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A REVIEW: DEEP LEARNING TECHNIQUES FOR IMAGE CLASSIFICATION OF PANCREATIC TUMOR

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Abstract

Pancreatic Cancer (PC) may be a leading reason behind death worldwide and its prognosis is extremely poor within the present scenario. There are numerous methods and techniques for tumor identification in brain, breast, lungs, but limited work was done on pancreatic tumor detection. Pancreatic tumor image classification is usually provided by computer-aided screening (CAD), diagnosis and quantitative evaluations in radiology images like CT and MRI. Tumor classification through these methods may help to trace, predict and endorse customized therapy as part of effective treatment, without invasions of cancer. Nowadays, Convolutional Neural Networks (CNN) have shown promising results for precise pancreatic image classification. As a prominent, the algorithms are required to work out and classify the categories of pancreatic tumors at early stages for saving most of the life. Because of the various shapes, huge sample size, processing and analyzing big databases, new statistical methods are to be implemented. On the opposite hand, detection of tumors within the medical images also become difficult since the standard of input images. This paper mainly concentrates on a study of carcinoma and also the recent research on tumor detection and classification in medical images. The convolution neural network (CNN) developed in recent years has been widely utilized in the sector of image processing because it's good at handling image classification and recognition problems and has brought great improvement within the accuracy of the many machine learning tasks. One in every of the foremost powerful approaches to resolve image recognition and classification problem is that the CNN. The experimental results demonstrate that the proposed approach can improve the performance of the classification accuracy.

Keywords:

CNN, Classification, Deep Learning, Medical Image Analysis, Pancreatic Cancer, Adenocarcinomas

1. INTRODUCTION

Deep Learning is a real time application in the wider part of the Machine Learning. Deep Learning takes a lot of data, which can make decisions about new data. This data is passed through Neural Networks, known as Deep Neural Networks (DNN). In Deep learning, Convolutional-Neural Network (CNN) [1] [2] is a popular type of deep neural networks. CNNs have some of the visual recognition such as traffic sign recognition [3], biological image segmentation [4], and image classification [5]. Deep learning for image classification is becomes essential use of machine learning method. Machine Learning extract the feature manually and the classification-algorithm classify the objects separately. But in Deep Learning the network itself extract the features without user interpretation also classify the objects.

Deep learning is part of a broader family of machine learning methods based on learning data representation, as opposed to hard code machine algorithms. [6]. One of the most frequently used deep learning method for image classification is the CNN because it reads the images data directly and eliminates manual feature extraction [7]. Common problem in image classification using deep learning is low performance for over fitting. To increase performance and preventing over fitting large dataset and model used. In this paper, a deep learning CNN is deployed using python for image classification.

1.1 PANCREATIC CANCER AND ITS SIGNIFICANCE FOR DETECTION

Pancreatic cancer is a very deadly and incurable disease that has not significantly improved survival rates in recent years [8]. MRI guided radiation therapy is currently used to shrink a tumor, however anatomical changes, such as breathing, are not affected because of the inter-patient variability and infarction [9]. Early and accurate diagnosis is difficult for the pancreatic tumor. The tumor has entered an advanced stage once the diagnosis is confirmed [10]. Improving early diagnosis, early detection, and early treatment is of great importance. High mortality of pancreas tumors leads to a great deal of interest in improving useful diagnostic and treatment which makes accurate classification of the pancreatic tumor [11].

Image recognition is one of the most important components. The process of recognition adenocarcinomas into two phases: feature extraction and feature selection [12]. There are typically two types of endocrine and exocrine pancreatic cancer that is the most active form of cancer derived from the pancreatic cell enzyme [13] during diagnosis. Exocrine tumors in pancreatic ducts are also called adenocarcinomas. This cancer is based on its growth stage, while the endocrine tumors are derived from a tumor, which impacts the cells of the hormone which are also known as the islet neuroendocrine cancer or cell cancer [14].

The pancreas is a gland that produces digestive juices and hormones. Pancreatic cancer is when abnormal cells in the pancreas start to divide and grow in an uncontrolled way and forms a growth (tumor). Over time, the cells can eventually grow into surrounding blood vessels or organs such as the small bowel (duodenum). And the cancer cells may spread to other areas of the body. Pancreatic cancer occurs within the tissues of the pancreas, which is a vital endocrine organ located behind the stomach. The pancreas located in the abdomen, has cells with endocrine (hormonal) and exocrine (digestive) functions; cancer cells can develop from both types of functional cells. There are different types of cells in the pancreas.

Most pancreatic cancers are adenocarcinomas. Cancer can start in the head, body or tail of the pancreas. The wide end of the pancreas is called the head. The thin end is called the tail. The bit in the middle is called the body. Most of the pancreatic cancers are the exocrine type. This means that they start in cells that produce pancreatic digestive juices. More than 80 out of 100 exocrine pancreatic cancers (>80%) are adenocarcinomas. Nearly all of these are ductal adenocarcinomas. They start in the cells lining the ducts of the pancreas.

1.1.1 Types of Pancreatic Tumors:

The types of exocrine pancreatic cancer include:

- ***Cystic Tumors***: Cystic Tumors cause a cyst or fluid filled sac in the pancreas. Most pancreatic cysts are not cancerous (they are benign) but some are cancerous (malignant). Cystic cancers can have a better outlook (prognosis) than other types of exocrine pancreatic cancer.
- ***Cancer of the Acinar Cells***: The acinar cells are at the ends of the ducts that produce pancreatic juices. These Tumors are generally diagnosed in people at a younger age than adenocarcinomas. They are slower growing and tend to have a better outlook.
- ***Endocrine Pancreatic Tumors***: Endocrine Tumors are uncommon. They start in the endocrine pancreas, where insulin and other hormones are made and released directly into the bloodstream. They are also called pancreatic neuroendocrine Tumors (PNETS) or islet cell Tumors.

1.1.2 Other Types of Pancreatic Tumors:

There are other rare types of cancer of the pancreas. They are treated differently to the more common types of pancreatic cancer.

- ***Pancreatoblastoma***: These very rare Tumors mainly occur in children. They are sometimes linked with rare genetic conditions called Beckwith-Wiedemann syndrome and familial adenomatous polyposis (FAP).
- ***Sarcomas of the Pancreas***: These are cancers of the connective tissue that hold together the cells of the pancreas. They are extremely rare.
- ***Lymphoma***: Lymphoma is a cancer of the lymphatic system. As the lymphatic system runs throughout the body, these Tumors can develop in any part of the body.

1.2 TNM STAGES OF PANCREATIC TUMOR

TNM stands for Tumor, Node and Metastasis. This system describes the size of the cancer (*T*), whether there are lymph nodes with cancer cells in them (*N*) and whether the cancer has spread to a different part of the body (*M*).

Tumor (*T*): Tis (carcinoma in situ) is very early stage pancreatic cancer. It has not grown into the deeper layers of tissue within the pancreas. It is uncommon for pancreatic cancer to be diagnosed this early (Table.1).

Table.1. Size and location of Cancer

Tumor	Size and Location
T1	The cancer is inside the pancreas and is 2cm or less in any direction.
T2	The cancer is more than 2cm but less than 4cm in size in any direction.
T3	The cancer is bigger than 4cm but is still within the pancreas.
T4	The cancer has grown outside the pancreas, into the nearby large blood vessels.

Node (*N*): Node (N) describes whether the cancer has spread to the lymph nodes. Cancer that has spread (Table.2) to the nearby lymph nodes means there is a higher risk that cancer cells may have spread further than the pancreas.

Table.2. Status of Cancer Spread at Nodes

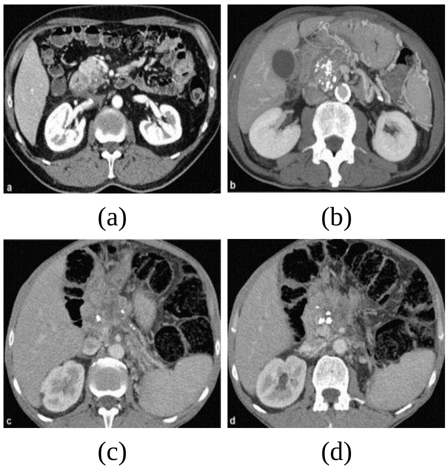
Node	Status of Spread
N0	There are no cancer cells in the nearby lymph nodes.
N1	There are 1 to 3 lymph nodes that contain cancer cells.
N2	There is a cancer in 4 or more lymph nodes.

Metastasis (*M*): Metastasis (M) describes whether the cancer has spread to a different part of the body.

Table.3. Status of Cancer Spread at Metastasis Stage

Metastasis	Status of Spread
M0	The cancer has not spread to other areas of the body such as the liver or lungs.
M1	The cancer has spread to other areas of the body.

Image classification is one of the complicated areas in an image processing. Image processing has some basic operations, namely image restoration/rectification, image enhancement, image classification, image fusion etc. The objective of image classification is the automatic allocation of image to thematic classes [15]. In the classification, there are two types namely Supervised Classification and Unsupervised Classification. In supervised classification, the set of classes is known in progress. However, in unsupervised classification, the set of classes is unknown. The process of image classification involves two steps, training and testing. The training process takes the images and form a sole description for a particular class. The process is depending on the type of classification problem such as a binary classification or multi-class classification. The use of CNNs for image detection and recognition has been in place for long time [16] [17]. CNNs used for generic object detection and recognition while Support Vector Machines (SVM) were trained on the features learned by the CNN to be used for classification purposes [18]. GPU implementation of image classification task using CNNs such that the network was flexible as well as fully online, i.e., the weights were updated after each image [19]. Use of efficient regularization techniques like dropout was made, along with data-augmentation to reduce over-fitting.



(a) (b)

(c) (d)

Fig.6. MRI of Pancreatic Tumor (a) (b) Head of Pancreatic Tumor (c) (d) Body of Pancreatic Tumor

2. RELATED WORK

Liu and Feng-Ping [20] has applied an optimized kernel function to reach a higher average accuracy and solve the problems of complex function approximation and poor classifier effect, thus further improving image classification accuracy.

Kumar and Kumar [21] implemented the Bat Algorithm. ANN-Bat approach was significant in reducing the time taken to yield an output as well as the accuracy.

Yadav and Jadhav [22] mainly focused on Linear support vector machine (LSVM) classifies local rotation and orientation free features. The high-quality effects came from the transfer learning of VGG16 with one retrained ConvLayer.

Xin and Wang [23] has analyzed time- consuming comparison on the SVM, KNN,BP, and CNN methods and the results show that the accuracy of CNN classifier is higher than that of other classifiers in the training set and test set.

Sun et al. [24] has implemented variable-length gene encoding is designed to represent the different building blocks and the unpredictable optimal depth in CNNs. The experimental result shows that the remarkable superiority of the proposed algorithm over the advanced algorithms in terms of classification error rate and the number of parameters (weights).

Penga et al. [25] has developed weighted constraint based dictionary learning algorithm to improve the classification performance.

Mikołajczyk et al. [23] used data augmentation method to solve the problem of lack of sufficient amount of the training data or uneven class balance within the datasets. As a result, this method allows generating the high perceptual quality of new images used to improve the training process efficiency.

Manju [27] has generated a modified swarm optimization approach used to extract the images for threshold-based segmentation process with the use of OTSU's binary threshold method. The structured support vector machine is proposed for the classification of the satellite image. The structured support vector machine is improved its performance. Since overall sensitivity, specificity, and accuracy is improved.

Wang et al. [28] implemented Particle Swarm Optimization (PSO) algorithm to encode the variable length particle vector to automatically search for the optimal architecture of CNNs. The proposed algorithm is a strong competitor to the advanced algorithms in terms of classification error.

Sun et al. [29] designed architecture design to implement the algorithms in terms of classification accuracy, parameter numbers, and consumed computational resources to shows the very comparable classification accuracy to the best one.

Park et al. [30] experimentally validated the proposed method using a well-known character and object recognition and is also has higher accuracy than other unsupervised feature-learning methods.

Ma et al. [31] has designed an autonomous and continuous learning (ACL) algorithm to generate automatically a DCNN architecture for the specific image classification problem.

Ahn et al. [32] has employed new hierarchical unsupervised feature extractor to improve the higher classification accuracy.

The authors in [33] proposed Discrete Wavelet Transform-Singular Value Decomposition (DWT-SVD) based perceptual hash function to reduce the execution time of CNN architecture and also achieved better classification performance with success 97.3%.

Li et al. [34] has employed Particle Swarm Optimization with binary encoding (BQPSO) is employed to solve difficult image classification problems and this algorithm achieved better performance and robustness.

Tuncer et al. [35] has proposed a method to reduce the images classification time and maintain the classification performance by using perceptual hash function CNN (PHCNN) and also achieved with 98.2% success.

Istrate et al. [36] developed a novel method to estimate the classification difficulty of the dataset and also used hyper-parameter search optimizers to neural network configurations.

Bera and Shrivastava [26] has presented a spatial feature extraction technique using deep CNN for Hyperspectral image (HSI) classification which performed on four hyperspectral data sets: KSC, IP, UP and SA and produced high classification accuracy (98.79%)with small training data set.

3. CNN

The convolution neural network (CNN) developed in recent years has been widely used in the field of image processing and has brought a great improvement in the accuracy of many machine learning tasks. It has become one of the powerful and universal deep learning models. CNN is a multilayer neural network, and it is also the most classical and common deep learning framework. A new reconstruction algorithm based on CNNs is proposed by Newman et al. [13] and its advantages in speed and performance are demonstrated. Wang et al. [14] discussed three methods, that is, the CNN model with pre-training or fine-tuning and the hybrid method. The first two executive images are passed to the network one time, while the last category uses a patch-based feature extraction scheme. The survey provides a milestone in modern case retrieval, reviews a wide selection of different categories of previous work, and provides insights into the CNN based approach.

CNN is very interested in machine learning and has excellent performance in image classification. The proposed method for learning contextual interaction features using various region-based inputs are expected to have more discriminant power. The experimental results of the widely used image datasets show that the proposed method can outperform any other traditional deep-learning-based classifiers and other advanced classifiers.

The architecture of the CNN contains the different layers as follows:

Input Layer: This input layer, gives inputs (mostly images) and normalization is carried out and forwarded to further layers for extracting features.

Convolution Layer: In this layer a filter passes over the image, scanning a few pixels at a time and creating a feature map that predicts the class to which each feature belongs.

Rectified Linear Unit (*ReLU*): ReLU combines non-linear and rectification layers on CNN. This does the threshold operation where negative values are converted to zero. However, ReLU does not change the size of the input.

Pooling: This layer reduces the amount of information in each feature obtained in the convolutional layer while maintaining the most important information, which helps for faster and effective training.

Fully Connected Layer: Takes the output of the previous layers, flattens them and turns them into a single vector that can be an input for the next stage.

Softmax Layer: This layer is present above the output layer. This layer gives the decimal values of 0 and 1 for each class.

3.1 COMPONENTS OF CNN

The network architecture of CNNs comprises of various different components. Artificial neural networks consist of various layers between the input and output layers. These layers known as the hidden layers, majorly consist of the following in the case of CNNs:

3.1.1 Convolutional Layer:

Each CNN consists of different number of convolution layers depending on network requirements. The first convolutional layers are responsible for learning low level features such as edges, corners, etc. The output of these layers is often fed to other convolutional layers which learn higher level features. Each neuron in this layer is connected to only a limited no. of neurons in the previous layer. The number of neurons they are connected to is known as the receptive field of the convolutional layer. These layers comprise of a filter which has a typical size of $n \times n$. The filter is more precisely convolved during the forward pass across the width and height of the input volume and dot products are computed between the entries of filters and the input position which comprises the final feature map. However, multiple filters are used for convolution since images have multiple features, and this signifies the depth of the feature maps (which is a hyper parameter) which is equal to the no. of filters used.

3.1.2 Pooling Layer:

The pooling layer is used to decrease the spatial size or the resolution of the image in order to decrease the number of parameters, hence decrease the computational burden. It does so by reducing the number of connections between the convolutional layers [15]. They usually alternate between the convolutional layers. The most common types of pooling are max pooling and average pooling. Though the use of average pooling has been decreased substantially lately, max pooling is still one of the most common methods. Another form of pooling is stochastic pooling, which is also used for regularization. It is a pooling method inspired from dropout [16]. It picks a random activation within each pooling region based upon a multinomial distribution rather than the maximum value, like in max-pooling, which ensures that non-maximal activations present within the feature maps can also be utilized. Though the training time error rates of max pooling are lesser but test time error of stochastic pooling is lesser than max the pooling. Another form of pooling is mixed pooling [17] which is the combination of average and max pooling. This method is proposed to perform better than max pooling and average pooling since it can solve problems related to over fitting more efficiently.

3.1.3 Fully Connected Layer:

These layers are present in varying numbers in a CNN, generally right before the softmax layers. Every neuron in this layer is connected to every neuron in the previous layer. It is used to achieve linearity in the networks, but can be replaced or converted into convolutional layers to turn the system into a fully convolutional network (FCN).

3.1.4 Softmax Layer:

The softmax layer is generally a linear layer with a softmax classifier which converts the activations into values between 0 and 1, such that their sum is 1. It helps determine the final output of the CNN by finding the output of a recognition or classification task by determining the class or category having the highest probability value. It basically represents a probability distribution.

3.2 ACTIVATION FUNCTIONS

The most necessary role of activation functions in CNNs is to ensure non-linearity, i.e., multiple neurons are activated as a result of activating a single neuron. Most common non-linear functions used in CNNs are listed below.

3.2.1 Logistic Function (Sigmoid Curve):

A sigmoid function is a function that is defined for all real input values. Also, it has a non-negative derivative at each point. It is defined by It has non-zero values and an activation range of [0,1]. This function updates at every point and hence are very smooth.

3.2.2 Hyperbolic Tangent Function:

One of the major advantages of tanh is that it gives faster convergence during back propagation, if the initial weight values are lesser, distributed quite uniformly and centered on 0. However, in the case of sigmoid function, the output activations are biased towards the lower half of the activation range [18].

3.2.3 ReLU Function:

ReLU is a linear function which retains the positive values of the input and the negative values are turned to zero. Using ReLU ensures faster computations compared to both tanh and sigmoid functions. Training larger networks with more parameters becomes easier as a result. Also, it is a numerically less complex function. A problem in ReLU is that the function is not differentiable at the value z=0. This, however, is overcome easily by defining the gradient at that point to be 0. ReLUs are really useful if sparsity in the hidden units is desired.

3.3 REGULARIZATION FUNCTIONS

The use of too many parameters in a CNN leads to a problem called overfitting. In order to overcome that, various regularization techniques are used. Some major techniques used for regularization are:

3.3.1 Dropout:

It is a regularization technique in which some neurons are randomly removed from the network. As a result of this, the learned weights of other neurons become insensitive to them. This helps the network to generalize better and the influence of an individual neuron in the output produced is reduced. The probability that a neuron is not dropped from the network is *p* (*p* is a hyper parameter) where p is decided using a validation set. As a result, (1-*p*) becomes the probability of a neuron being dropped and its activation turned to 0 [19]. The probability *p* of each neuron is completely independent of the probabilities of all the other neurons. If half the activations in each layer are randomly deleted, the errors too will be calculated using back propagation on only half the activations. The error values are lower when $0.4 \leq p \leq 0.8$ and increase as *p* becomes greater than this and close to 1. The lowest error value is for 0.6, however the default value considered is $p=0.5$ which is very close to optimal.

3.3.2 Drop-Connect:

In this method, the weights connected to a certain neuron are set to zero with some probability. The probability of keeping a connection in the network is *p*. The probability of dropping a connection in this case rather than an output unit is (1-*p*). This model introduces sparsity in the weights compared to Dropout which introduces dynamic sparsity to the output vector layer. As a result, the fully connected layers become sparsely connected layers since only certain connections are chosen at random.

3.3.3 Data Augmentation:

Data augmentation is another technique used for the reduction of overfitting in a network. The total amount of information available in the training set was increased by manipulating the data already available in the training set. Various techniques are used to achieve them, many of which can be categorized by data warping which includes augmenting the input data directly to the model available in the data space, the idea behind which was conceptualized in [20]. Most commonly used data augmenting practices include flipping, cropping, translating, rotating the image along with changing or inverting the colors of the image.

3.3.4 Stochastic Pooling:

One of the drawbacks of dropout are that it does not benefit convolutional layers much which are pivotal in the working of CNNs. Hence, this approach aims at making pooling, which occurs at all convolutional layers stochastic [16]. A pooled map response in this case is selected in a probabilistic manner using a multinomial distribution of the activations instead of averaging or calculating the maximum of the activations in a particular pooling region.

Table.4. Analysis of Algorithms in Various Works

Type of Network	Details of the Network	Pros	Cons
CNN	Each layer accepts an input 3D volume and transforms into an output 3D volume through a differentiable function. Popular choice of neural networks for different computer vision tasks such as image recognition.	Very good for visual recognition. Learning and recognition is very fast and accurate.	Highly dependent on the size and quality of the training data. Need more labeled data for classification, highly susceptible to noise.
Recurrent Neural Networks (RNN)	RNN uses the same parameters for each inputs to produce the output. As a result, they find a lot applications in real-world domains such as natural language processing, speech synthesis and machine translation.	RNN shares the same parameters across all steps. This greatly reduces the number of parameters that need to learn, It can be used to generate accurate descriptions for unlabeled images.	RNNs find it difficult to track long-term dependencies. RNNs cannot be stacked into very deep models. This is due to the activation function makes the gradient decay over multiple layers.
Deep Neural Networks (DNN)	Deep neural networks have a unique structure and also relatively large and complex hidden component between the input and output layers. The DNN finds the correct mathematical manipulation to turn the input into the output, whether it be a linear relationship or a non-linear relationship.	It is widely used with great accuracy.	It requires very large amount of data in order to perform better, and it is extremely expensive to train due to complex data models. The training process is complex. The learning process is very much slow.
Deep Autoencoders (DA)	Autoencoders apply the principle of back propagation in an unsupervised environment. Autoencoders usually represent data through multiple hidden layers such that the output signal is as close to the input signal.	Autoencoders is primarily based on the data rather than predefined filters and very less complexity.	Training time can be very high sometimes. If the training data is not representative of the testing data, then the information that comes out of the model can be obscured and unclear.
Generative Adversarial Networks (GAN)	Generative modeling is an unsupervised learning task that involves automatically discovering and learning the regularities or patterns in	GANs allow for efficient training of classifiers in a semi-supervised manner. Due to the improved accuracy of the	Generator and discriminator working efficiently is crucial to the success of GAN. Trained with different loss functions.

	input data such that the model can be used to generate or output new examples that plausibly could have been drawn from the original dataset. It finds large and important applications in computer vision, especially image generation.	model, the generated data is almost similar to the original data.	Time required to train the entire system can get quite high.
LSTM Networks	LSTM is a unique type of RNN capable of learning long-term dependencies, which is useful for certain types of prediction that require the network to retain information over longer time periods.	Handles noise distributed representation and continuous values, Broad range of learning rate.	Takes longer time to train, require more memory to train, Easy to overfit, Dropout is much harder to implement, sensitive to different random weight initializations.
Deep Belief Network (DBN)	DBN composed of binary latent variables, and they contain both undirected layers and directed layers. Each layer learns the entire input. Deep belief networks work globally and regulate each layer in order.	It supports a number of different deep learning frameworks such as Keras and TensorFlow, for compute-intensive algorithms, helps the system classify the data into different categories, Efficient usage of hidden layers, Robustness in classification.	Ineffective if errors are present in the first layers. Such errors may cause the network to learn to reconstruct the average of the training data.
Deep Stacking Networks (DSN)	DSN consists of deep set of individual networks, each with its own hidden layers. This architecture is a response to one of the problems with deep learning: the complexity of training.	It views a set of individual training problems and also to learn more complex classification, the capacity to execute feature engineering on its own, enable faster learning without being explicitly.	-
Deep Convolutional Extreme Learning Machine (DC-ELM)	DCELM consists of multiple alternate convolution layers and pooling layers to effectively abstract high level features from input images.	Better generalization performance with faster learning speed. Better testing accuracy with significantly shorter training time.	-

4. CONCLUSION AND FUTURE WORK

In this paper, we presented prediction of the pancreatic tumor by utilizing the CNN method based on deep learning techniques. Furthermore, their applications to medical image analysis are also surveyed for pancreatic tumor. Pancreatic cancer classification in MRI and CT scans through the CNN method is examined. A comparative analysis is made on various algorithms along with its advantages and disadvantages. While comparing with machine learning, deep learning directly learns the image data without object segmentation or feature extraction. Thus, it is the power of CNN, which is a powerful, versatile technology with higher performance that brings the state-of-the-art performance of medical image analysis to the next level. Further it is expected that CNN will be the mainstream technology in medical image analysis in the next few decades.

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