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# DEEP LEARNING APPROACHES TO BIOMEDICAL IMAGE SEGMENTATION

***S.K. Kurbanov***
*Assistant-professor of Tashkent university of information technologies named after Muhammad al-Khwarizmi*

***S.S. Beknazarova***
*Professor of Tashkent university of information technologies named after Muhammad al-Khwarizmi, Doctor of technical science*

*Audiovisual technologies department, Television technologies faculty*
*Tashkent university of information technologies named after Muhammad al-Khwarizmi, Uzbekistan*
*E-mail: abstrakt88@gmail.com*

***S.K. Kurbanov***

*He has graduated Tashkent university of information technologies named after Muhammad al-Khwarizmi. He is working at the department of Audiovisual technologies Tashkent university of information technologies named after Muhammad al-Khwarizmi.*

***S.S. Beknazarova***

*Professor of the department of Audiovisual technologies Tashkent university of information technologies named after Muhammad al-Khwarizmi. Doctor of technical science.*

**Abstract.** The review considers automatic image segmentation using deep learning methods in the field of medical imaging. Current developments in the field of machine learning, especially those related to deep learning, are useful for identifying and quantifying models in medical images. The main point of these achievements is the significant ability of deep learning approaches to obtain hierarchical representations of characteristics directly from images, which, in turn, eliminates the need for manually created functions. Deep learning is rapidly transforming into state-of-the-art medical imaging technology and has led to improved productivity in various clinical applications. This review discusses the basics of deep learning methods, as well as an overview of successful implementations that include image segmentation for various medical applications. Finally, some research questions are highlighted, and the need for further improvements is indicated in the future.

**Keywords:** machine learning, deep learning-based classifier (DLC), convolutional neural network (CNN)

*Introduction.* Medical imaging is an integral part of a modern healthcare system for performing non-invasive diagnostic procedures. This includes the creation of visual and functional representations of the inside of the human body and organs for clinical analysis. Its various types include: x-ray methods such as conventional radiography, computed tomography (CT), and mammography; molecular imaging; magnetic resonance imaging (MRI) and ultrasound (USA). In addition to these medical imaging techniques, clinical images are increasingly being used to diagnose various conditions, especially skin-related [1].

There are two components of medical imaging: 1) image formation and reconstruction, and 2) image processing and analysis [2]. Image formation includes a set of processes by which two-dimensional (2D) images of three-dimensional (3D) objects are generated, while reconstruction is based on a set of iterative algorithms for generating 2D and 3D images, as a rule, from projection data of an object. Image processing, on the other hand, involves the use of algorithms to improve image properties, such as noise removal, while image analysis extracts quantitative information or a set of characteristics from an image to identify or classify an object.

Machine learning

A typical application of the machine learning-based image segmentation approach is the ROI classification, for example. a sick region or a healthy region. The development steps for such an application begin with a preprocessing step, which may include using a filter to remove any noise or to increase contrast. After the pre-processing step, the image is segmented using a segmentation technique such as threshold processing, clustering based approach and edge based segmentation. After segmentation, elements are extracted based on color, texture, contrast, and size information from the area of interest. Dominant features are then determined using feature selection methods, such as basic component analysis (PCA) or statistical analysis. Subsequently, the selected functions are used as input to the ML classifier, such as SVM or NN. The ML classifier uses the vector of input objects together with the labels of the target class to determine the optimal boundary separating each class [3]. After training the ML classifier, it can be used to classify new unknown data to determine its class. Typical problems include determining the appropriate pre-processing requirements based on the raw image properties, determining the appropriate features and the length of the feature vector, and the type of classifier among others.

**Deep learning-based classifier (DLC)**

The DLC can process the raw image directly, which means that no preprocessing, segmentation, or feature extraction is required. However, most deep learning approaches require image resizing due to input limitation. While some methods require normalization of intensity and increased contrast, which can be avoided if during training methods of increasing data are used, which will be discussed later. As a result, the DLC has a higher classification accuracy, since it can avoid errors associated with an erroneous feature vector or inaccurate segmentation [3]. A comparison of the ML and DLC approaches is shown in Fig. 1 below. DLC-based approaches have shifted the focus of research from traditional image processing techniques to designing functions to designing a network architecture for optimal results. DLC networks typically have several hidden layers, which means that more mathematical operations are performed than ML-based approaches, and thus models require more computational resources.

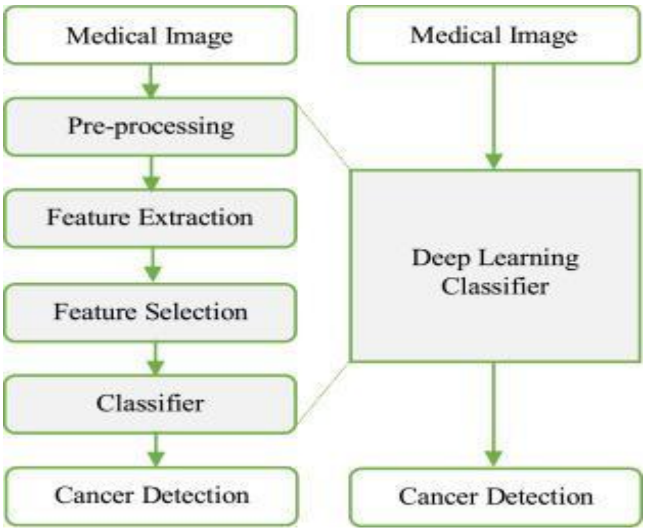


Figure *1.* – Change in classifier approach using typical machine learning algorithm and deep learning.

**Deep learning architecture – convolutional neural network (CNN)**

Among the many deep-learning architectures, CNN is the most widely used because it is very similar to regular NN. Unlike typical NN shown in fig. 2 (a), CNN accepts the image as input and has a three-dimensional arrangement of neurons that connects to a small area of the previous layer instead of the entire layer, as shown in Fig. 2 (b) below. CNN contains levels that include a convolutional level, a non-linear activation level, such as a straightened linear unit (ReLU) level, a union level, or a fully related level. The convolutional layer applies the convolution operation between the pixels of the input image and the filter to obtain the volumes of maps of objects containing objects extracted by the filter. Re LU is a non-linear activation level that applies the function f (x) = max (0, x) to input values to increase non-linearity and increase learning speed. The pool layer lowers the sample of input values to reduce the spatial dimension of the image, to improve computational costs and prevent overlapping, and are invariant for translation, since the calculations are based on neighboring pixels [4]. A fully connected layer is usually the last CNN layer and is similar to the hidden layers of a traditional NN in the sense that all the neurons in this layer are connected to the neurons in the previous layer. As mentioned earlier, CNN is commonly used for classification tasks. To use CNN for semantic segmentation, the input image is subdivided into small sections of the same size. CNN classifies the center pixel of a patch. The patch then slides forward to classify the next center pixel. However, this approach is ineffective, since the overlapping elements of the sliding sections are not reused, which leads to the loss of spatial image information when the objects are moved to the final fully connected network layers. To overcome this problem, the use of a fully convolutional network (FCN) was proposed in which the final fully connected CNN layers were replaced by transposed convolutional layers, as shown in Fig. 2 (c), which applies up sampling on low resolution maps of objects to restore the original spatial dimensions while performing semantic segmentation [5].

Typically, deep neural networks are trained using the back propagation algorithm in combination with an optimization algorithm such as gradient descent. The process includes determining the gradient of the loss function, which is used by the optimization algorithm to update the network weights in order to minimize the value of the loss function.

**Types of Biomedical Images**

There are various types of biomedical images that depend on the imaging method. Some of the commonly used methods of biomedical imaging are presented below. The list below is not exhaustive, because with the development of technology, new imaging methods are being introduced to ensure better and timely diagnosis.

**Clinical images**

Clinical images are digital images of the patient’s body and are often used to document injuries, burns, or skin lesions. The automatic analysis of these images can be used to track the effectiveness of treatment over time. These images are widely used for dermatological and cosmetic procedures to track before and after the presentation of the skin or anatomical structure. The most widely used application of clinical imaging for the detection of skin cancer known as melanoma.

**X-ray imaging**

Radiography is the most widely used imaging technique for detecting bone fractures and dislocations. The generated image is two-dimensional. The National Institute of Health (NIH) provided open access to 100,000 chest x-rays with relevant data and diagnoses to improve image analysis methods [6]. Similarly, the Massachusetts Institute of Technology (MIT) has published a dataset containing a collection of more than 350,000 chest x-rays for developing machine learning models to automatically detect 14 common diseases, such as pneumonia or an punctured lung, etc. [7].

**Computed tomography (CT)**

CT refers to a computer imaging procedure in which X-rays are directed at the patient 360 degrees to obtain detailed images of cross sections of internal organs, bones, soft tissues and blood vessels in the body. Images are traditionally taken in the axial or transverse plane and perpendicular to the long axis of the body. However, these images, which are also known as slices, can be reformatted into several planes and can generate a three-dimensional image. It is widely used to detect cancer by localizing the presence of tumors and their size and is one of the most widely solved problems of biomedical imaging. The National Institute of Health (NIH) provided open access to 32,000 CT scans with associated data and diagnoses to improve lesion recognition accuracy [8].

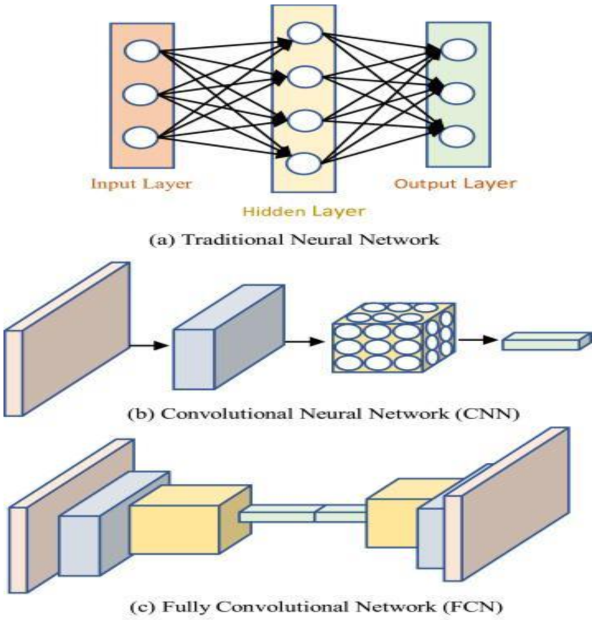


Figure *2*. – (a) A 2-layer Neural Network (one hidden layer of 4 neurons and one output layer with 3 neurons), and three inputs, (b). Convolutional Neural Network (CNN) and (c) Fully Convolutional Network (FCN).

**Conclusion**

A review of deep learning approaches for segmenting biomedical images highlighted some key points. All of these studies were based on empirical results that demonstrated the effectiveness of the proposed approach for this application with limited data sets. The question that remains is why deep learning approaches work for this problem. Understanding the answer to this question is an open area of research. Many researchers are working on creating new visual approaches that will help to intuitively understand the characteristics maps obtained from hidden layers [9,10,11]. In addition, many researchers do not address the problem of generalizing the network response if the source of data changes. This is what will be affected by the change in the data acquisition device, as this can lead to changes in image characteristics, such as light levels or color intensities. Lack of generalization can adversely affect network performance.

Deep learning methods have made unprecedented effects in a variety of biomedical applications - from automated imaging analysis of CT to segmentation of skin lesions. However, if more tagged images are open to all, there is more to be done. Manually setting image data by experts is a serious challenge for discovering fundamental truths. In the absence of basic truths, more emphasis should be placed on the study of uncontrolled learning methods.

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# ПРИМЕНЕНИЕ МЕТОДОЛОГИИ DEEP LEARNING В БИОМЕДИЦИНСКОЙ СЕГМЕНТАЦИИ ИЗОБРАЖЕНИЯ

***С.К.Курбанов***
*Ассистент-профессор Ташкентского университета информационных технологий имени Мухаммеда аль-Хорезми*

***С.С.Бекназарова***
*Профессор Ташкентского университета информационных технологий имени Мухаммеда аль-Хорезми, Доктор наук*

*Кафедра аудиовизуальных технологий, факультет телевизионных технологий*
*Ташкентский университет информационных технологий имени Мухаммеда аль-Хорезми, Узбекистан*
*Ташкентский университет информационных технологий имени Мухаммеда аль-Хорезми, Узбекистан*
*E-mail:* abstrakt88@gmail.com

**Аннотация**. В статье проводится обзор автоматической сегментации изображений с использованием методов глубокого обучения в области медицинской визуализации. Современные разработки в области машинного обучения, особенно связанные с глубоким обучением, полезны для идентификации и количественной оценки моделей в медицинских изображениях. Главным моментом этих достижений является значительная способность подходов обучения получать иерархические представления характеристик непосредственно из изображений, что, в свою очередь, устраняет необходимость создания особых функций. Обучение быстро превращается в современную технологию медицинской визуализации и привело к повышению производительности в различных клинических приложениях. В этом обзоре рассматриваются основы методов обучения, а также обзор успешных реализаций, включающих сегментацию изображений для различных медицинских приложений. К тому же, освещаются некоторые исследовательские вопросы, указывается на необходимость дальнейших улучшений в будущем.

**Ключевые слова:** машинное обучение, классификатор на основе глубокого обучения (DLC), сверточная нейронная сеть (CNN)