Chapter

Deep Neural Networks and Applications in Medical Research

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Abstract

Artificial Intelligence (AI) has played a significant role in improving decision-making within the healthcare system. AI includes machine learning, which encompasses a subset called artificial neural networks (ANNs). These networks mimic how biological neurons in the brain signal one another. In this chapter, we conduct a seminal review of ANNs and explain how prediction and classification tasks can be conducted in the field of medicine. Basic information is provided showing how neural networks solve the problem of determining disease subsets by analyzing huge amounts of structured and unstructured patient data. We also provide information on the application of conventional ANNs and deep convolutional neural networks (DCNNs) that are specific to medical image processing. For example, DCNNs can be used to detect the edges of an item within an image. The acquired knowledge can then be transferred so that similar edges can be identified on another image. This chapter is unique; it is specifically aimed at medical professionals who are interested in artificial intelligence. Because we will demonstrate the application in a straightforward manner, researchers from other technical fields will also benefit.

Keywords: artificial intelligence, artificial neural networks, deep learning, deep convolutional neural networks, medical images

1. Introduction

Artificial intelligence in medicine, for some, is an intimidating thought. But consider this scenario:

> *A patient visits a physician's office and presents their condition/complaint to the nurse, who takes notes, the patient's vitals, and says, "the doctor will see you soon." The nurse then reports all information about the patient to the physician. While the patient waits, the physician takes 10 to 15 minutes to Google this condition before seeing the patient. Without realizing it, the physician is using artificial intelligence to help treat their patient. Indeed, AI has infiltrated many fields and has made a great impact on science, including medicine.*

An ever-increasing amount of patient data is now being collected and stored; this requires significant effort to evaluate. AI fills this need. While it can never replace a physician, AI has made positive advances in medicine:

1.1 Diagnostic assistance

AI has been utilized to assist healthcare professionals in diagnosing diseases and conditions [1, 2]. Machine learning algorithms can analyze large amounts of patient data, such as medical images [3, 4], genetic information [5, 6], and other information contained in electronic health records [7], to identify patterns and make accurate determinations about the presence of disease. This helps doctors in making more informed decisions and improving the accuracy of diagnoses.

1.2 Predictive analytics

AI enables predictive analytics by analyzing patient data and identifying patterns that may indicate potential health risks [8, 9]. By analyzing a patient's medical history [10], genetic information [11], lifestyle factors [12], and real-time monitoring data [13], AI algorithms can predict the likelihood of developing certain conditions or complications. This helps healthcare providers identify high-risk patients, intervening earlier, and implementing preventive measures.

1.3 Personalized treatment plans

AI can aid in developing personalized treatment plans for patients [14–17]. By analyzing individual patient data, including medical history, genetics, and responses to various treatments, AI algorithms can recommend tailored treatment options that are more likely to be effective. This approach allows for precision medicine, where treatments are customized to the specific needs of each patient, leading to improved outcomes and reduced adverse effects.

1.4 Drug discovery and development

AI has the potential to accelerate the process of drug discovery and development [18–23]. Machine learning algorithms can analyze vast amounts of biological and chemical data to identify potential drug candidates, predict their efficacy and safety profiles, and even optimize drug formulations. This can significantly reduce the time and cost associated with traditional drug development processes.

1.5 Workflow optimization

AI can help streamline administrative tasks and optimize healthcare workflows [24–26]. Natural Language Processing (NLP) algorithms can analyze and extract relevant information from medical documents, such as electronic health records and research papers, enabling faster and more accurate information retrieval. AI-powered chatbots and virtual assistants can handle routine patient inquiries, freeing up healthcare professionals' time for more complex tasks.

1.6 Remote patient monitoring

AI technologies, coupled with Internet of Things (IoT) devices, allow for remote patient monitoring [27–29]. Wearable devices and sensors can collect real-time data on patients' vital signs, activity levels, and medication adherence, among other parameters. AI algorithms can analyze this data, detect abnormalities, and provide timely alerts to healthcare providers, enabling early intervention and reducing hospital readmissions. See **Figure 1** summary.

Thus, AI can evaluate complex information. Patient data, as described above, is presented as either structured or unstructured [30]. Structured patient data refers to information that is organized in a predefined format or schema; for instance, patient characteristics or clinical information listed in specific categories, such as diagnoses and type of medication. Each data field has a well-defined structure, allowing for standardized storage and easy analysis. However, these data may pose challenges in statistical processes, especially given rare events with few cases and many characteristics, such as genetic information.

Conversely, unstructured patient data refers to information that does not have a predefined format or organization. It is typically free-form text, narrative, or clinical notes, often created by healthcare providers during patient encounters. Because these lack a fixed structure, it makes searching, analyzing, and integrating with other data more challenging [30]. These data may include images or doctor and patient notes that are not readily classifiable. In addition, medical imaging and other developments in hardware technology provide high-resolution data that cannot be evaluated with conventional statistical approaches. The inherent heterogeneity of these types of data makes it difficult to obtain valuable insights. In fact, 90% of the digital universe of data is unstructured [31]. While 57% of all health data would be useful if appropriately labeled and analyzed, only 3.1% meet these criteria.

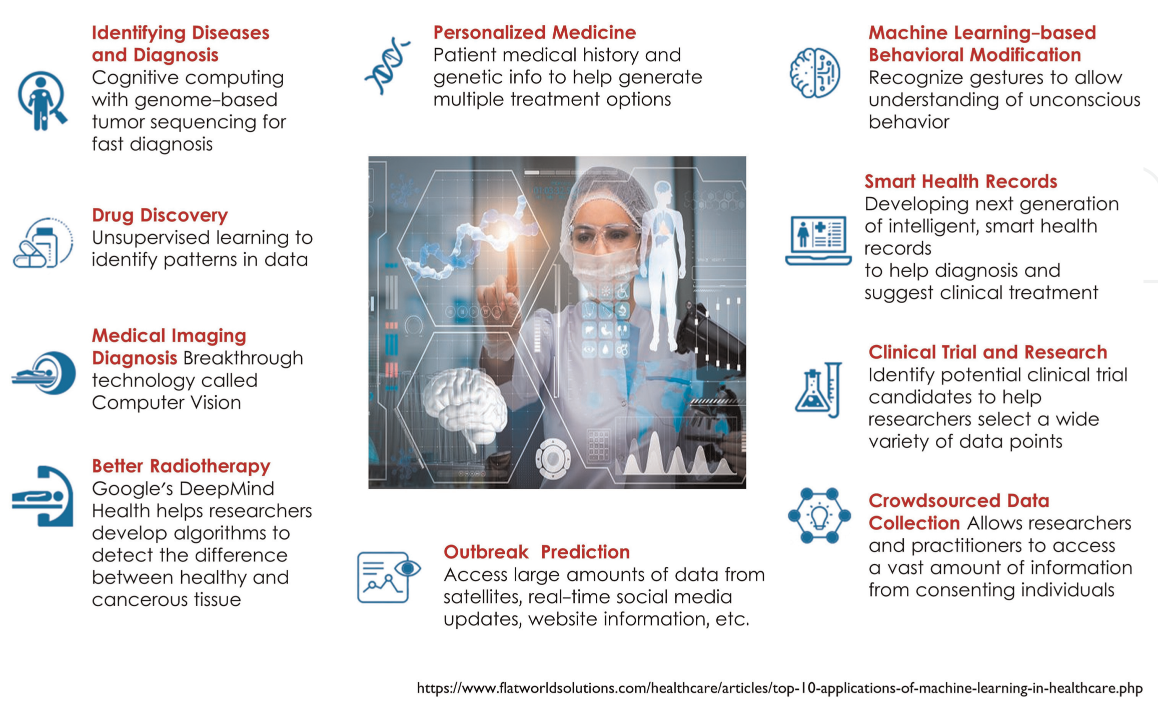

Figure 1.
Contributions and impacts made by AI to the field of medicine.

Big data refers to the large volume of structured and unstructured data sets with sizes beyond the ability of commonly used software tools and traditional data processing practices. The International Data Corporation (IDC) reported that global data volume has grown exponentially from 4.4 zettabytes to 44 zettabytes between 2013 and 2020. By 2025, IDC predicts there will be 163 zettabytes of data [32]. The storage, distribution, review, and interpretation of tremendous amounts of big clinical data poses challenges in terms of high-quality patient care. AI emerges as an effective solution tool in making sense of big health data [33–35]. For example, transformations that facilitate standardization, structuring, and automation of unstructured patient data are suggested [36–38].

AI is a broad discipline that involves various methods and approaches. It is a general term that encompasses machine learning (ML) and artificial neural networks (ANNs), each with its own algorithms, processes, and architecture (**Figure 2**). While AI has the ability to imitate intelligent human behavior, ML allows a system to automatically learn and improve from experience. ANNs, on the other hand, are an application within ML that uses complex algorithms to classify and predict disease versus no disease. Effectively utilizing these systems to evaluate medical data requires an understanding of all these mechanisms.

Contemplate, for example, cardiomegaly, an often-undiagnosed condition. Amin and Siddiqui [39] provide a detailed discussion of this disorder including a definition, etiology, epidemiology, pathophysiology, and evaluation. Briefly, they define this condition in terms of an increased cardiothoracic ratio: the transverse diameter of the cardiac silhouette is greater than or equal to 50% of the transverse diameter of the chest as observed on a posterior-anterior projection of a chest radiograph or a computed tomography. The most common cause is coronary artery disease, such as myocardial infarction and ischemia, along with a variety of other heart, pulmonary, and infectious diseases. It is more prevalent in males than females and occurs more often in Blacks than Whites. They also mention that a detailed history may indicate the possible presence of the disorder, such as shortness of breath, peripheral edema and abdominal distension, fatigue and poor exercise tolerance. One notable and specific

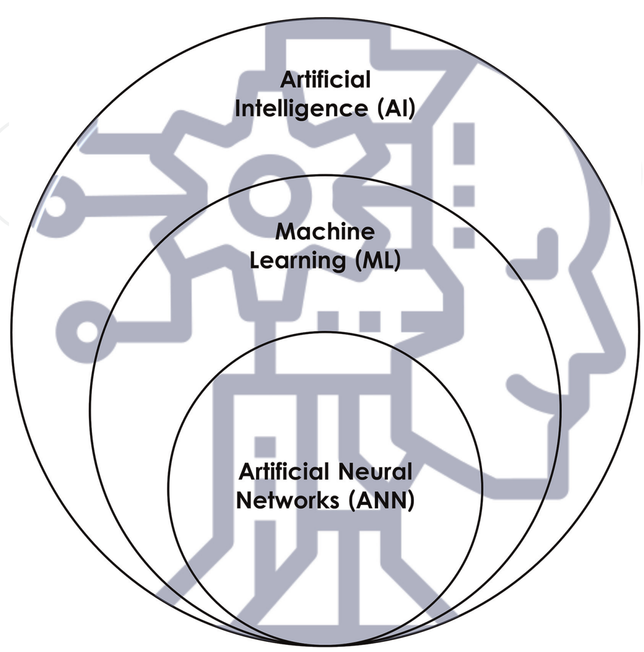

Figure 2.
Representation of the hierarchical position of artificial neural networks within artificial intelligence.

sign of cardiomegaly is a displaced point of maximal impulse. Among other exam findings is the holosystolic murmur of mitral and/or tricuspid regurgitation. Diagnosis of cardiomegaly is primarily through imaging techniques that assess the heart's size and function.

Together, these are some of the "rules" a physician uses for determining a diagnosis of cardiomegaly. To duplicate the effort of decision-making by a physician, a computerized version of these rules would consist of many thousand lines of programming code [40, 41]. Using standard statistical models of prediction, such as logistic regression, these rules would be input along with an image to determine disease versus no disease.

Utilizing ANNs turns this idea on its head. Images that have been positively identified as cardiomegaly versus no disorder are fed into the system. ANNs then learn all the "rules" for identifying the disorder from the images. This may include many hidden layers of information, potentially unrecognized by the physician. This part is called the training dataset, where the system evaluates and learns the cardiomegaly rules. To test the training process, additional data is fed into the system to check the accuracy of the outcome. This architecture is now ready to accept an undiagnosed image to determine disorder vs. no disorder.

Thus, deep learning tools are part of ANNs and can produce effective solutions in accelerating the processes required for diagnosing disease. As an example, deep learning models identified a brain tumor in a patient within 30 seconds [42]. This deep learning model completed its training with more than 2.5 million stimulated Raman histology images before making the diagnosis. In cases where patients are required to be prioritized according to their urgency in the medical field, deep learning models also help with a fast response feature. Although medical doctors prioritize patient urgency efficiently, AI provides greater advantages in terms of speed, scale, and accuracy [42]. Overall, AI has the potential to enhance decision-making within the healthcare system by providing healthcare professionals valuable insight, improve diagnostic accuracy, facilitate personalized treatment, expedite drug discovery, optimize workflows, enable remote monitoring, and generate advances in medical research.

In this chapter, we conduct a seminal review of ANNs and explain how prediction and classification tasks can be conducted for the field of medicine. The organization of the chapter includes an explanation of the biological neuron, McCulloch and Pitts neuron model, as these apply to classification and prediction utilizing ANNs, and deep convolutional neural networks (DCNNs). Next, we briefly discuss the theory associated with ANNs and DCNNs and provide practical applications of each with medical examples. The chapter ends with a general overview of AI as it applies to the field of medicine.

2. Biological neuron and McCulloch and Pitts neuron model

Mammals carry out specific activities through the utilization of brain regions associated with those functions [40]. The cerebral cortex, the most significant component of the mammalian brain, consists of approximately 10 billion neurons. Each neuron in the human brain is interconnected with neighboring neurons, forming extensive networks that process visual, auditory, and sensory information. These connections enable the central nervous system to interpret and comprehend the received data [43].

According to neurophysiological research, the neural network of the nervous system is formed by the combination of structures called neurons, each consisting of a soma and an axon (**Figure 3a**). When forming a biological neural network, neurons are connected, where the axon of one neuron is linked to the soma of another. In a biological neuron, a threshold value needs to be exceeded to initiate a stimulus when transmitting information. The decision of whether the information is transmitted or not is determined by the internal structure and properties of that neuron rather than external factors. Once the stimulation point is reached, the impulse is transmitted along the axon in very short durations ranging from 1 ms to 150 ms, depending on the morphological structure. Consequently, the time elapsed for axonal transmission is minimal. Neurons transmit information from axon to dendrite and to other neurons in a consecutive manner, enabling the representation of information throughout the entire network.

McCulloch and Pitts proposed a widely used mathematical model [44] mimicking the biological neuron, based on the all-or-none principle and physical assumptions, which later became known as the perceptron model (**Figure 3b**). Actions within the biological neuron involve dendrites receiving synaptic inputs from axons, processing this information, and determining whether the neuron will fire an action potential (make a decision). Likewise, in their mathematical model, inputs are labeled s_{i} (t), processing the information includes weighting, w_{in}, and application of the activation function applied to the sum of the weighted inputs, and making predictions (decisions), $\hat{t}\ (t+1)$. They expressed their model in a 1943 publication [44]:

> *Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time.*

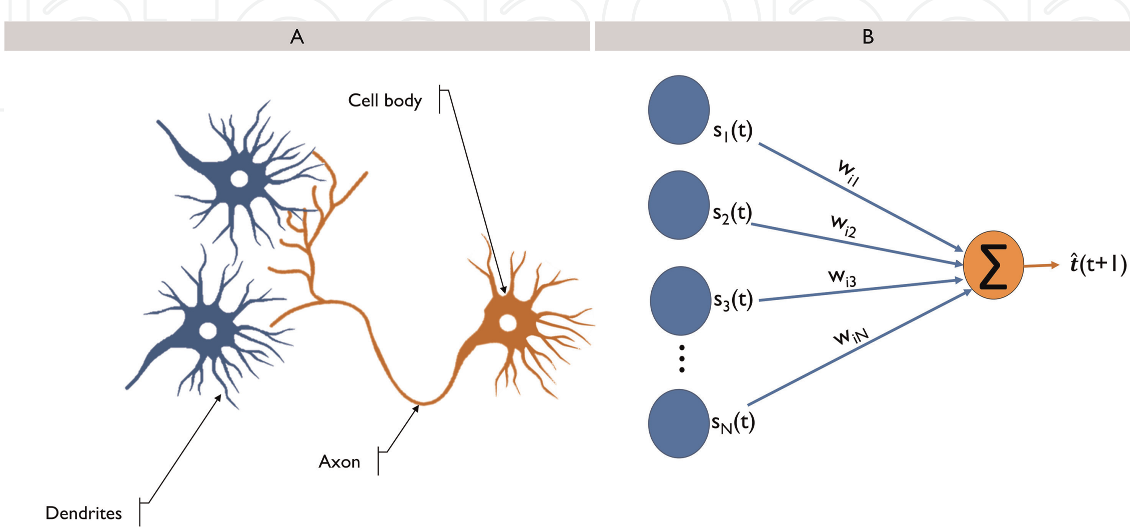

Figure 3.
(a) Human neuron cell and (b) McCulloch and Pitts model.

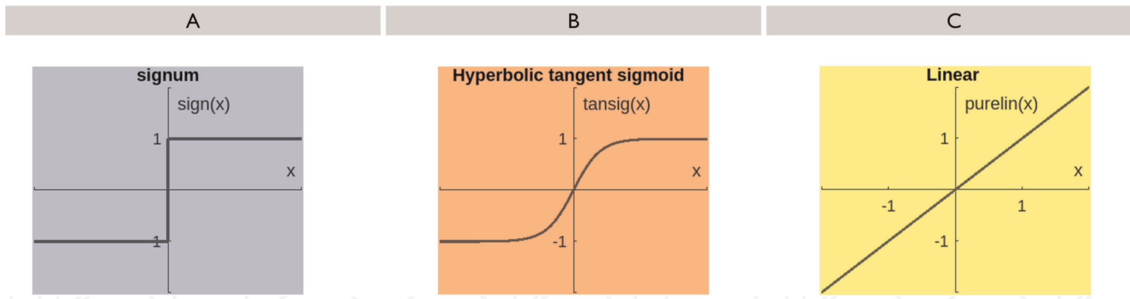

Figure 4.
Some activation function used in neural networks are (a) signum function, (b) hyperbolic tangent sigmoid activation function, and (c) linear activation function.

To uncover the mathematical representation of an individual neuron's behavior and to generalize the behavior of the entire network, they proposed that information from N neurons is transmitted to a single neuron through weighted connections. By applying the signum function, *sgn* (**Figure 4a**), this neuron can be classified as active, +1, or inactive, −1. [43]

$$\hat{t}_i(t+1) = sgn\left(b_i + \sum_{j=1}^{N} w_{ij}s_j(t)\right) \tag{1}$$

The output or state of neuron$j$ at time step$t$, denoted as$s_j(t)$, is determined by the signum function of the weighted sum of inputs from all input neurons$i$, where the weight of connection between input neuron$i$ and neuron$j$ is denoted asw_{ij} . In Eq. (1) and **Figure 4a**, the signum function yields results of either −1 or +1, which are referred to as "inactive" and "active," respectively, as follows:

$$sgn\,(x) = \begin{cases} -1, & x < 0, \\ +1, & x \geq 0. \end{cases} \tag{2}$$

While this function is not capable of modeling the entire brain system, it proves sufficient for solving numerous complex problems. However, it was observed that the signum function encounters a jumping issue from -1 to $+1$, particularly for values of x close to 0. As a result, the signum function was modified in the following manner:

$$\hat{t}_i(t+1) = g\left(b_i + \sum_{j=1}^{N} w_{ij}s_j(t)\right) \tag{3}$$

Thus, the activation function$g$ can be linear or nonlinear (**Figure 4b** and **c**), providing a continuous output [43].

3. A brief theory: ANNs and DCNNs

ANNs are a type of computer program that can be "taught" to emulate relationships in sets of data. Once the ANN has been "trained," it can be used to predict the outcome of another new set of input data, for example, another composite system or a different stress environment. ANN structures are obtained by modifying the perceptron structures (from **Figure 3b**), which are the building blocks of the architecture.

In a fully connected ANN, there is a forward and backward phase; together, these are called epochs. The forward phase computes a "functional signal," the feedforward propagation of input pattern signals through the network, much like a biological neuron. The backward part computes the "error signal," and propagates the error backward through the network, starting at the output units. These constitute training or learning. The "training" in ANNs happens by changing the synaptic strengths, eliminating some, and building new ones. The main idea is to distribute the error function across the hidden layers, corresponding to their effect on the output. Standard backpropagation is a gradient descent algorithm (as is the Widrow–Hoff learning rule) in which the network weights are moved along the negative gradient of the performance function. The term backpropagation refers to the manner in which the gradient Is computed for nonlinear multilayer networks. This algorithm looks for the minimum error function in weight space using the method of gradient descent. The combination of weights that minimizes the error function is considered a solution to the learning problem.

Figure 5 shows how neural networks solve the problem of determining disease subsets by analyzing huge amounts of structural and unstructured patient data.

Medical images are fed into the network architecture as inputs. Next, DCNN plays a role in dimension reduction, where important information is extracted from the images and used to construct a matrix of data, which is converted to a vector. The fully connected neural network processes this vector and determines the outputs, e.g., makes a prediction or classification of the images.

3.1 Classification/prediction with ANN

Classification, in the context of machine learning, refers to the task of categorizing or assigning predefined labels or classes to input data based on certain patterns or characteristics. It is a supervised learning problem where the algorithm learns from labeled training data to make predictions on unseen or test data. In a classification problem, the input data consists of a set of features or attributes that describe each instance or sample. These features could be numerical, categorical, or even textual in nature. The goal is to build a model that can accurately classify new instances into one of the predefined classes or categories. The choice of the classification algorithm

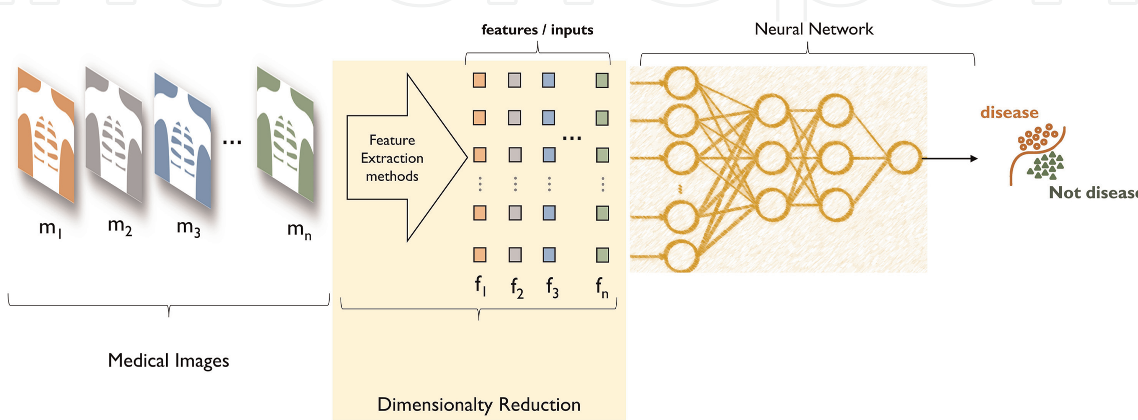

Figure 5.
A demonstration of how ANNs with DCNN provide a solution to a medical image processing problem.

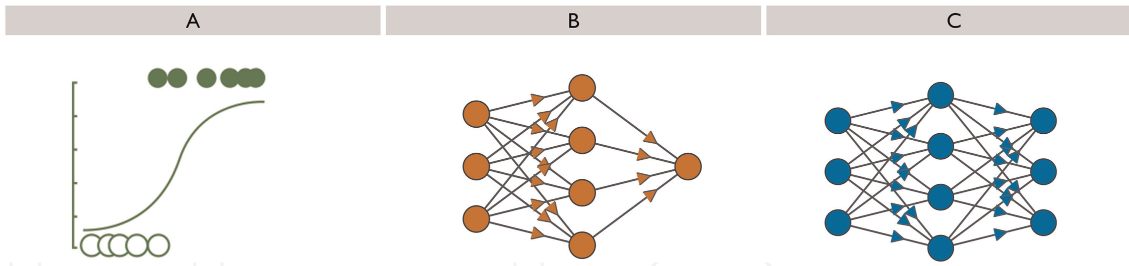

Figure 6.
Classification problem solvers (a) logistic regression, (b) ANN classifier to identify the target, and (c) application of multiclass ANN classifier.

depends on the characteristics of the dataset and the complexity of the problem at hand. **Figure 6** shows several methods of classification.

Logistic regression (**Figure 6a**) is a simpler model compared to ANNs (**Figure 6b** and **c**). It uses a linear decision boundary to separate classes, while ANNs can learn complex nonlinear decision boundaries through multiple layers of interconnected neurons. Classification ANNs seek to categorize an observation as belonging to some discrete class as a function of the inputs (dependent variable). The input features (independent variables) can be categorical or numeric types; however, the dependent variable must be a categorical feature. For example, in a study [45] aiming to automatically predict gender from frontal face photographs, features representing the faces are extracted using various methods and classified as "female" and "male" as the output in an ANN-based classifier. ANNs have three layers that are interconnected. The first layer consists of input neurons. Those neurons send data on to the second layer, which in turn sends the output neurons to the third layer. ANNs are considered nonlinear statistical data modeling tools where complex relationships (patterns) between inputs and outputs are discovered and modeled [46]. ANNs, like a regression model, can be used to model experimental outcomes and subsequently make predictions about untested levels [47–51].

The emergence of these structures is based on the idea of feeding the entire dataset to ANN architectures without preprocessing. However, classical ANN structures face two main challenges in achieving this type of learning. The first challenge is the requirement for long training durations; the second, is obtaining large amounts of data. Initially, attempts were made to solve these problems by extending the training duration (e.g., increasing the number of epochs) and expanding the training set, but the desired performance levels could not be achieved.

4. Deep convolutional neural networks (DCNNs)

DCNNs, short for deep convolutional neural networks, are widely used artificial intelligence tools in the medical field. DCNNs enable the automatic learning of problem-specific features within big data, bypassing the need for manual feature engineering and statistical procedures. As a result, the insignificant portion of data within big data can be effectively disregarded. While DCNN structures were discovered by modifying ANN structures, the most significant part highlighted in **Figure 5** is the dimensionality reduction section, where medical images with disease and nondisease probabilities undergo preprocessing before serving as input to the ANN. This stage is known as feature extraction, and there is extensive literature on this topic. DCNNs, represented by the orange box in **Figure 5**, can automatically perform the dimensionality reduction step. Prior to DCNNs, problem-specific statistical methods were developed to find the best approach in this stage. Automating the dimensionality reduction step in DCNNs has eliminated significant workload and enabled high-accuracy problem-solving.

Figure 7a shows an example of a deep network with an input size of $224 \times 224 \times 3$, followed by interconnected three-dimensional layers (*tensors, explained below*) and three one dimension fully connected layers [42]. The matrix contains one image that measures 224×224 pixels and 3 RGB colors. **Figure 7b** shows a feedforward neural network structure with input layer, hidden layer, and output layer sizes of 5, 10, and 2, respectively. While the input size of the ANN (**Figure 7b**) structure is only five, the deep neural network is large enough to accommodate very large images. Thus, DCNN reduces the dimensions of the matrix so that ANN can make an accurate prediction without any extraneous information.

In another example, DCNN structures, such as AlexNet [52], GoogLeNet and ResNet-50 [53], and VGGNet-16 [54], are designed to solve image classification problems with 1000 category labels in their outputs. It is understood that DCNNs are structures that can take in large-sized images with a large number of categories obtained from a large number of samples as their inputs. However, considering that the increase in the number of categories in the output requires an increase in the sample size, DCNNs do not guarantee effective solutions for problems obtained from small sample sizes. Imagine trying to differentiate between the letters

by only using the information above the lines. The letters P, B, and R all appear similar, and only K can be differentiated. However, if you use the information below the line, R and K are similar and cannot be differentiated. Thus, large samples are required to accurately predict among the categories.

In deep neural networks, the term “tensor” refers to a concept used to represent multidimensional data structures. Tensors are a generalized form that encompasses scalar values (0D), vectors (1D), matrices (2D), and higher-dimensional data structures (**Figure 8**). While the structures shown in **Figure 7** can accept a 1D vector as

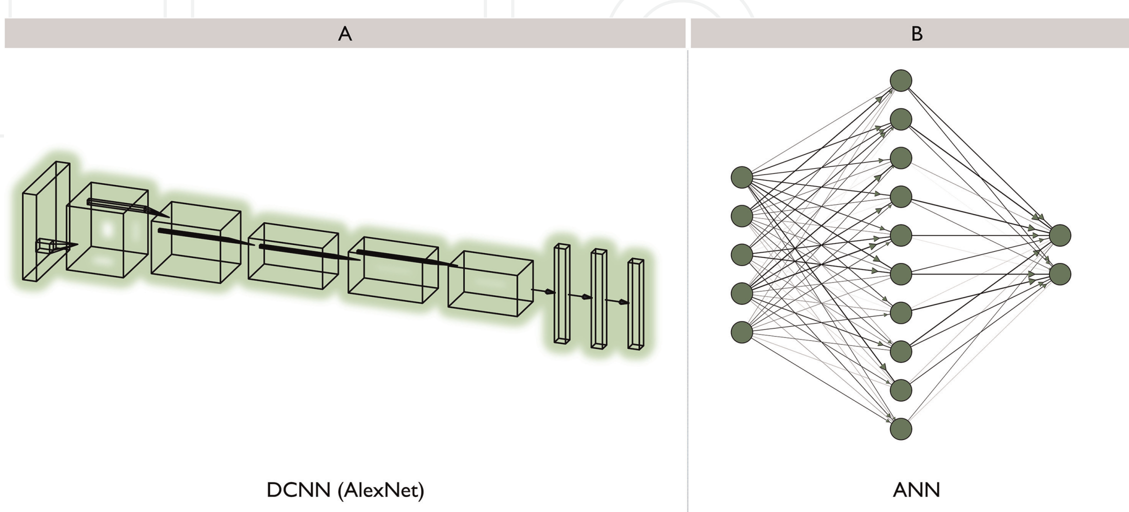

Figure 7.
Semantic representations of neural network models used in image processing. (A) Deep convolutional neural network (DCNN), AlexNet [52] (B) feedforward neural network.

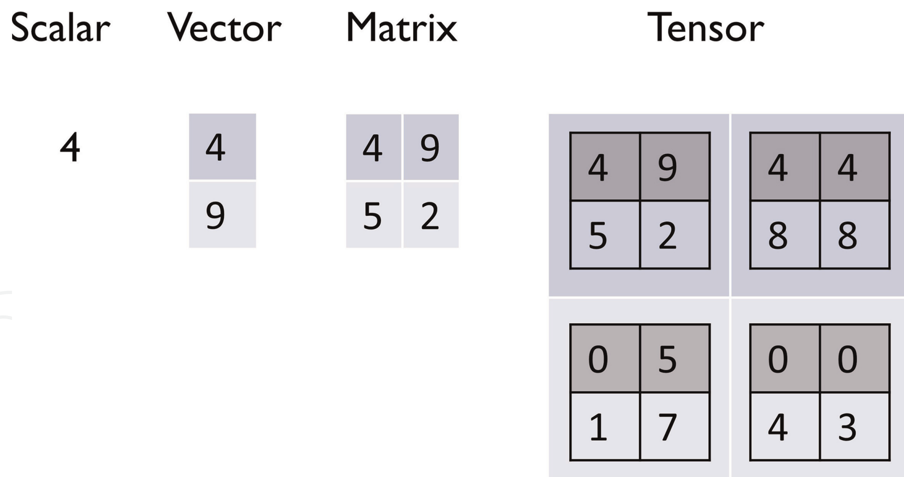

Figure 8.
The shapes of some data structures.

input in the case of ANN, DCNN structures can take a 3-dimensional tensor as input, allowing this system to accommodate images.

5. Examples: application to medicine

Artificial intelligence has become a field that holds the potential to solve a variety of important problems in the medical field. Significant advancements have been made using artificial intelligence techniques in areas such as medical imaging analysis, disease diagnosis, treatment planning, disease prognosis, drug development, and patient care. These techniques are able to successfully perform tasks such as analyzing large amounts of data, recognizing complex patterns, predicting disease risks, and developing personalized treatment strategies. Artificial intelligence contributes to more effective diagnoses, optimization of treatment processes, and improvement of patients' quality of life in the medical field. Below are some studies on the application of classical ANN approach in solving medical problems, followed by examples of DCNN structures in medical applications. Next, we present several examples of studies that utilized ANNs to classify and predict disease status. Each used different methods for classification. We close out this section with a presentation of the percentage of articles published that incorporated deep learning and medical image analyses conducted between 2014 and 2022.

5.1 Application of conventional ANNs

For applications of conventional ANNs, data (inputs) are from mammogram images, EEG signals, ultrasound images, brain MRI, endoscopy images, kidney and lung images, and ECG signals. Each method produced varying levels of ability to accurately differentiate between disease and no disease. Notice the small sample size in some of these studies.

For the first example [55], mammogram images of 322 samples, including normal, benign, and malignancies, were classified using the scale-invariant feature transform method and a backpropogated neural network classifier. Classification accuracy has been reported as 96.57%.

Another study [56] focused on classifying Autism Spectrum Disorder (ASD) using EEG signals from 15 ASD subjects and 10 normal subjects. Here, multiscale entropy was used for feature extraction, and various classifiers including Sine Net neural networks, logistic function, sequential minimal optimization, K-contractive map (K-CM), naïve Bayes, and random forest, were employed. The prediction accuracy ranged from 84% to 92.8%.

For tumor prediction and characterization, a study [57] used a dataset of 20 brain MRI images (10 with tumor, 10 without tumor) and applied the right set theory for feature extraction. The classification was performed using a feedforward neural network. In the context of tissue segmentation from ultrasound images, a study [58] utilized discrete Fourier transform and discrete cosine transform for feature extraction. The incremental neural network was employed for classification. The classifier yielded the following results: specificity of 0.9, sensitivity of 1, and accuracy of 0.95.

Kidney stone classification was investigated in a study [59] which used 100 kidney images (normal and abnormal). Gray level co-occurrence matrix (GLCM) was employed for feature extraction, and support vector machines were used for classification. The combination of ANN with SVM-based classification achieved an accuracy of 95% using a reduced set of features, while utilizing all available features resulted in an accuracy of up to 99%.

In the domain of colorectal cancer diagnosis and detection of precancerous polyps, a study [60] used normal and abnormal endoscopy images. Discrete wavelet transform and second-order statistical features were extracted, and a multilayer perceptron neural network classifier was employed. The detection accuracy of the proposed system has been reported to exceed 95%.

A study [61] focused on the classification of interstitial lung disease (ILD) patterns using a database of ILD images and the VIA/ELCAP CT lung image dataset. Multiscale directional mask pattern (MSDMP) was used for feature extraction, and a feedforward neural network was employed for classification. Classification accuracy has been reported as 90.44%.

Lastly, for the diagnosis of premature ventricular contraction, a study [62] utilized ECG records from the MIT-BIH arrhythmia database. Derivatives of Lyapunov exponents were extracted as features, and a learning vector quantization (LVQ) neural network was used for classification. Classification accuracy has been reported as 93.72%. When examining the ANN studies mentioned above, the most significant aspect that stands out is the inclusion of feature extraction or different dimensionality reduction methods that require significant programming and technical expertise. This is due to the inability of ANNs to use tensor structures, as shown in **Figure 7**. Therefore, medical images require a handcrafted feature extraction stage before entering ANN structures.

5.2 Application of deep convolutional neural networks (DCNNs)

There have been significant advancements in the application of Convolutional Neural Networks (CNNs) in the field of medical research. Notably, recent studies have focused on utilizing deep convolutional neural networks (DCNNs) for various medical tasks. DCNNs replace the need for manual feature extraction and traditional rule-based algorithms, allowing for more automated and efficient analysis of medical data. With their ability to learn intricate patterns and representations directly from raw input, these deep-learning models have shown great promise in various medical applications.

There are several valuable review articles discussing the use of CNNs in various medical applications, including the diagnosis of COVID-19 [63], counting microorganisms [64, 65], image captioning [66], detection of medical instruments in ultrasound images [67], classification of breast cancer [68], analysis of CT and PET images [69], and transfer learning in medical image processing [70].

For instance, recent studies have focused on automatically detecting the mandibular canal using DCNNs [71, 72]. Accurately determining the position of this canal is necessary to avoid nerve Further, correctly identifying the position is important for diagnosing lesions near the mandibular canal and planning oral and maxillofacial surgeries. Where the mandibular canal was automatically detected, the *success rate reported was 84.7%* [61]. This study utilized images obtained through the orthopantomogram (panoramic image) imaging technique, which has higher resolution but causes more radiation exposure compared to Cone beam computed tomography (CBCT). In another study [72], Kwak et al. aimed to automatically locate the mandibular canal on CBCT images to enhance clinical usability. Preprocessing procedures were performed on the Cone beam computed tomography (CBCT) scans of 102 patients, where the irrelevant upper jaw region was not included in the analysis, leaving only the mandibular part. This process was conducted to improve the performance of the CNN. Two 2D image segmentation networks named U-Net [73] and SegNet [74] were utilized. Furthermore, some filters in the original U-Net network structure were eliminated to obtain a modified version. Experiments were conducted using a 3D U-Net [75], an enhanced version of U-Net, resulting in a total of four different networks being tested. A *success rate of 99% was reported* with 49,094 images trained using a 6:2:2 train-validation-test split.

To address the issue of variable resolutions in laryngeal disease classification, Wang et al. [76] proposed a CNN model called Hierarchical Dynamic Convolutional Network (HDCNet). This model dynamically routes input images to small or large networks based on their resolution. Their dataset consisted of 3057 images from 1950 patients, *achieving a 91% success rate* in terms of AVG AUC performance.

Last, a study conducted by van Hespen et al. used an anomaly detection approach to identify chronic brain infarcts on MRI [77]. The neural network was trained to learn the visual appearance of normal brains in 697 patients. The performance of the architecture was evaluated with 255 patients diagnosed with chronic brain infarcts. The system detected 97.5% of these cases, with an additional 26 new brain infarcts originally missed by the radiologist.

5.3 Published articles that included deep learning in the medical field

The percentages of deep learning studies published between 2015 and 2022 are presented for some medical fields in **Figure 9**. Results were taken from a search conducted in Medline for deep learning and field of medicine names. Deep learning studies showed a significant upward trend in the field of Radiology, followed by Ophthalmology, Neurology, and Oncology. For example, Radiology articles for 2022 numbered 77,969; of those, 3255 utilized deep learning, or over 4%. Similarly, for Ophthalmology, the total number of articles was 28,286, with 514 involving deep learning, about 2%. Perhaps the reason for the surge of articles in these four fields is the availability of large amounts of data, such as the national registry of cancer

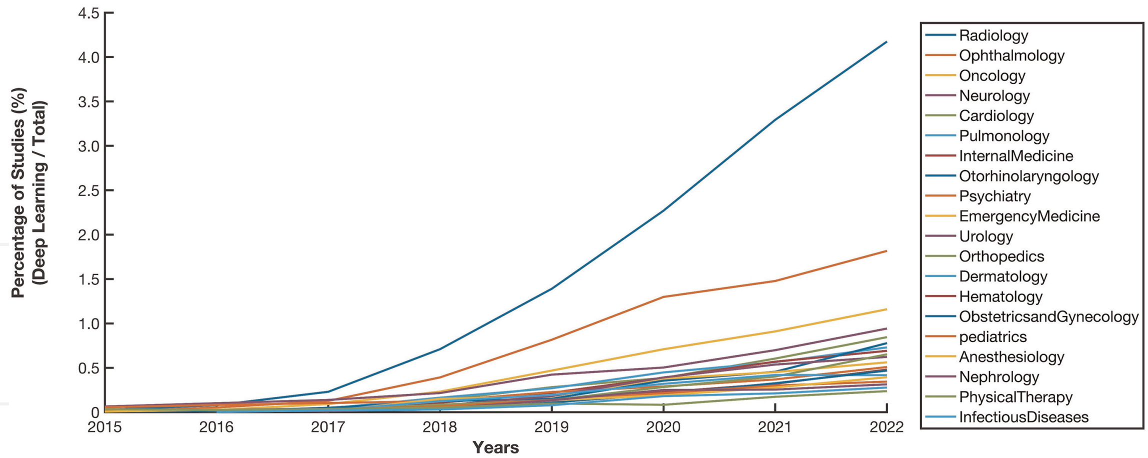

Figure 9.
The percentages of deep learning studies published in certain medical fields.

database. Data sources such as medical imaging studies, biomedical images, and patient records are generally rich and diverse. Deep learning models handle these complex big data. Considering that each field has its own dynamics and characteristics, we can expect significant surges of new discoveries and solutions in many areas of medicine through applications of deep learning models.

6. Conclusions

A continuous rise in high-dimensional data occurs in almost all fields, including medicine. With the ever-increasing amount of data generated by individuals worldwide through sensors and imaging techniques, making sense of this information becomes increasingly challenging. Therefore, the automatic extraction of valuable information from data and the ability to interpret its meaning has become a priority in advancing medical science and other fields of study.

This chapter provided information about studies that have led to paradigm shifts in solving medical problems using CNN models. There is extensive research on CNN structures in the field of data science, leading to the emergence of new and highly complex approaches. These models are sophisticated tools that were initially assumed to require extensive programming expertise. Contrary to this assumption, CNNs will enable medical professionals to perform their tasks with less technical knowledge in the future. This architecture can greatly reduce the need for separate feature extraction procedures and handcrafted engineering for each problem because they are capable of establishing the rules used in medicine.

As CNN structures offer a global solution approach, we anticipate the development of user-friendly software in the near future, allowing individuals without engineering knowledge to utilize these models. With the increasing understanding of CNNs among medical professionals, new problems in computer science can be approached from different perspectives. CNNs have demonstrated remarkable performance in tasks such as medical image classification, segmentation, and detection, aiding in accurate disease diagnosis and treatment planning. The adoption of DCNNs in the medical field has paved the way for advancements in computer-aided diagnosis, personalized medicine, and precision healthcare. This trend signifies a shift toward data-driven approaches and signifies the potential of deep learning to revolutionize medical research and clinical practice.

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Conflict of interest

The authors declare no conflict of interest.

Notes/thanks/other declarations

Interesting thing happened while writing this manuscript … . AI provided us with additional information about AI in a popup on our PC!

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