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Deep learning techniques for medical image segmentation & classification

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Abstract---Imaging in medicine plays a significant part in a broad number of clinical applications, including those that are utilised for early detection, monitoring, diagnosis, and assessment of therapy for a wide variety of medical diseases. Deep learning and artificial neural networks are two concepts that you need to have a firm grasp on if you want to become an expert in medical image analysis using computer vision. Rapid progress is being made in the field of research known as deep learning approach (DLA), which focuses on medical image processing. DLA has had widespread use in the field of medical imaging as a diagnostic tool for determining the presence or absence of disease. Along with the construction of artificial neural networks and a comprehensive investigation of DLA, some of the potential applications for medical imaging are covered in this article. Digital pictures from X-rays, CT scans, mammograms, and histology are the primary focus of the majority of DLA applications. This article offers an in-depth analysis of the research that has been done on DLA for the classification, detection, and segmentation of medical images. When researchers use this summary, they may be better able to think about ways to enhance DLA-based medical image analysis.

Keywords---deep learning, convolutional neural networks, medical images, segmentation, classification, detection.

Introduction

X-rays, computed tomography (CT) scans, mammograms, ultrasounds, magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), positron emission tomography (PET) scans, and other types of medical imaging services are being used more often in the medical field. In addition, there is a shortage of radiologists, which may make it harder to assess medical pictures and make the process of analysis more time consuming. Artificial intelligence is the solution to these issues (AI). In the domain of artificial intelligence (AI), the term "machine learning" (ML) refers to a technology that allows computers to learn from data and make predictions or judgments based on that data without being expressly programmed to do so. ML makes use of three distinct approaches—supervised, unsupervised, and semisupervised—in its educational process. It is necessary to recover features by using machine learning techniques, with feature selection being handled by a subject matter expert. If you make use of deep learning (DL) strategies, you won't have to exert much effort in order to choose the appropriate data for your model. A subset of machine learning that may automatically derive meaningful attributes from unprocessed input data [28]. The study of information theory and the study of the mind provided the groundwork for the development of the earliest concepts for DL algorithms. General characteristics of DL include (1) its capacity to learn feature presentations on each layer through either unsupervised or supervised training, and (2) its multi-layered structure, which enables it to learn features of input at varying levels of abstraction. Both of these characteristics are referred to as "feature learning" in the following paragraphs. Recent research that has been published in the fields of MRI [8], Cardiology [11], and Neurology [15] has shed light on the significance that state-of-the-art DLA has in the medical field.

A variety of distinct DLA approaches that were first created for use in computer vision have been adopted for use in medical image analysis. These methods were initially designed for use in computer vision. Supervised deep learning techniques include a wide range of technologies, including recurrent neural networks and convolutional neural networks, amongst others. Unsupervised learning techniques, such as Deep Belief Networks (DBNs), Restricted Boltzmann Machines (RBMs), Autoencoders, and Generative Adversarial Networks (GANs), have also been investigated for their potential use in medical picture processing [14]. The DLA has the potential to assist in the diagnosis and categorization of a significant number of different diseases. Convolutional neural networks (CNN) are perfectly suited for a variety of tasks when DLA is applied on medical pictures [19, 14]. These tasks include classification, segmentation, object identification, and registration. Convolutional neural networks, often known as CNNs, are a kind of artificial visual neural network structure that is frequently employed for the identification of medical picture patterns. Figure 1 demonstrates how deep learning (DL) is now being used in the field of medical picture analysis.

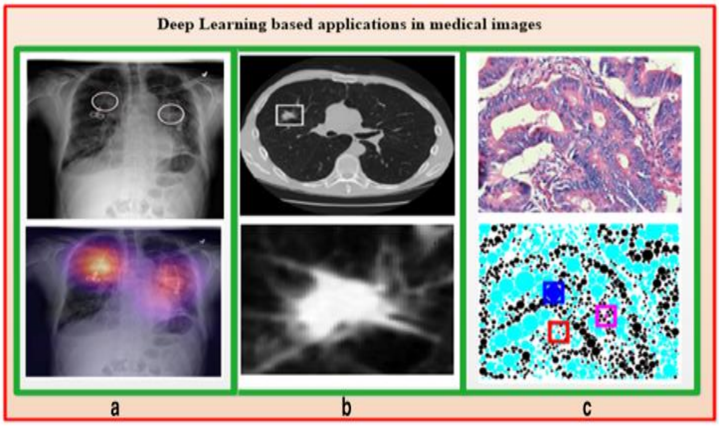

Fig. 1 a X-ray image with pulmonary masses [11] b CT image with lung nodule [12] c Digitized histo pathological tissue image [13]

Deep learning

Deep learning is a subfield of machine learning concerned with creating artificial neural networks that mimic the structure and function of the human brain.

Autoencoder

One of the deep learning models known as autoencoder (AE) is a prime example of unsupervised representation learning. This occurrence is shown in Figure 4a. The optimal conditions for the operation of AE are those in which the input contains a greater quantity of unlabeled data than labelled data. AE receives x as its input and produces a vector with dimension z as its output. After going through one hidden layer z, the input x is approximated by x', which is the result of decoding the encoded representation after it has been processed by the network [18].

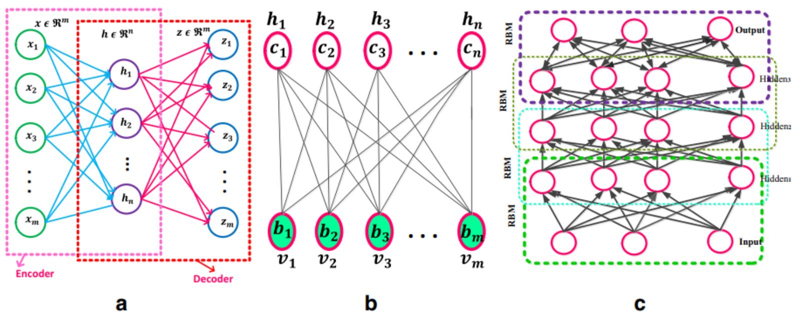

Fig. 4. a Autoencoder [17] b Restricted Boltzmann Machine with n hidden and m visible units [18] c Deep Belief Networks [89]

Basic AE consists of three main steps

Encode: Hidden state h = f(wx + b), where w is represented by the array with dimensions Rm*n and b is represented by the array with dimensions Rn; m and n refer to the dimensions of the input vector and the encoded hidden state, respectively. When h is a hidden layer, the dimensions of that layer have to be fewer than x.f, where x stands for an activation function. Deciphering the message may be done as follows, with the h given above serving as a starting point: z is equal to f' (w' h + b'), where w' represents Rn*m and b' represents Rm. Exists, in a manner analogous to the activation function that was discussed before, f '. The reconstruction error cost function, Lrecons(x, z), may be calculated as follows: Lrecons(x, z) = x z2. Cost function optimization leads to a reduction in reconstruction errors (2)

$$J(\theta) = \sum(x, z) \qquad \theta = \left\{w, w', b, b'\right\} \tag{2}$$

The term "stacked autoencoder" refers to a specific kind of unsupervised algorithm representation (SAE). The SAE is constructed using many layers of autoencoders that are layered one on top of the other, with the outputs of each layer being coupled to the inputs of the one above it. Denoising Autoencoders, often known as DAEs, were first introduced by From Vincent et al. [15]. The DAE discovers how to recreate the original data from the input by taking into account the random noise. [16] The variational autoencoder, also known as VAE, makes adjustments to the encoder so that it can more properly display pictures having a Gaussian distribution. In this model, there are two different kinds of losses: the mean squared error and the Kull back Leibler divergence loss. The mean squared error is a measurement of how well the latent variable matches the Gaussian distribution unit. The Kull back Leibler divergence loss is a measure of how poorly the latent variable matches the Gaussian distribution unit. Both the sparse autoencoder [16] and the variational autoencoder have been shown to be effective in a wide variety of applications, including semi-supervised learning, unsupervised learning, and segmentation, to name just a few of them.

Restricted Boltzmann machine

Figure 4b depicts the connection between the two-layer undirected probabilistic generative model and a Restricted Boltzmann machine (RBM), which is similar to a Markov Random Field (MRF). The RBM's v-units, which represent the input, are visible to everybody, but the h-units, which represent the output, are kept secret (output). One of the most important aspects of the idea is that the two revealed units are unable to communicate with either of the two units that are being concealed. The random variables (v, h) in binary RBMs have the potential to take on any value within the range [0, 1]m + n. The RBM is an energy-based model, similar to the classic Boltzmann machine [20]. The equation that represents the potential energy of the v, h state is: (3)

$$E(v,h) = -\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} h_i v_j - \sum_{j=1}^{m} b_j v_j - \sum_{i=1}^{n} c_i h_i \tag{3}$$

Where vj, hi are the binary states of the visible unit (j), hidden unit I and their respective biases (bj, ci), and wij is the symmetric interaction term between the two units (vj, hi). The Gibbs distribution in Eq. gives the joint probability of (v, h) (4)

$$P(v,h) = \frac{1}{Z} e^{-E(v,h)} \tag{4}$$

Deep belief networks

Hinton et al. [11] propose Deep Belief Networks (DBNs) as an alternative to convolutional models that can still extract features and build a deep hierarchical representation of training data. DBNs, or generative models, are the result of stacking many RBMs. A directed generative model is implemented after the first two RBM-like layers in a DBN. Several hidden layers (h(1), h(2),..., h(l)) sit under the surface of a DBN, as shown in Fig. 4c. Using the DBN model, we can express the distribution of both the visible units v and the hidden layers hk(k = 1,..., l) as (9)

$$P(v, h^1, \ldots, h^l) = \left(\prod_{k=0}^{l-2} P\left(h^{(k)} | h^{(k+1)}\right)\right) P\left(h^{(l-1)}, h^{(l)}\right) \tag{9}$$

A conditional distribution (10) for the layer k given the units of k + 1 is provided by P(hk| hk + 1), where v = h(0)

$$P\left(h_i^{(k)} = 1 | h^{(k+1)}\right) = \sigma\left(b_i^{(k)} + W_{:,i}^{(k+1)} h^{(k+1)}\right) \forall i, \forall k \epsilon 0, 1, \ldots..l-2, \tag{10}$$

A DBN has l weight matrices: W(1), ... , W(l) and l + 1 bias vectors: b(0), ..., b(l) P(h(l) , h(l − 1)) is the joint distribution of top-level RBM (11).

$$P\left(h^{(l)}, h^{(l-1)}\right) \propto e^{\left(b^{(l)} h^{(l)} + b^{(l-1)} h^{(l-1)} + h^{(l-1)} W^{(l)} h^{(l)}\right)} \tag{11}$$

The probability distribution of DBN is given by Eq. (12)

$$P\left(v_i = 1 | h^{(1)}\right) = \sigma\left(b_i^{(0)} + W_{:,i}^{(1)} h^{(1)}\right) \forall i \tag{12}$$

Convolutional neural networks (CNN)

The convolutional neural network (CNN) is a distinct subset of the family of deep learning algorithms used in the field of neural networks. The Convolutional Neural Network, or CNN, is an essential artificial visual network for pattern detection in medical imaging data. A main source of information for the CNN family may be found in the visual brains of animals [17, 16]. The fundamental drawback of a fully connected feed-forward neural network is the fact that the number of neurons may be rather big even for shallow topologies. This makes it difficult to implement in image processing tasks because of the complexity of the network. The Convolutional Neural Network, or CNN, is an example of a parameter-sparing strategy that enables deeper networks to be built with a less number of parameters. Shared weights, local receptive fields, and spatial subsampling are the three architectural concepts that are used during the construction of CNNs [20]. The convolutional approach, which is used to handle data that is not structured, is at the heart of CNN. Convolution, in which the filtered input x(t) signal is combined with the filtered output h(t) signal, has the potential to expose more information than each signal by itself. The discrete signals X(t) and h(t) are subjected to a convolution in a single dimension (1D) (13)

$$y(t) = x(t) * h(t) = \sum_{t=-\infty}^{\infty} x(\tau) h(t-\tau) \tag{13}$$

When selecting the most important invariant feature inside a pooling zone, the max-pooling approach is the one to utilise. When using the average pooling approach, a single characteristic from the pooling region is chosen to represent the mean of all of the other features. Therefore, the max-pooling method keeps the texture information, which may result in quicker convergence [13], while the average-pooling method is known as the Keep background information approach. The research literature has a variety of pooling methods, some of which are as follows: detailed preserving pooling [23], multi activation pooling [24], stochastic polling [23], Def-pooling [19], and spatial pyramid pooling [28]. The CNN model is finished once it has a fully linked top layer. The operation of fully linked layers [14] is identical to that of a standard neural network. The result of the pooling layer is fed into this layer, which accepts a number vector as an input and produces another, more extensive vector with N dimensions as its output (N number of classes). After the layers have been pooled together, the previously layered maps no longer retain their own characteristics and are instead blended into a single, consistent layer. The first seven-layer Convolutional Neural Network (CNN) that was successful at recognising handwritten digits was built by Yann LeCunn in the year 1990. AlexNet is a deep convolutional neural network that was proposed by Krizhevsky and colleagues [8]. It consists of 5 convolutional layers and 3 fully-connected layers. In order to accelerate the process of model training, AlexNet changed the sigmoid activation function from its original implementation to the user-friendlier ReLU activation function.

Recurrent neural networks (RNN)

RNNs are a subset of neural networks that are specifically designed for the processing of sequential data (deal with sequential data). A recurrent neural network (RNN) is seen in Figure 5a. This RNN has a topology that is similar to that of a fully-connected neural network (FFNN), but it also has recurrent connections between the hidden nodes. In order to activate the recurrent connection hidden unit of a generic RNN model at time t, the current data xt and the preceding hidden state ht 1 are taken into consideration. The key to achieving the desired outcome yt is to make use of the hidden state ht. Equations (18) and (9) provide a mathematical representation of this in its respective forms (19)

$$h_t = f(w_{hx}x_t + w_{hh}h_{t-1} + b_h) \tag{18}$$

$$y = softmax(w_{yh} + b_y) \tag{19}$$

Here, Wh is the matrix of recurrent weights between the hidden layers and itself, Whx is the weight matrix between the input and hidden layers, and F is a nonlinear activation function.

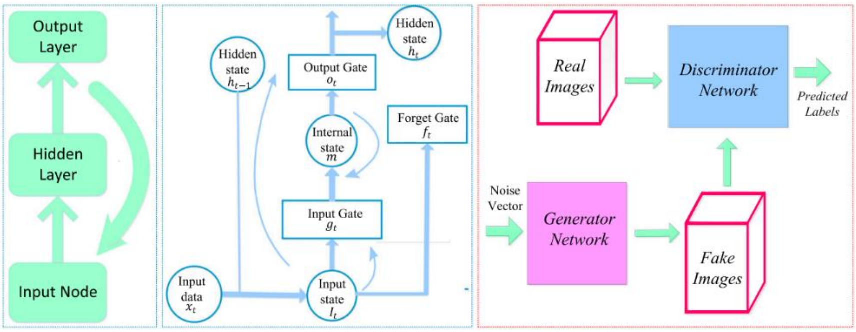

Fig. 5. a Recurrent Neural Networks [23] b Long Short-Term Memory [13] c Generative Adversarial Networks [24]

Generative adversarial networks (GAN)

The Generative Adversarial Network (GAN) is an example of a deep generative model that can be found in the area of deep learning. Good Fellow was the one who first presented the concept of the GAN in [23]. Generalized Approximation Neural Networks, or GANs, have the potential to generate synthetic pictures that are very accurate recreations of the originals. The GAN shown in Figure 5c requires concurrent training of two neural networks, namely the discriminator and the generator. The discriminator D is "tricked" by the generator G, which gives it data that is not only fake but statistically improbable as well. This is done in an effort to fool the discriminator D. According to reference [24], D and G participate in a two-player minimax game in which the cost function is (26).

$$\min_G \max_D V(D,G) = E_{x\sim p_{data(x)}}[logD(x)] + E_{z\sim P_z(z)}[log(1-D(G(z)))] \tag{26}$$

Use of deep learning in medical imaging
X-ray image

The diagnosis of lung and heart disorders, such as TB, atelectasis, consolidation, pleural effusion, pneumothorax, and hyper cardiac inflation, may often be made with the use of chest radiography. Because X-ray images are quicker to get, less expensive, and more dose-effective than images obtained using other imaging technologies, they are an excellent option for screening an entire population [24]. The DL approaches that were used in the analysis of the X-ray image are summarised in Table 3. S. Hwang et al. [27] presented the first deep convolutional neural network (CNN)-based tuberculosis screening system that made use of a transfer learning approach. Modality-specific ensemble learning was suggested by Rajaraman et al. [29] as a method for the diagnosis of anomalies using chest X-rays (CXRs). In order to reduce the amount of uncertainty associated with the prediction, these model projections are blended using a variety of ensemble methodologies. Class selective mapping of interest is a technique that is used in order to identify aberrant areas in CXR images (CRM). It was suggested by Loey et al. [90] that a GAN with deep transfer training might be used to recognise COVID-19 in CXR photos. In light of the fact that the COVID-19 dataset could not be accessed, extra CXR pictures were produced by the GAN network. Waheed et al. [26] made the suggestion that a CovidGAN model based on the Auxiliary Classifier Generative Adversarial Network may be used to produce synthetic CXR pictures for the purpose of COVID-19 identification (ACGAN). In order to increase the size of the training dataset and enhance COVID-19 identification in CXR pictures, S. Rajaraman and S. Antani [22] developed a method known as weakly labelled data augmentation.

Computerized tomography (CT)

Images of a human body's cross-section may be created with the help of CT by combining the usage of computers with spinning X-ray equipment. A CT scan may disclose a wide variety of structures, ranging from soft tissues and arteries to bones and organs, depending on the area that is being examined. The CT scan is superior to other diagnostic procedures in that it provides a more complete picture and has a high detection efficiency; it is able to pick up even the smallest abnormalities. CT scans are often used for finding pulmonary nodules [93]. In order to arrive at an accurate diagnosis of lung cancer at an earlier stage, it is necessary to search for cancerous nodules in the lungs [22]. The most recent advancements in the use of deep learning to CT image processing. Deep Convolutional Neural Networks (CNN) was first suggested in 2016 by Li et al. [27] as a method for the identification of nodules with semisolid, solid, and ground-glass opacities.

In their study [5] Balagourouchetty et al. suggested employing a Google DeepMind Network known as an ensemble FCNet classifier in order to categorise liver disorders. The fundamental structure of Googlenet was altered in three different ways in order to make the process of feature extraction more user-friendly. For the identification and classification of lung nodules, Masood et al. [25] introduced the multidimensional Region-based Fully Convolutional Network (mRFCN), which has a classification accuracy of 97.91%. The greatest obstacle in lung nodule detection is the identification of micronodules, which are nodules smaller than 3 millimetres in diameter, without sacrificing sensitivity or accuracy. DLA, which is based on supervised MSS U-Net and 3DU-Net, was suggested by Zhao and Zeng 2019 [30] in order to autonomously partition kidney tumours and kidneys themselves from CT images. During the current pandemic, Fan et al. [25] and Li et al. [29] employed algorithms based on deep learning to determine whether or not COVID-19 was present in CT scans.

Mammograph (MG)

When it comes to cancer, breast cancer is one of the most common causes of death amongst females. In the early stages of breast cancer diagnosis, magnetic resonance imaging (MRI) is considered the gold standard (MG). MG is a low-dose x-ray imaging approach that is used to view the architecture of the breast [30]. This method is used for the purpose of breast cancer detection. Mammography scans may miss some types of breast cancers like this one because tumours make up such a tiny portion of the total breast picture. In the process of analysing MG breast lesions, there are three steps: detection, segmentation, and classification [29]. There is also ongoing research being conducted in the field of automated categorization and early mass identification in MG. During the course of the last ten years, DLA has made great strides in improving its capacity to identify and categorise breast cancer. The most recent improvements made by DLA regarding mammography image analysis are shown in Table 5.

According to Fonseca et al. [27], the ACR standard recommends using CNN for feature extraction for classifying breast composition. This recommendation is in accordance with what the researchers at Fonseca et al. A twelve-layer convolutional neural network (CNN) was presented by Wang et al. [21] as a method for the identification of Breast Arterial Calcifications (BACs) in mammography pictures for the purpose of determining the likelihood of coronary artery disease. Ribli et al. [24] created a computer-aided diagnosis (CAD) system that was based on Faster RCNN with the goal of automatically identifying and classifying benign and malignant lesions on mammography images. The authors of this study, Wu et al. [26], present a deep convolutional neural network (CNN) for the purpose of categorising breast cancer screening tests. More than a million mammogram photos were used throughout the CNN's training and evaluation processes. In order to differentiate between calcified and soft lesions in digital breast tomosynthesis (DBT) pictures, an artificial intelligence system that was created by Conant et al. [26] and was based on a Deep Convolutional Neural Network (CNN) was used. The fuzzy fully connected layer (FFCL) architecture was presented by Kang et al. [22]. This design incorporates fuzzy rules into conventional CNN in order to score semantic BI-RADS. The FFCL design that was proposed produced higher BI-RADS scores for both triple and multi-class classifications.

Histopathology

Histopathology is the examination of human tissue using a microscope that has a stage made of sliding glass. This method may be used to diagnose a wide range of malignancies, including those that affect the kidney, lung, and breast. Hematopathologists make use of staining to bring attention to a particular area of tissue and to facilitate a more thorough examination of that location [25]. In tissue that has been stained with hematoxylin and eosin (H&E), the nucleus comes out looking dark purple, while the surrounding components stay pink. For the greater part of a century, the H&E stain has been a significant factor in the diagnosis and grading of cancer, in addition to the identification of a broad variety of illnesses. Imaging in digital pathology is a practise that is considered to be cutting edge. Deep learning [28] is becoming a powerful tool for the analysis of histopathological pictures, including the identification of nuclei, the classification of images, the segmentation of cells and tissues, and other similar tasks. The present development of deep learning in the subject of pathology is broken down and summarised using tables 6 and 7. The most recent breakthrough in the research on digital pathology image analysis is a technique known as whole slide imaging (WSI). With the use of WSI, one is able to get high-resolution digital pictures of stained tissue sections mounted on glass slides. The difficulties associated with analysing multi-gigabyte WSI pictures for the purpose of developing deep learning models were investigated by Dimitriou et al. [30]. A. Serag et al. [25] provide an overview of a variety of public "Grand Challenges" and highlight breakthroughs in computational pathology that are based on DLA.

Limitations and challenges

In spite of these challenges, the use of deep learning algorithms to medical imaging looks to hold considerable promise. The diversity in data (resolution, contrast, and signal-to-noise) that is produced as a result of clinical practise procedures is one of the challenges that must be overcome in order to use DL in the analysis of medical images [23]. Another issue that arises with medical image analysis is the lack of standardised procedures for the acquisition of medical images. The application of deep learning in medical image analysis requires the preceding step of having medical images that have been annotated. The fundamental issue is a lack of data, and in comparison, to sharing data from other datasets, medical data sharing presents a significant challenge. It is necessary to do research on the social as well as the technical elements of medical data privacy. The creation of DLA calls for a significant quantity of data that has been annotated. A further significant obstacle is the annotation of medical photographs.

Radiologists are the most qualified professionals to do the specialised duty of labelling medical pictures. The accurate annotation of medical data is thus a time-consuming process. The problem of "few labelled data" may be circumvented by using semi-supervised learning in conjunction with a large amount of unlabeled data as a potential solution. The problem of "data scarcity" may also be circumvented through the creation of learning algorithms that make much less use of the available data. In spite of the fact that DL technology has achieved a great deal of success, it is still subject to a number of limitations and challenges in the medical sector. It is unknown at this time whether or not using DL in the healthcare industry will result in cost savings, an increase in productivity, and happy patients. Nevertheless, it is essential for the success of clinical studies to provide evidence that deep learning algorithms are effective and to establish criteria for their use in the processing of medical images.

Conclusion and future directions

The information obtained from medical imaging is used to guide clinical decision-making. This article presents a summary of the most recent developments that have been made in the algorithms and methodologies used in deep learning. A few goals will be accomplished at the end of this short introduction to DLA for medical image analysis. The first part of this guide will provide an introduction of deep learning and the principles that underlie it. The second objective is to provide an overview of the DLA-based medical image analysis sector at a high level. The procedure started in the 1940s with the construction of the very first neural network, and it is still going on today with the production of DL algorithms that might have potential uses in the medical field. The initial approaches that are going to be described are both supervised and unsupervised deep learning methods. These methods include auto-encoders, recurrent, CNN, and limited Boltzmann machines.

This article covers a variety of different optimization frameworks and approaches, including but not limited to Caffe, TensorFlow, Theano, and PyTorch. After that, the deep learning algorithms that were determined to be the most effective were analysed for the possible applications they may have in medical picture segmentation, detection, and classification. In the research that has been done, applications of RBM networks in medical image processing have only sometimes been discussed. CNN-based models have demonstrated to be useful in a variety of contexts, including classification and detection tasks. There are many different therapies available today for a wide range of ailments. However, there are still a lot of obstacles to overcome in the field of medical image processing, and the only way to do it is with the assistance of deep learning. In spite of the fact that deep learning is increasingly shifting toward unsupervised and semi-supervised learning to deal with real-world data without the requirement for manual human labelling, many current DL implementations still rely on supervised approaches. This is because supervised approaches are easier to implement.

References

1. Abadi M et al. (2016) TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems, [Online]. Available: http://arxiv.org/abs/1603.04467.
2. Agarwal, S., Patra, J. P., & Swarnkar, S. K. (2022). Convolutional neural network architecture based automatic face mask detection. International Journal of Health Sciences, 6(S3), 623–629. https://doi.org/10.53730/ijhs.v6nS3.5401 (Scopus)
3. Apostolopoulos ID, Mpesiana TA (2020) Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks, Phys Eng Sci Med, no. 0123456789, pp. 1–6, DOI: https://doi.org/10.1007/s13246-020-00865-4.
4. Arun NT et al. (2020) Assessing the validity of saliency maps for abnormality localization in medical imaging, pp. 1–5, [Online]. Available: http://arxiv.org/abs/2006.00063.
5. Bastien F et al. (2012) Theano: new features and speed improvements, pp. 1–10, [Online]. Available: http://arxiv.org/abs/1211.5590.
6. Basu S, Mitra S, Saha N (2020) Deep Learning for Screening COVID-19 using Chest X-Ray Images, pp. 1–6, [Online]. Available: http://arxiv.org/abs/2004.10507.
7. Bindeshwari Chandel , Suman Kumar Swarnkar, “Stock Prediction Using Financial Data And News Sentimental Analysis", Journal of Xi an Shiyou University, Natural Science Edition (JXSU), ISSN: 1673-064X, Volume.16, Issue 9, pp 279-285, September 2020. (Scopus)

8. Bulten W, Litjens G (2018) Unsupervised Prostate Cancer Detection on H&E using Convolutional Adversarial Autoencoders, [Online]. Available: http://arxiv.org/abs/1804.07098.
9. Cai H et al. (2019) Breast Microcalcification Diagnosis Using Deep Convolutional Neural Network from Digital Mammograms, Comput Math Methods Med, vol. 2019, DOI: https://doi.org/10.1155/2019/ 2717454.
10. Candemir S, Rajaraman S, Thoma G, Antani S (2018) Deep learning for grading cardiomegaly severity in chest x-rays : an investigation. In: 2018 IEEE Life Sciences Conference (LSC), pp 109–113. https://doi. org/10.1109/LSC.2018.8572113
11. Capizzi G, Lo Sciuto G, Napoli C, Połap D (2020) Small Lung Nodules Detection based on Fuzzy-Logic and Probabilistic Neural Network with Bio-inspired Reinforcement Learning, IEEE Trans Fuzzy Syst, vol. PP, no. XX, p. 1. https://doi.org/10.1109/TFUZZ.2019.2952831.
12. Chen C, Li S, Qin H, Pan Z, Yang G (2018) Bilevel feature learning for video saliency detection. IEEE Trans Multimed 20(12):3324–3336. https://doi.org/10.1109/TMM.2018.2839523
13. Chen C, Li S, Wang Y, Qin H, Hao A (2017) Video saliency detection via spatial-temporal fusion and low-rank coherency diffusion. IEEE Trans Image Process 26(7):3156–3170. https://doi.org/10.1109/TIP. 2017.2670143
14. Chen C, Wang G, Peng C, Zhang X, Qin H (2020) Improved robust video saliency detection based on long-term spatial-temporal information. IEEE Trans Image Process 29:1090–1100. https://doi.org/10. 1109/TIP.2019.2934350
15. Chen C, Wei J, Peng C, Zhang W, Qin H (2020) Improved saliency detection in RGB-D images using two-phase depth estimation and selective deep fusion. IEEE Trans Image Process 29:4296–4307. https:// doi.org/10.1109/TIP.2020.2968250
16. Chen DS, Jain RC (1994) A robust back propagation learning algorithm for function approximation. IEEE Trans. Neural Networks 5(3):467–479. https://doi.org/10.1109/72.286917
17. Chen H, Qi X, Yu L, Dou Q, Qin J, Heng PA (2017) DCAN: deep contour-aware networks for object instance segmentation from histology images. Med Image Anal 36:135–146. https://doi.org/10.1016/j. media.2016.11.004
18. Choi J, Shin K, Jung J, Bae HJ, Kim DH, Byeon JS, Kim N (2020) Convolutional neural network technology in endoscopic imaging: artificial intelligence for endoscopy. Clin Endosc 53(2):117–126. https://doi.org/10.5946/ce.2020.054
19. Chougrad H, Zouaki H, Alheyane O (2018) Deep convolutional neural networks for breast cancer screening. Comput Methods Prog Biomed 157:19–30. https://doi.org/10.1016/j.cmpb.2018.01.011
20. Clevert DA, Unterthiner T, Hochreiter S (2016) Fast and accurate deep network learning by exponential linear units (ELUs). In: 4th International Conference on Learning Representations, ICLR 2016, pp 1–14
21. Collobert R, Kavukcuoglu K, Farabet C (2011) Torch7: A matlab-like environment for machine learning, BigLearn, NIPS Work, pp. 1–6, [Online]. Available: http://infoscience.epfl.ch/record/192376/files/ Collobert_NIPSWORKSHOP_2011.pdf.

22. Conant EF et al (2019) Improving Accuracy and Efficiency with Concurrent Use of Artificial Intelligence for Digital Breast Tomosynthesis. Radiol Artif Intell 1(4):e180096. https://doi.org/10.1148/ryai. 2019180096
23. Coudray N, Ocampo PS, Sakellaropoulos T, Narula N, Snuderl M, Fenyö D, Moreira AL, Razavian N, Tsirigos A (2018) Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning. Nat Med 24(10):1559–1567. https://doi.org/10.1038/s41591-018-0177-5
24. Dercle L, Henry T, Carré A, Paragios N, Deutsch E, Robert C (2020) Reinventing radiation therapy with machine learning and imaging bio-markers (radiomics): State-of-the-art, challenges and perspectives, Methods, no. May, pp. 0–1, DOI: https://doi.org/10.1016/j.ymeth.2020.07.003.
25. Dhillon A, Verma GK (2019) Convolutional neural network: a review of models, methodologies, and applications to object detection Prog Artif Intell, no. 0123456789, DOI: https://doi.org/10.1007/s13748- 019-00203-0.
26. Dimitriou N, Arandjelović O, Caie PD (2019) Deep Learning for Whole Slide Image Analysis: An Overview. Front Med 6(November):1–7. https://doi.org/10.3389/fmed.2019.00264
27. L. Balagourouchetty, J. K. Pragatheeswaran, B. Pottakkat, and R. G, "GoogLeNet based ensemble FCNet classifier for focal liver lesion diagnosis," IEEE J Biomed Heal Inf, vol. 2194, no. c, pp. 1–1, 2019, DOI: https://doi.org/10.1109/jbhi.2019.2942774, 1694.
28. Sriram, A., Sekhar Reddy, G., Anand Babu, G. L., Bachanna, P., Gurpreet, S. C., Moyal, V., Shubhangi, D. C., Sahu, A. K., Bhonsle, D., Madana Mohana, R., Srihari, K., & Chamato, F. A. (2022). A smart solution for cancer patient monitoring based on internet of medical things using machine learning approach. Evidence-Based Complementary and Alternative Medicine, 2022, 1–6. https://doi.org/10.1155/2022/2056807
29. Suman Kumar Swarnkar, Dr. Asha Ambhaikar, "Improved Convolutional Neural Network based Sign Language Recognition" International Journal of Advanced Science and Abbas A, Abdelsamea MM, Gaber MM (2020) Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network, pp. 1–9, [Online]. Available: http://arxiv.org/abs/2003.13815.
30. Suman Kumar Swarnkar, Dr. Asha Ambhaikar, "Optimized Convolution Neural Network (OCNN) for Voice-Based Sign Language Recognition: Optimization & Regularization" Fifth International Conference on Information and Communication Technology, 2020. (Scopus, Springer)
31. Suman Kumar Swarnkar, Multimodal Biometric Face and Fingerprint Recognition Using APEX Algorithm and Feed Forward Back Propagation, International Journal Of Scientific Progress And Research, Volume 9 Issue 1-2015. ISSN [ONLINE] 2349-4689
32. Suman Kumar Swarnkar, Multimodal Biometric Face and Fingerprint Recognition Using XOR Configuration, International journal of Computing, Volume 4 Issue 4-OCT2014. ISSN [ONLINE] 2230-9039
33. Technology, Volume 27, Issue 1, pp 302-317, 2019. (Scopus)
34. Virendra Kumar Swarnkar, Dr. AshaAmbhaikar, Suman Kumar Swarnkar, "Big Data Security Enhancement Based Intrusion Detection System Using K-Mean Clustering of Decomposited Features" Journal of Information Technology in Industry, 2021. (ESCI)

The healthcare industry is under enormous pressure to deliver high-quality care and healthcare services as the world's population continues to grow. People now more than ever want smart healthcare services, programmers, and wearable's that will improve their quality of life and increase their lifespan. The healthcare industry has consistently been one of the biggest supporters of cutting-edge technology, and machine learning and artificial intelligence are no exception. Similar to how ML and DL quickly impacted the commercial and e-commerce sectors, they also discovered a wide range of applications in the healthcare sector. In fact, Machine Learning and Deep Learning have come to play a crucial role in the field of healthcare, from enhancing the delivery system of healthcare services, reducing costs, and handling patient data to the development of novel treatment methods and drugs, remote monitoring, and so much more.

The potential for Machine Learning and Deep Learning applications to join the biomedical and healthcare industries is growing as a result of the need for "better" healthcare services. Healthcare is not exempt from the effects that ML, and DL are having on today's world. Additionally, the need for incorporating artificial intelligence and machine learning into the healthcare sector's design is made all the more pressing by the fact that the sector's data burden is growing at a rapid rate (due to the rising incidence of diseases and the world's population). The potential applications of artificial intelligence and machine learning are limitless. AI & ML are advancing applications that are improving the healthcare sector.

The developments and applications of artificial intelligence and machine learning in biomedicine and healthcare are covered in this Special Issue. The integration of computer science, life science, healthcare, and statistical concepts into statistical models using current data, finding patterns in data to extract the information, and forecasting changes and diseases based on this data and models will all be covered. The practical uses of artificial intelligence and machine learning for disease diagnosis and management will be covered in this SI. In addition, the impact of AI and machine learning will be discussed in relation to conditions including diabetes, cancer, mycobacterium TB, Covid-19, and others. Using machine learning and artificial intelligence, this SI will serve as working examples of how various types of biological and healthcare data may be used to create models and forecast diseases. With concrete examples, this SI will also discuss transfer learning, personalized medicine, and precision medicine. The use of machine learning and artificial intelligence for disease visualization, prediction, detection, and diagnosis will also be covered. Programmers, medical professionals, and researchers who are interested in learning about the uses of AI and ML in biomedical and healthcare informatics will find this to be a useful resource.