into the discriminator. The generator creates data that could be mistaken for the actual data. Using deep learning, the generative model and training the provided images can be screened if there are possible diseases like cancer or lesions. The discriminator is trained to differentiate between fake and authentic photos.

C. One Class Learning Models

As the name suggests, one-class learning models (OCL) are trained to identify a particular data set in the case of many data sets. This specific model is helpful in the context of illness diagnosis in medical imaging. OCL models detect irregularities or defects by figuring out what in a given dataset is normal. Any change from this ingrained routine raises a red flag for a possible illness or anomaly [11]. This method is beneficial for uncommon diseases or situations, such as cancer or lesion detections, when the number of regular instances far outweighs the number of irregular ones.

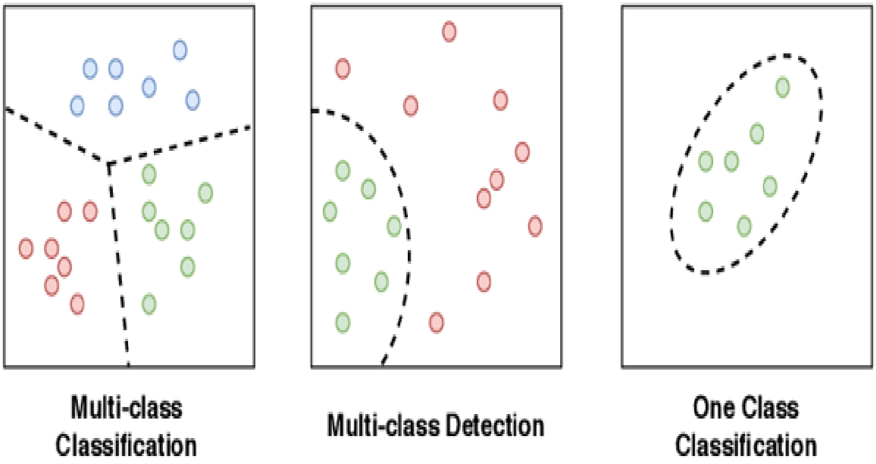

Fig. 5. A Representation of One Class Classification

This AI model, Figure 5, can be trained to only select one particular set of data in a group of different data. The one-class classification is crucial because it processes fed images in the modules and compares them against already set images, helping in detecting the possibility of diseases.

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D. Reccurrent Neural Networks (RNNs)

RNNs are a type of neural network employing contextual memory to identify patterns in sequential data. Recurrent Neural Networks (RNNs) are designed for sequential data analysis. This makes them perfect for time-series data applications in medical imaging, such as sequences of 3D medical pictures or dynamic cardiac images. RNNs are exceptional in gathering contextual and temporal information, unlike Convolutional Neural Networks (CNNs), which are skilled at picture categorization. In the healthcare sector, RNNs are crucial in specialties like cardiology, which examines changing data over time. They provide an essential advantage for identifying and diagnosing conditions early since they can predict cardiac events and recognize illnesses by recognizing long-term trends. RNNs offer continuity, allowing them to find anomalies that could elude individual static pictures. RNNs help improve illness identification and monitoring in dynamic medical environments because of their capacity for sequential data processing.

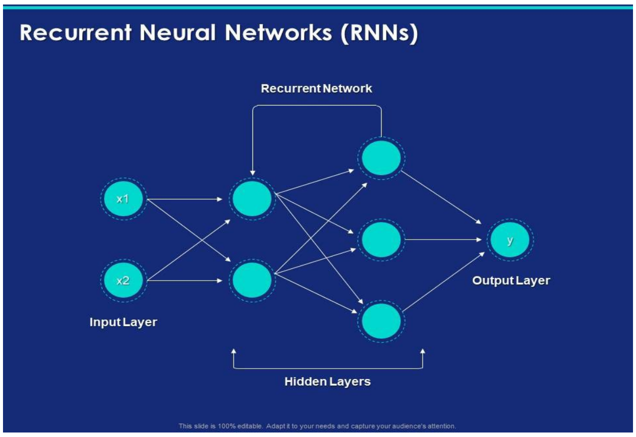

Fig. 6. (a) How Reccurrent Neural Network operates [14].

From the diagram above, data is entered at the input layer stage; at this point, the layer data is hidden in the hidden layers part, where there is continuous data checking to determine if a desired output could be. This model can be trained to detect tumor growth over time since the data is constantly checked for any abnormalities.

E. 3D and Multimodal Models

Medical imaging 3D and multimodal models enable enhanced illness detection accuracy and a more thorough knowledge of complicated medical diseases, and they constitute a significant leap in the healthcare field. The field of 3D, combined with deep learning technologies such as convolutional neural networks, can provide more complete, detailed, and accurate pictures. A single 2D slice might not give the whole image in many medical applications, particularly those requiring CT scans and MRIs. The purpose of 3D Convolutional Neural Networks is to analyze volumetric data, such as collections of 2D photographs, to identify spatial connections and three-dimensional bodily components. This offers a variety of benefits in disease detection; for instance, they frequently have more sensitivity in picking up on subtle irregularities and inconsistencies that individual 2D slices could miss. This is especially useful for situations in intricate 3D systems [13]. In addition, 3D CNNs are capable of 3D segmentation, which precisely recognizes and delineates structures or lesions in volumetric medical photos. This helps in planning treatments and keeping track of illness development.

Conversely, multimodal models combine various data from several imaging techniques, including MRI, CT, and PET scans, in disease evaluation to ensure that disease identification is accurate. Multimodal AI models also incorporate non-imaging data such as clinical information and genomics. A more accurate and thorough assessment of illness is made possible by merging several data sources. These multimodal models help in offering complementary information since they capture various aspects of the same pathology. For instance, in different cases, CT scans provide anatomical data, while PET scans offer functional data that, when combined, can help in accurate disease detection and classification. Also, comparing data from many sources, multimodal models can decrease false positives and boost the sensitivity of illness identification. This is essential for reducing pointless treatments or incorrect diagnoses.

Fig 7. A 2D CT scan of the lungs to help identify cancer cells [17].

Figure 8. A 3D CT scan of the lungs to help identify cancer cells [16].

A look at the two images above (Figures 7 and 8) shows a clear difference in the visibility of the cancer cells. In Figure 7, a stellate ganglion-tumor mass can be seen in the right lung; compared with Figure 8, whose cancer cells are blue on the upper right, the visibility differs. This is a clear presentation that AI (3D emulations) can help better detect the exact location of tumors within the body. This can aid in providing treatment options specifically tailored to the traits of the disease. This is crucial in cancer since therapy choices there may be highly customized. Figure 7, which is 2D, is vague and cannot be analyzed thoroughly to help in management.

IV.CHALLENGES IN AI-BASED DISEASE DETECTION

AI-based models for disease detection also display various drawbacks that undermine their effectiveness. One major challenge is generalization and bias. Making sure AI models generalize well to different patient demographics and imaging situations is essential [18]. Models may function less effectively in another region or hospital when trained on data from one location. Furthermore, biases in the training data can be carried over into AI models, which may lead to incorrect diagnoses and health inequities. Besides, AI-based disease detection faces various regulatory and ethical considerations. Every healthcare institution must maintain patient privacy, have informed authorization, and follow data protection laws. In guaranteeing patient safety and high-quality care, defined norms and standards for AI-based medical hardware and software must also be created.

V. CONCLUSION

A crucial turning point in healthcare technology development has been reached using AI models for autonomous illness identification and categorization in medical imaging. Improved accuracy, early illness diagnosis, and increased efficiency are just a few of the many possible advantages. However, difficulties must be addressed, including data bias, ethical issues, and related issues. The future of AI is bright, but since it cannot replace human intelligence, developments like explainable AI and personalized care will significantly improve human life. As experts in healthcare technology, we should push for vast research in AI and ensure that AI is integrated ethically, contributing to a healthier and more equitable society.

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