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A Survey of Diabetic Foot Ulcer Image Analysis Using Deep Learning: Segmentation

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Abstract

Diabetes mellitus (DM) is a long-lasting condition marked by hyperglycemia. It could result in lower limb amputation if not treated in a timely manner. Diabetic foot ulcer (DFU) identification is especially challenging in the early stages. Deep learning has been used to analyze images of DFUs and has proven to perform at the cutting edge in a number of disciplines. The models were based on architectures like Fully Convolutional Networks (FCNs), U-Net, V-Net, or SegNet for semantic segmentation tasks. With an accuracy of 94.96%, the U-Net model surpassed the other models. The models were based on architectures such as mask R-CNN for tasks like segmentation. The precision parameter for the mask R-CNN model was 0.8632, and the mAP value was 0.5084.

Keywords: Diabetic Foot Ulcer, Deep Learning, Semantic Segmentation.

1. Introduction

Diabetes mellitus (DM) is a chronic illness brought on by either or both of insulin resistance and/or inadequate insulin secretion [1].The International Diabetes Federation estimates that there are 500 million adults worldwide who have diabetes as of 2019 [1], and that figure is predicted to rise to 700 million by 2045 [2]. A number of DM-related problems, such as heart attack, stroke, blindness, renal failure, and lower limb amputation [3], will raise mortality and lower quality of life [2]. The prevalence of diabetic foot ulcers (DFUs) ranges from 19% to 34% in diabetic patients [4]. A DFU patient runs the risk of experiencing slow wound healing, worse limb amputation and worse survival rates are potential outcomes of DFU [5].

Artificial intelligence algorithms have been applied to numerous medical images since its development. The traditional artificial intelligence method of machine learning has long since taken over. Here are some examples of machine learning-based applications for DFU analysis. They used super pixels in the classifier training to extract features from diverse colors and textures on images of foot ulcers in order to identify the wound boundaries. A foot-ulcer detecting system identifies and categorizes DFUs. However, the following drawbacks of standard machine learning methods are Skin tone, lighting, and image resolution all have an impact on manual feature extraction, making it more susceptible to the population's huge variation in normal and pathological patterns [6], [7]. A multi-level abstract data representation, insufficient domain expertise, and the limits of dealing with massive image data are only a few of the difficulties that standard machine learning algorithms must overcome.

Deep learning algorithms demonstrated exceptional performance in image-processing applications as a result of the advancement of computer vision. The development of deep learning methodologies allowed for efficient end-to-end automatic learning models from raw images, as opposed to traditional machine-learning techniques. Reviews of the use of deep learning technology for medical image analysis may be found. Medical image analysis based on deep learning was summarized by [7] to help with diagnosis and address numerous related issues. The accomplishments and difficulties of medical image segmentation using deep learning algorithms were enumerated [8]. A review of the use of deep learning in the classification and segmentation of medical images was written [9]. The use of deep learning in other medical images was widely covered in these reviews, but none of the articles particularly examined the use of this technology in the medical imaging of DFU.

The review will be evaluated in light of the following criteria: (1) well-known deep-learning architectures for image analysis, with an emphasis on their advantages and disadvantages; (2) deep learning applied to images of DFUs, with four applications: classification, object detection, semantic segmentation, and instance segmentation; (3) a variety of challenges related to images of DFUs analyzed using deep-learning techniques; and (4) a conclusion and the future of deep learning.

2. Techniques for Deep Learning and Application Categories

Deep learning, a branch of machine learning, has advanced quickly in recent years. Deep learning may automatically extract features with a switch from hand-designed to data-driven features, in contrast to standard machine learning, which necessitates human feature extraction and takes domain expertise into account (10). Figure 1 illustrates how deep learning differs from traditional machine learning in terms of how it extracts characteristics.

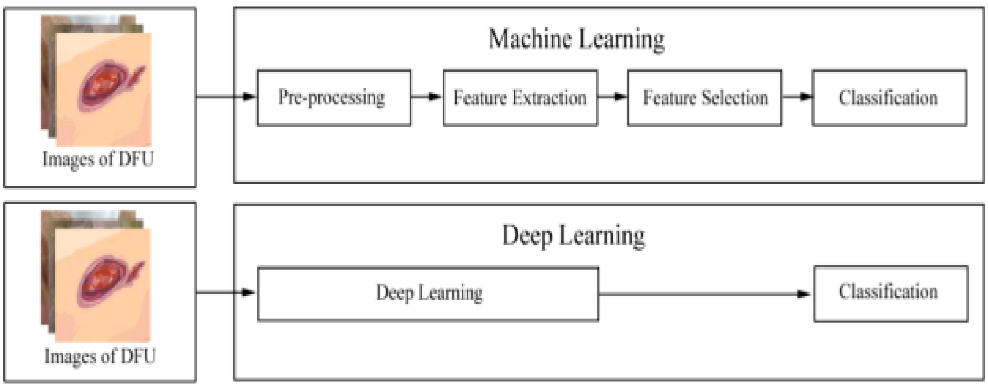

Figure 1. The distinction between deep learning and traditional Machine learning

In traditional machine learning, feature extraction frequently entails a number of steps, including pre-processing and feature extraction or feature selection. Deep learning, on the other hand, is frequently a computer model made up of numerous processing layers to automatically learn representations of data by abstracting input data into multiple tiers (11) using straightforward but nonlinear modules. Deep learning models will learn a very complex function through these modifications. Importantly, deep learning makes it simple to analyze thousands of cases that even human experts might not see and remember because the learning process is automated. Deep learning can therefore be more resistant to a variety of feature differences between various categories (12). Classification, object recognition, semantic segmentation, and instance segmentation are the four primary subcategories of deep learning applications (6, 13). Classification is frequently used to specify the type of object class in an image or to present a list of object classes in an image based on classification scores. The process of classifying various items in an image and locating the locations of those objects, which are indicated by border boxes, is known as object detection (14). In semantic segmentation, each pixel of an image is divided into instances, each of which is assigned to a class (15).

3. Image Segmentation Using Deep Learning for DFU Images

The two categories of semantic segmentation and instance segmentation are covered in this section along with other frequently used deep learning image segmentation architectures. Then, a thorough explanation of how deep learning is used to segment images for DFU images is presented.

3.1 Semantic Segmentation

With semantic image segmentation, each pixel of an image is assigned the class of the object it contains without separating individual object instances (13). In other words, semantic segmentation focuses on identifying and classifying related items from a pixel as a single class level. FCN (16), SegNet (17), and U-Net (18) are now well-liked designs for semantic picture segmentation.

3.2 Overview of the Fully Convolutional Network (FCN) Architecture

Long et al. (16) presented an FCN based on CNN, adopting existing classification models like AlexNet, VGG net, and GoogleNet by substituting a fully convolutional layer for semantic segmentation for the prior FC layers in CNNs. Downsampling and upsampling are frequently used in FCNs. The spatial resolution of the image is downsampled in the model's first half to create intricate feature mappings. More precise visual information is obtained with each convolution. At this point, highly effective classification discrimination is achieved, but the location data is lost. After downsampling, an upsampling process that uses many lower resolution photos as input and produces a high-resolution segmentation map with each pixel placed into the highest likelihood class is used to retrieve the position information.

3.3 Overview of the U-Net architecture

U-Net based on FCN was designed by Ronneberger et al. (18). U-Net is a common and successful algorithm used in semantic segmentation for images. The architecture of FCN includes an FC layer at the end, while U-Net simply applies convolutional layers. U-Net is a perfectly symmetric architecture with a U shape and consists of two paths, namely, a contracting path and an expansive path. Ronneberger et al. (18) created a typical U-Net based on FCN for the contracting path. A popular and effective algorithm for semantic segmentation of images is U-Net. FCN uses an FC layer at the very end of its architecture, whereas U-Net only uses convolutional layers. With a U-shape and two paths—a contracting path and an expanded way—U-Net is a fully symmetric architecture. A convolutional network's usual topology, known as the contracting route, creates a low-dimensional representation in order to extract features. By upsampling the numerous feature maps from the contracting path, the expansive path improves the output's resolution. Figure 2 depicts the U-Net architecture. With only a small number of training examples, U-Net can converge on dense prediction problems where each pixel must be labelled (a process known as semantic segmentation) (18).

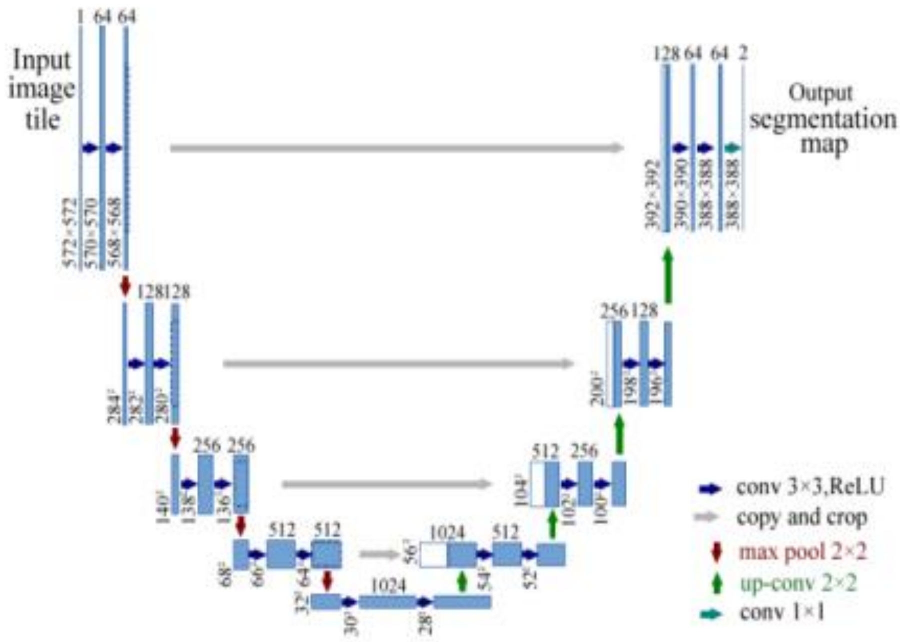

Figure 2. Architecture of U-Net for semantic segmentation (18).

3.4 Instance segmentation

The accurate recognition of all objects in an image is handled by instance segmentation, which also offers distinct labels for various instances of the same class, simultaneous object detection and semantic segmentation (13). Mask R-CNN (19) is an illustration of a neural network that is used, for instance, in segmentation.

3.5 Overview of the mask R-CNN architecture

He et al. (19) presented mask R-CNN in 2017, which was based on faster RCNN, for object instance segmentation. ROIs are chosen in the first section of the mask R-CNN. A portion of the input image known as a ROI contains an object with high likelihood. Each input image receives several ROI identifications. Each ROI can obtain three model outputs simultaneously from the faster R-CNN, including a class label and bounding box for each candidate object, as well as an object mask to extract a more precise spatial layout of an object. As a result, mask R-CNN is an improvement over faster RCNN. It operates by adding a branch for object mask prediction (ROIs) in addition to the existing branch for boundingbox recognition.

3.6 Deep learning in the semantic segmentation for DFU images

There are not many articles regarding deep learning for DFU images semantic segmentation and instance segmentation.

In order to teach the FCNs to automatically partition the ulcer and surrounding skin, Goyal et al. (20) suggested a two-tier transfer learning method. For segmenting images of DFUs, they used three models, namely the FCN-32s, FCN-16s, and FCN-8s based on the VGG-16 network, as well as one model known as the FCN-AlexNet. These models can retrieve feature hierarchies, they discovered. With two-tier transfer learning, FCN designs outperformed random initialization of weights for all layers of the network in terms of pixel-wise segmentation performance and weight convergence.

Compared to the FCN-AlexNet and FCN-8s models, the FCN-16s and FCN-8s models can produce more asymmetrical outlines of the DFU and the surrounding skin. Because the FCN-32s models were unable to recognise the small DFU, discriminate surrounding skin, or detect very small pieces of them, they had difficulty drawing irregular boundaries to carry out correct segmentation. Among all the FCN architectures, FCN-16s had the best performance while FCN-AlexNet had the poorest. Figure 3 depicts the FCN architecture's overall layout.

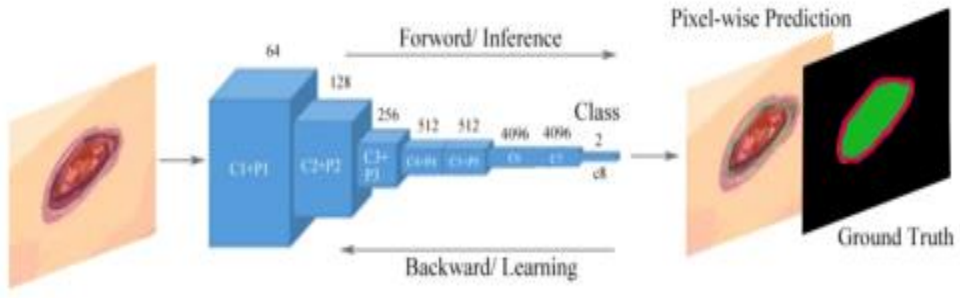

Figure 3. Fully convolutional networks (FCNs) for the semantic segmentation of DFUs.

U-Net was used by Rania et al. (21) to segment DFUs. Images containing thermal information were obtained using a smartphone and a small thermal camera. Using thermal imaging markers, tissue inflammation and infection can be found. Then, using the Keras framework with the TensorFlow backend, 112 DFU images were downsized to a resolution of 512 X 512 pixels, 92 photos were used to train the U-Net model, and 22 images were used for validation. The U-Net model demonstrated accurate DFU segmentation by automatically calculating the ulcer area after segmentation and performing wound tissue analysis based on colour and temperature using a small number of images and a mask that was similar to the ground truth.

Using multimodal pictures, Hernández et al. (22) established a model of automatic segmentation based on U-Net architecture to recognise and define images of foot.. The architecture is depicted in Figure 4. They were able to obtain a foot image that contained both RGB and depth information. Of the 59 thermal infrared images, 30 were utilised to train the supervised system and 29 were used to evaluate it. The temperature of two photographs of a patient's feet were then compared in order to track DFUs.

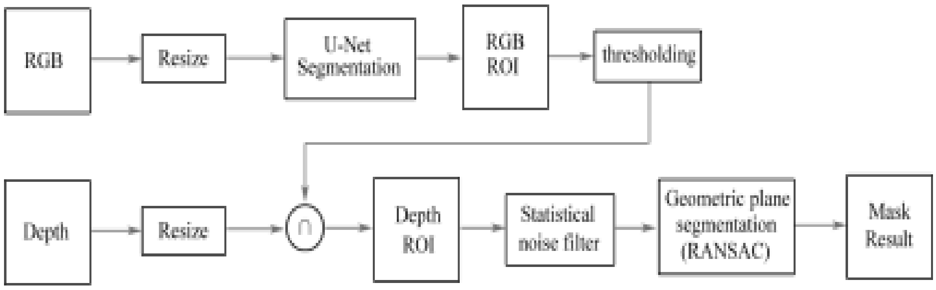

Figure 4. Architecture based on U-Net for the automatic segmentation of DFUs

The architecture used U-Net to automatically segment the feet using the RGB information of the images, and it used the depth information of the image to segment planes in the depth image to enhance the segmentation results delivered by U-Net. An strategy known as RANDOM SAmple Consensus (RANSAC) was used to find the optimum segmentation of planes in images using the depth information, which enhanced the segmentation results. The model also showed excellent performance when the encoder path was fine-tuned using a limited training data set, and it could quickly produce results for automatic segmentation. The model outperformed a straightforward U-Net segmentation system and other conventional segmentation techniques.

A mask R-CNN model was put up by Gamage et al. (23) to automatically locate and segment ulcer edges for diabetic patients. The model is depicted in Figure 5 and enhanced the R-CNN architecture's speed. First, two different backbone CNNs, ResNet-50 and ResNet-101, were used to generate region proposals. The features were then extracted from the backbone network, with low level features being extracted in the early layers of the network and object instances being detected in the later layers. Then, a region proposal network produced ROIs and bounding boxes.

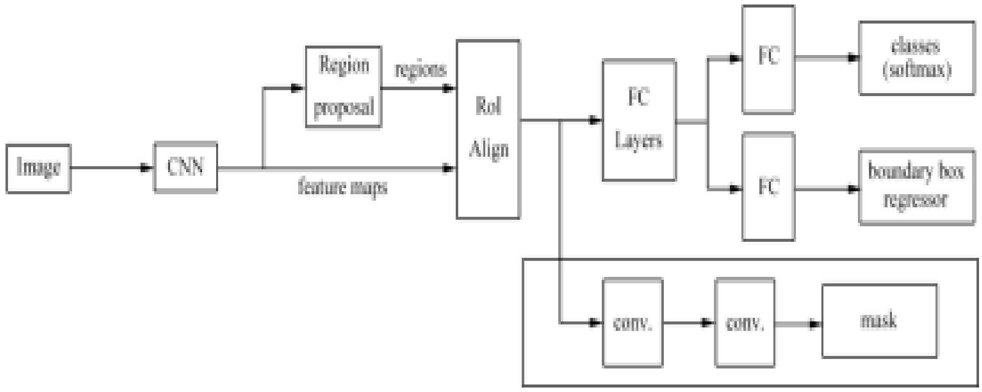

Figure 5. The mask R-CNN architecture proposed by Gamage et al. (23)

The classifier categorised the ROIs, and the bounding-box regressor improved the bounding boxes. A mask was eventually created for the identified ROIs. The model can be used to ulcer pictures for object recognition, localisation, and instance segmentation. The mask R-CNN model outperformed U-Net models in accuracy and performance and can take the position of hand-measuring ulcers.

With the help of 1,042 photos of DFUs, Zhao et al. (24) developed an intelligent measuring model for DFUs based on mask R-CNN and RetinaNet. Mask R-CNN was used for ulcer tissue colour instance segmentation and RetinaNet for the identification of digital scale targets. For the training set and the test set, the mAPs of the colour region segmentation were 87.9% and 63.9%, respectively. The average inaccuracy of the intelligent measurement result was about 3 mm, which compared to the manual measurement of DFUs. The mAPs of the ruler scale digital detection were 96.5% and 83.4% for the training set and test set, respectively. Table 3 provides a summary of deep learning's application to the semantic segmentation of DFU picture data.

Table.1. Summary of Deep Learning in Image Segmentation for Images of DFU

References	Purpose	Network structure	Contributions	Limitations	Results
Goyal et al., 2017 (20)	•Automatic segmentation	•Two-tier transfer learning with three models	•Better convergence • Pixel-wise prediction • Feature hierarchy retrieval • Creating erractic shapes	•Issues of small size and part •Accuracy of irregular boundaries •Some similar tissues of DFU and surrounding skin	• Dice (ulcer):0.794 ± 0.104 •Dice (surrounding): 0.851 ± 0.148 •Combination: 0.899 ± 0.072
Rania et al., 2020 (21)	•Semantic segmentation	•U-Net •V-Net •SegNet	•Superior segmentation	•Fewer images	•Accuracy: 94.96% •IoU: 94.86% •DSC: 97.25%
Hernández et al., 2019 (22)	•A automatic segmentation monitoring system using multimodal images	•No FC layers based on U-Net	•Excellent performance •Improved Segmentation •RANSAC based plane segmentation	•Fewer images	•Short time •Better results
Gamage et al., 2019 (23)	•The segmentation of the ulcer boundaries and location are both done automatically.	•Mask R-CNN and ResNet-50 •Mask R-CNN and ResNet-101	•Object detection, localization, and instance segmentation •High accuracy and performance	•Not mentioned	•Precision: 0.8632 •mAP: 0.5084
Zhao et al., 2021 (24)	•An intelligent DFU measuring model.	•Mask R-CNN •RetinaNet	•Instance segmentation of ulcers •Digital scale target detection •High accuracy compared with the manual measurement of DFUs	•Not mentioned	•mAP of the region of segmentation: 63.9% •mAP of the ruler scale digital detection: 83.4%

4. Improving performance

Droupout and transfer learning are two techniques for enhancing the performance of Deep Learning models for the DFU analysis.

4.1 Droupout

There are two drawbacks to deep learning models built on deep neural networks with plenty of parameters: Deep neural networks can learn complex associations and overfit when they have a lot of non-linear hidden layers and little training data. Additionally, combining machine-learning models can enhance performance, but training various model architectures on various datasets is expensive. As a result, overcoming overfitting by mixing numerous models at test time is challenging (25).

Dropout is proposed as a strategy, similar to regularisation, to address the aforementioned problems. It can effectively merge numerous distinct neural network topologies while lowering the danger of overfitting (25). The deep learning network's neurons are randomly turned on and off in each layer during training in the dropout concept (26), or temporarily eliminated from the network along with their incoming and outgoing connections. Dropout can help neural networks perform better on a variety of benchmark data sets.

4.2 Transfer Learning

Transfer learning allows for the recognition of previously acquired knowledge and abilities and their application to new activities. To enable training a vast target network, transfer learning can be an effective approach without being overfit (27) and doing better (8). By training and testing on image data sets like ImageNet, Alzubaidi et al. (26) used three pre-trained CNN models: GoogleNet, AlexNet, and VGG16. These models were then fine-tuned using medical image data sets.

Pre-trained models use transfer learning to improve performance. On a DFU data set, Goyal et al. (6) improved segmentation using two-tier transfer learning. First-tier transfer learning involves training pertinent CNN models on the ImageNet data set (28). The Pascal Visual Object Challenge (VOC) segmentation data set was used to train the models in second-tier transfer learning. Instead than using random initialization of weights, these pretrained models are trained on DFU data sets to improve weight convergence.

5. Challenges

5.1 Smaller Data Set

Several neural network layers make up a typical deep-learning framework, therefore several parameters must be established and optimised. If the training contains few photos of medical procedures the deep learning model's data set and numerous parameters need to be optimised to prevent overfitting (8). The publications we identified utilised as few as 59 DFU photographs and as many as 4,500 DFU images, with most of them using hundreds and a few of them using more than 2,000 DFU due to the time-consuming and difficult nature of collecting medical images.

Despite the fact that there is no set size requirement for the minimum training data set, it is generally recommended to have at least ten times as many samples as parameters in the network (29). Additionally, the deep-learning model is unlikely to produce reliable findings if the training data set cannot accurately reflect the traits of actual patients. The following options could be used to address these issues: Try to gather more medical image data, employ more diversified image-capture tools, increase the variety of the data sets, and use data augmentation.

5.2 Limited Annotated Data

When labels are few or expensive to get, Semi-Supervised Learning (SSL) offers a potent framework for using unlabeled data.

DFU photos must typically be annotated by a podiatrist who specialises in the diabetic foot for deep learning techniques. By using the annotator built by Hewitt et al. (30) and exporting the output to an extensible markup language (XML) file, Goyal et al. (20) created ground truth for each image with DFU. Annotating a huge number of photographs is a hard operation, but deep learning models require a big number of annotated images to train the models. Presented by Oliver et al. (31), SSL. It aims to spread a small number of labelled samples to other unlabeled data. SSL addresses the issue of limited annotated data by enabling the classifier to increase accuracy more quickly while using fewer annotated examples.

5.3 Choosing the right deep-learning architecture and hyperparameters

Different deep-learning architectures have various benefits and drawbacks, and they will be chosen based on the features of the input data and the goals of the research. Semantic segmentation, object detection, and classification can all be used in the study of medical pictures of DFU. For instance, faster R-CNNs are good for object identification, FCNs are good for semantic segmentation, and CNNs are good for classification. Choosing the best deep-learning architecture is difficult right now, and future research will need to try more models and methods.

When a deep-learning architecture is selected, several hyperparameters will be defined and optimised by training the deep-learning model, in which hyperparameters are automatically set to maximise performance and minimise human effort (32). At the moment, Bayesian optimisation (33) or other random searches are frequently used in automatically optimising hyperparameters.

5.4 Changing the black box into a white box

A deep-learning model is still a black box with no explanation of its fundamental process, making it challenging for physicians to understand its outcomes even if it has produced positive results in many domains. It is crucial for the interpretability of deep learning-based systems for medical image analysis. For the benefit of the patients, it can assist doctors in better understanding the illness and providing the appropriate diagnosis. Local interpretable model-agnostic explanations (LIME), reported by Xiang et al. (34) was used to derive proof from the skin images to back up the classification outcomes by visualising models.

A deep learning-based image-similarity algorithm was presented by Wulczyn et al. (35) that produced human-interpretable histologic characteristics by clustering embeddings. The majority of the variance could be explained by the model. Wu et al.'s (36) model was utilised to find interpretable representations that might explain predictions from medical imaging. Even though certain models have currently produced interpretable visualisation results, some researchers believe that these results are still far from adequate and that some explanations may even be inaccurate. It is thought that research on the switch from black box to white box is still in its early phases.

6. Conclusion and Future Trends

Medical image classification, target detection, and segmentation using current deep learning have all been successful. With the advancement of technology, more multimodal data may be gathered. These information include medical imaging (such as X-ray, CT, MRI, and PET scans) as well as other types of medical resources (such as genetics, bioinformatics, drug reactions, and electronic medical records). Because of the complexity of the diversity of data, more sophisticated deep learning architectures must be created.

Medical image classification, detection, and segmentation challenges as well as disease diagnosis and prediction as well as other issues have all been successfully solved using deep learning. In order to better apply deep learning models to all phases of medical diagnosis and treatment, which frequently involve multiple stages in the occurrence and development of diseases, three factors are required: technological development, increased data collection, and increased medical expertise.

Many excellent algorithms are currently in use in the medical field, but deep learning model parameters and training data require more time to set, so it is necessary to speed up deep learning model development, enhance the deep learning algorithm, and produce better and faster hardware. Algorithms should be improved, or multiple architectures should be combined, to increase their efficiency and accuracy.

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