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DEEP LEARNING TECHNIQUES IN IMAGE PROCESSING: A COMPREHENSIVE REVIEW

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Abstract: In recent times, a significant transformation in the field of processing the medical image is due to advancements in deep learning techniques by providing powerful tools for feature extraction, classification, segmentation, and generation. In this document, an extensive examination is conducted on the utilization of AI with deep methodologies in a range of image processing tasks. We begin by discussing the fundamentals of machine learning subset, entailing artificial neural networks (ANNs), generative adversarial networks (GANs), recurrent neural networks (RNNs), fully convolutional networks (FCNs), and convolutional neural networks (CNNs), highlighting their strengths and weaknesses in image analysis. Afterwards, we explore various practical uses of deep learning in the field of image processing. These include tasks like identifying objects within images, classifying images, segmenting images based on their content, enhancing image resolution, and transferring artistic styles onto images. Furthermore, we discuss challenges and future directions in leveraging advanced techniques in artificial intelligence, specifically deep learning, which are being utilized to enhance image processing, including interpretability, robustness, and scalability. By synthesizing existing literature and presenting insights into the latest advancements, this review serves as a valuable resource for researchers, practitioners, and enthusiasts seeking to harness the potential of deep learning for solving real-world image processing problems.

***Index Terms* -** Image Processing, artificial networks, generative networks, recurrent networks, fully convolutional, and Convnet.

I. INTRODUCTION

Deep learning has had a significant influence on the field of image processing, completely transforming it by its capacity to autonomously acquire hierarchical representations from unprocessed data. Here is an extensive explanation of the application of DL in the realm of processing a medical image:

1.1 Convolutional Neural Networks (CNNs):

CNNs play a pivotal role in image processing within the field of ML subset (see Figure 2). Their primary purpose is to effectively process grid-like data, such as images. CNNs consist of convolutional layers that learn features from input images by applying filters across the image spatially. These filters capture patterns at different levels of abstraction, such as edges, textures, and shapes. Pooling layers are frequently employed to decrease the size of feature maps, thereby reducing the computational workload while retaining significant features. CNNs are trained end-to-end using backpropagation and optimization algorithms like stochastic gradient descent to minimize a loss function, typically categorical cross-entropy for classification tasks.

1.2 Image Classification:

Models, especially ConvNets (CNNs), demonstrate exceptional performance in tasks involving classification of medical images. They achieve this by directly learning distinctive features from the raw pixel data. Models are trained on labeled datasets such as ImageNet, consisting of an extensive collection of categorized images, amounting to millions in number. These images span across thousands of different categories. Popular architectures entail AlexNet, VGGNet, ResNet, InceptionNet, and more recently, efficient models like MobileNet and EfficientNet.

1.3 Object Detection:

Object detection involves not only classifying objects within an image but also localizing them by predicting bounding boxes. ConvNets-based object detection frameworks such as R-ConvNets, Fast R-ConvNets, Faster R-ConvNets, and YOLO (You Only Look Once) have advancements made in these fields that have greatly improved the state-of-the-art. These frameworks employ region proposal networks and anchor-based methods to efficiently detect and localize objects in images with high accuracy and speed.

1.4 Semantic Segmentation:

Semantic segmentation is the process of assigning a specific class label to every pixel present in an image, effectively dividing the image into meaningful regions. Deep learning architectures like U-Net, FCN (Fully Convolutional Network), and DeepLabv3+

achieved prosperity in endeavor pertinent to semantic segmentation. These models utilize up-sampling layers and skip connections to generate pixel-wise predictions while preserving spatial information.

1.5 Instance Segmentation:

Instance segmentation extends semantic segmentation by labeling alone pixels besides distinguishing among different object instances in the same class. Mask R-CNN is a popular instance segmentation scaffold that builds upon the Faster R-CNN model, a new component has been introduced. This addition involves incorporating a branch that enables the prediction of segmentation masks in extension with bounding and class with labels.

1.6 Image Generation:

Generative Models (GANs) have the ability to produce lifelike images, Variational Autoencoders (VAEs) as well. GANs learn to generate images by training a generator network to produce samples that are indistinguishable from real images, while a discriminator network learns to distinguish in the midst of real and generated images. StyleGAN and its variants have demonstrated impressive results in generating high-quality images with realistic details and diversity.

1.7 Transfer Learning and Fine-Tuning:

Transfer learning enables the utilization of pre-trained deep learning models on extensive datasets for tasks that have a scarcity of labeled data. By refining pre-existing models using datasets that are specific to the task at hand, professionals can achieve impressive results using fewer computational resources and data.

1.8 Applications:

The application of this concept can be seen in a wide range of fields, such as healthcare (for tasks like analyzing medical images and diagnosing diseases) and autonomous vehicles (object detection, scene understanding), surveillance (object tracking, activity recognition), and entertainment (image editing, content generation).

In summary, deep learning has revolutionized image processing by enabling the development of highly accurate, efficient, and versatile algorithms for core division. Continued advancements in deep learning research promise even more sophisticated techniques and applications in the future.

II. RELATED WORK

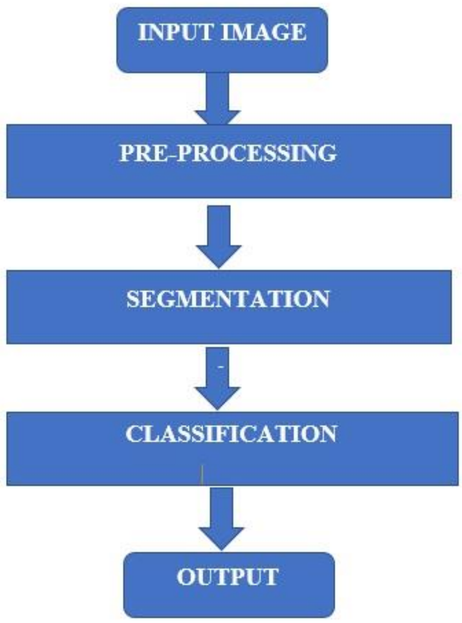

Figure 1: Process involved in Image Processing

The fundamental steps of image processing are elucidated in Figure 1. These procedures encompass deep learning methodologies, different techniques, and their respective precision are indicated as follows.

2.1 ANN in Image processing:

The article [10] discusses a method for spot and label leaf diseases in crops using image processing techniques. The process involves four main stages: acquiring digital images using hardware, partitioning an image based on certain criteria, Relevant descriptors are extracted, and classes based on their features. The methodology section also references related research on disease detection using support vector machine (SVMs) classifiers, genetic algorithms, and artificial neural networks for classifying various plant diseases. Additionally, it provides specific accuracies for individual diseases, such as 90% for bacterial leaf spot, 80% for target spot, and 100% for leaf mold. The accuracy metrics showcase the efficiency of the suggested automated system for detecting diseases in plant leaves by distinguishing between healthy and diseased ones. The focus of the study revolves around the identification of leaf diseases in cotton and tomato plants. More specifically, it highlights water-soaked lesions, oval lesions on the leaves, combination of cultural and chemical methods, and fungus fulvia fulva as the specific bugs.

The study discussed in the paper [11] focuses on the detection of plant diseases through the use of image processing and classification based on neural networks. The methodology involves acquisition of image, segmenting an image, extraction from image, and classification using k-means clustering and connectionist model techniques. The study reports an average classification accuracy of 92.5% for detecting and classifying the diseases, with specific accuracies for individual diseases. The proposed system demonstrates potential applications in sustainable agriculture, environmental resilience, and global food security. The study also highlights the potential for collaborative research and knowledge exchange in the field of automated disease detection.

In this study[13] proposes a technique for classifying three types of tumors using k-clustering by mean and artificial networks. The method consists of several steps, including deblurring and inpainting, regions of interest within an image, statistical properties of pixel values and classified predefined categories using ANN. The proposed technique achieved an optimal accuracy of 95.4% after 19 repetitions. The trail run accuracy was found to be 98.7%, validation accuracy 89.3%, and test accuracy 85.7%. Overall, the study demonstrates the potency of the model in accurately classifying different types of tumors.

2.2 RNN in Image processing:

In [12] details the process of data collection and image acquisition for a system development project, outlining pre-processing algorithms, contrast enhancement techniques, and clustering methods for region of interest (ROI) detection. It also covers feature extraction, system training using a neural network, and testing and validation processes. Additionally, the document explores various image classification techniques, such as supervised and unsupervised approaches, and discusses popular classifiers like ANN, SVM, KNN, and DT, theoretical knowledge regarding the advantages and disadvantages of image processing is being provided.

The articles [14][15] address the difficulties associated with monitoring data in microscope images caused by factors such as image interference, clustering of particles, and the presence and absence of particles. It also introduces a deep learning method called Deep Particle Hypotheses Tracker (DPHT) for particle tracking in fluorescence microscopy. The DPHT methodology surpasses previous techniques and has been assessed using data from the Particle Tracking Challenge, as well as actual microscopy image sequences featuring HIV-1 and HCV proteins. The document also includes tracking performance metrics and experimental results.

In this particular research [16], the primary objective was to utilize deep learning classification methods in order to anticipate and categorize illnesses in watermelon crops. The scientists successfully established connections between disease prediction indicators and the productivity of watermelon crops by analyzing and dividing images of the leaves. The study employed image acquisition, image processing, and image segmentation techniques to identify and distinguish illness in melon plants. K-means clustering was utilized to extract diseased spots, and the RNN included stacked was applied for disease identification. The implemented prediction and classification model achieved reliability and performance compared to other existing models. The Tensor-Flow and Keras-framework, along with the Adam optimization algorithm and ReLu and SoftMax activations, were used in the classification process. Overall, this research contributes to improving disease detection and management in watermelon crops, potentially benefiting the watermelon-exporting industry in India.

The content[17] explores the difficulties associated with tracking particles in sequences of images caused by factors such as image noise, clustering of particles, and the appearance or disappearance of particles. It provides details about the microtubule and receptor data, including particle characteristics and motion behavior. The evaluation of tracking performance involves the use of five metrics: α, β, JSC, JSCθ, and RMSE. The experimental findings encompass the assessment of the DPHT method using data from both the Hands-on hurdles and live data of cells with fluorescence microscopy. The document also compares the DPHT approach with other methods and provides tracking performance results for different scenarios. Additionally, it discusses the termination of object tracks and the loss function used for network training.

The suggested [18][19] framework for identifying lung cancer exploits an Attention-based Recurrent to enhance precision and expedite the prediction of cancerous areas. The ARNN incorporates an attention layer that enables the encoding and decoding of variable-length vectors within individual sequences. It also automatically extracts features from processed images and classifies them using the Stacked RNN technique. The methodology aims to prevent lung cancer, which is crucial for improving diagnosis applications in real-time. The proposed ARNN has shown improved classification accuracy within a limited computational time, making it advantageous for real-time diagnosis applications.

2.3 GAN in Image processing:

The papers [4][5][8] [20] delves into the application of these models as classifiers in various image processing tasks, including image classification, style transfer, corresponding category, process of enhancing the resolution and quality of an image, image that are streams to optimize storage, image partitioning an image, change detection, and image denoising. It highlights the recent progress in research, underscores the influence of deep learning on image processing, and tackles unresolved matters, ongoing challenges, and potential future avenues.

GANs have revolutionized image processing by enabling the generation, enhancement, translation, and manipulation of images in various ways, leading to advancements in fields such as computer vision, graphics, and digital art.

Table 1: Overview of various deep learning algorithm techniques with accuracy

S. No	Application area	Author	Techniques	Accuracy	year	Conference/ Journal
1	Lung Cancer Prediction Using ANN Algorithm	Deepak Rawa, et al.	ANN	92.23	2022	IEEE conferences
2	Breast Histopathology	Xiaomin Zhou, Chen Li[1]	(MLP), Probabilistic Neural Network (PNN)	98.32	2022	IEEE conferences

3	Brain Tumor	Hossam H. Sultan, et al.[2]	CNN	98.7	2019	IEEE conferences
4	Mulberry fruit grading based on ripeness level	Hossein Azarmdel, et al.	ANN with SVM	98.26	2020	Elsevier
5	Leaf Disease Detection	Ch. Usha Kumari, et al. [10]	ANN with K mean cluster	92.5	2019	Proceedings of the Third International Conference on Computing Methodologies and Communication (ICCMC 2019). IEEE Xplore
6	Brain Tumor	Angona Biswas, et al.[13]	ANN with K mean cluster	95.4	2021	2021 2nd International Conference on Robotics,Electrical and Signal Processing Techniques (ICREST). IEEE Xplore
7	Pattern Recognition	Oludare Isaac Abiodun, et al.	RNN CNN MLP	83.89 83.76 83.56	2019	IEEE Access
8	Lung Cancer Detection	Özge GÜNAYDIN, et al.	ANN	82.43	2019	IEEE Xplore
9	Superpixel Segmentation	Fengting Yang Qian Sun, et al.	FCN	Desirable Result	2020	IEEE Xplore
10	Superpixel Segmentation	Eunsoo Park, et al.	FCN	89	2019	IEEE Xplore
11	Automated detection of COVID-19	Ozturk, T., et al. [7]	CNN	98.08	2020	sciencedirect assets
12	Screen coronavirus pneumonia	Butt et al.[6][9]	CNN	98.5	2019	Elseiver
13	Satellite images using segnet	Batuhan Sarıtürk, et al [22]	FCN	90.55	2020	International Journal of Engineering and Geosciences
14	Medical Image Segmentation	Chaitanya Kaul, et al.[24]	FCN	92.14	2019	IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)

2.4 CNN in Image processing:

The document [30] discusses the use of deep ConvNet (DCNN) for medical image classification, particularly for various body organs. It highlights the challenges posed by the large number of medical images and the need for classification methods to assign relevant classes to these images. The document also covers system specifications, and references to related research. Additionally, it delves into the use of pre-trained GoogleNet and traditional neural networks for image classification, as well as the transfer learning application and unsupervised classification techniques in medical image classification. The authors also discuss the use of

CNNs for 3D medical image data and the importance of selecting appropriate network architectures for specific medical image classification applications.

The suggested approach attained a 98% accuracy rate in categorizing medical images of different body organs. The accuracy results for specific classes ranged from 96% to 100%. This method outperformed other advanced techniques, showcasing its dependability and effectiveness in the classification of medical images.

In conclusion, the document emphasizes the significance of developing automated systems for processing medical images to aid in diagnosis and decision-making by doctors and physicians. The proposed deep convolutional network-based approach is positioned as a valuable tool to assist in making informed medical decisions. The authors have stated their desire to delve deeper into the analysis of extensive image datasets in the medical field for the purpose of classifying and detecting images. They plan to pursue this avenue in the future.

A thorough examination of the latest advancements in deep learning algorithms and their utilization in image processing is presented. The objective of the authors [31] is to provide a concise summary of the applications of cutting-edge deep learning models, assess their efficacy, and provide recommendations for future development and enhancement.

The survey focuses on the criteria used to choose these models: unique topological structure, strong ability to generalize in specific image processing tasks, and recognition and continued development by the scientific community. The document concludes by recognizing the urgent need to advance deep learning and highlighting the ongoing efforts and future directions in the field, particularly in relation to network modeling based on neurocognitive mechanisms and the understanding of biological neural processes.

An advanced image processing algorithm [32] to aid in the autonomous navigation of the European Space Agency's Hera mission. This mission is part of the international Asteroid Impact Deflection Assessment collaboration with NASA, with the goal of planetary defense against asteroid impacts, specifically targeting the binary asteroid system Didymos.

These models are used in this paper [19][20] as a classifier or feature extractor in several image processing tasks. These tasks include image classification, style transfer, object recognition super-resolution, image compression, image segmentation, change detection, and image denoising. The paper emphasizes the recent advances in research, the importance of deep learning in image processing, and some open problems, current difficulties and possible future directions.

The proposed CNN architecture, known as the High-Resolution Network, is designed to detect keypoints with high spatial precision, overcoming disturbances and ensuring robust and autonomous navigation for the Hera mission. The algorithm demonstrated accurate performance throughout the entire trajectory of the Early Characterization Phase and for 77.33% of the trajectory in the Detailed Characterization Phase (Kaluthantrige et al., 2023).

2.5 FCN in Image processing:

Discusses a method [21] to classify images as containing text ("text positive") or not containing text ("text negative"). This classification is crucial for various computer vision applications such as vehicle navigation and blind assistance systems. The paper focuses on separating these two categories of images using a lightweight, fully convolutional network model. The model does not require text localization or recognition and aims solely at discerning whether an image includes textual cues. Extensive experiments on a standard dataset demonstrate that the proposed FCN model outperforms traditional methods. The paper is structured into sections that cover related work, details of the proposed FCN-based model, results, discussions, and conclusions along with suggestions for future work. The proposed model in the document, which utilizes a fully convolutional network for the task of text or non-text image classification, achieves high margin accuracy compared to other previous methods. This suggests that the model is highly accurate in classifying natural scene images as either containing text or not.

The paper [22] compares two convolutional neural network architectures, FCN and U-Net, for the task of segmenting roads from high-resolution satellite images. The goal is to analyze which model performs better in terms of accuracy for this specific application. When analyzing the test data, which matched the size of the training datasets, the FCN architecture reached around 97% extraction accuracy on the 512x512 dimension images. The paper also discusses challenges in image segmentation such as shadow, occlusion, and changes in lighting that affect object appearance. The conclusion drawn from the comparison was that the FCN model showed high accuracy when trained and evaluated on high-resolution imagery, which is critical for real-world applications like road segmentation in intelligent cities and autonomous driving.

The document [23], focuses on the use of ML in advance for object detection and classification from high-resolution satellite images, with an emphasis on building segmentation. It points out the technological advancements in Photogrammetry and Remote Sensing that have allowed for such images to be obtained and the historical benefits of using remote sensing for mapping and updating urban areas. Traditional methods, however, still require significant human intervention for accurate detection.

The study compares the performance of two deep learning architectures: SegNet and Fully Convolutional Networks, using the Inria Aerial Image Labeling Dataset. The outcomes suggest roughly equivalent accuracy for building segmentation tasks, with the FCN architecture being slightly more successful by 1%. Results are dependent on the specifics of the training dataset. The study is conducted using Python in a Google Colab environment. [23]. The FCN model(Figure 3) achieved a training accuracy of 94.39% and a validation accuracy of 90.55%.

It [24] proposes a new architecture for integrating attention mechanisms within convolutional neural networks to enhance medical image segmentation. The architecture, named FocusNet, employs a dual-branch system which includes a separate attention-generating branch built using an encoder-decoder structure with skip connections. This setup encourages the specialization of the two branches for learning different representations.

The performance of FocusNet has been assessed using standard datasets for the segmentation of skin cancer and lung lesions. It has shown competitive results when compared to U-Net and its residual variant, while also requiring minimal pre- and post-processing. The results imply that FocusNet's novel attention integration can yield accurate predictions by allowing the network to concentrate on the most relevant parts of the input data [25].

In the context of lung segmentation, FocusNet showcases a high level of sensitivity at 0.9757, specificity at 0.9981, accuracy at 0.9932, and Jaccard index at 0.9965. When applied to the skin cancer dataset for melanoma testing, the algorithm achieves a sensitivity of 0.7673, specificity of 0.9896, accuracy of 0.9214, Jaccard index of 0.7562, and Dice index of 0.8315. These findings indicate the strong performance of the FocusNet architecture in the respective medical segmentation tasks [26].

III. RESULT AND DISCUSSION

The use of ConvNet and Fully Convolutional [27][28][29] has revolutionized the field of medical image processing. These advanced technologies have significantly enhanced the accuracy and efficiency of disease detection, diagnosis, and treatment planning. By leveraging the power of deep learning and image recognition CNN and FCN models have the potential to transform the way medical professionals interpret and analyze complex imaging data.

One of the key factors driving the adoption of CNN and FCN in medical imaging is their ability to automatically extract intricate features from images, allowing for precise identification of anomalies, tumors, and other abnormalities. This level of sophistication is particularly valuable in radiology and pathology practices, where accurate and timely diagnoses are critical.

Moreover, the development of CNN and FCN models has paved the way for more personalized and targeted medical interventions. By analyzing vast amounts of imaging data, these technologies can assist healthcare providers in tailoring treatment plans to individual patients, ultimately leading to improved clinical outcomes. Furthermore, CNN and FCN models have proven to be highly effective in various applications within medical image processing.

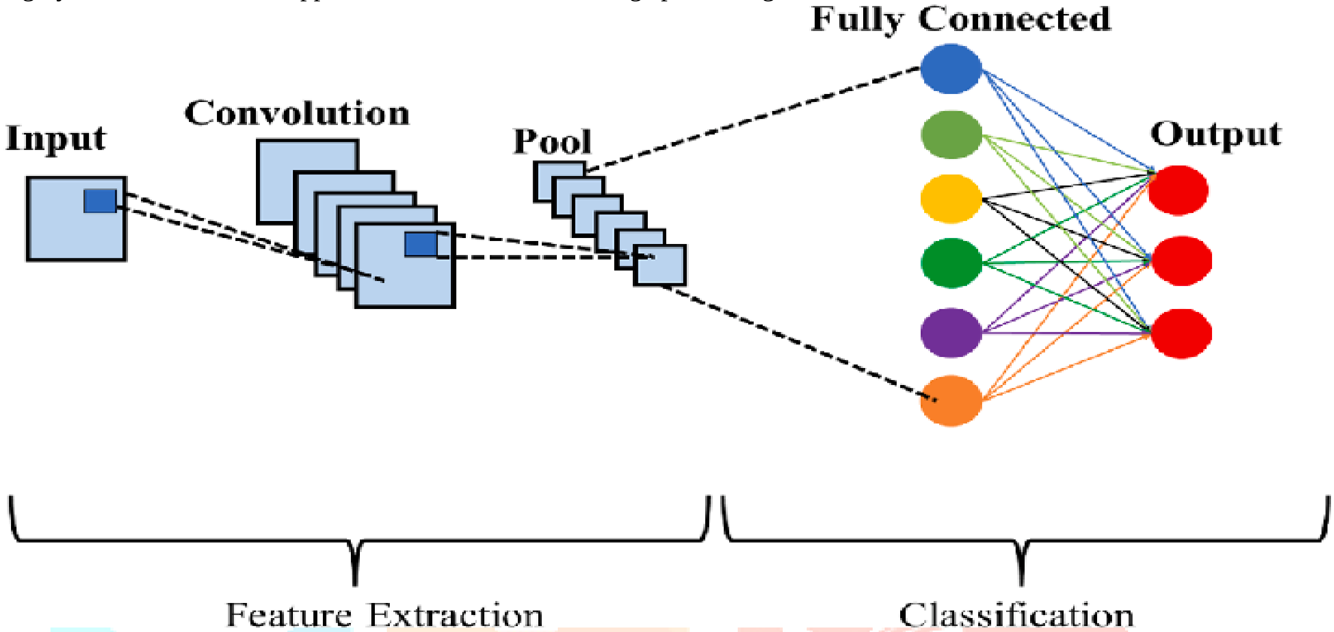

Figure 2: Convolution neural network

Despite their numerous advantages, CNN and FCN also pose certain challenges in the medical imaging domain. Ensuring the robustness and reliability of these models, addressing ethical considerations related to patient data privacy, and integrating them seamlessly into existing healthcare workflows are some of the obstacles that need to be overcome for widespread adoption.

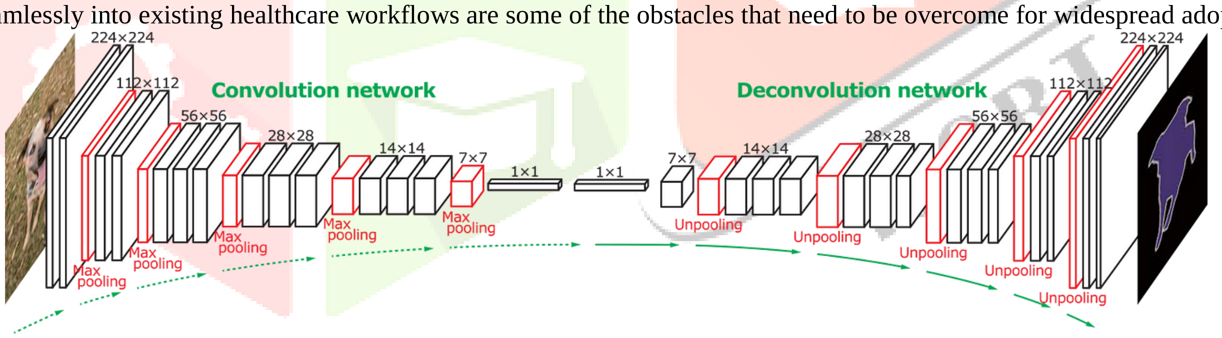

Figure 3: Fully convolutional neural network

Looking ahead, the future prospects of CNN and FCN in the healthcare industry are promising. As research and innovation continue to drive advancements in these technologies, we can expect to see further optimization of medical image analysis, expansion of diagnostic capabilities, and ultimately, greater accessibility to high-quality healthcare services for patients worldwide.

In summary, the CNN model incorporates a Multilayer Perceptron (MLP). (Figure 2 AND Figure 3) However, when there are a larger number of features, the implementation becomes more complex. As a result, it is preferable to use the FCN model. The FCN model includes convolutional and deconvolutional layers, making it easier to implement and comprehend.

IV. CONCLUSION

Table 1 illustrates the crucial role that deep learning techniques play in the field of image processing. When compared to other deep learning techniques, Convnet has been found to yield more precise and accurate results. FCN offers several advantages over CNN in the context of dense prediction.

Particularly in tasks requiring dense pixel wise prediction and spatial information preservation. Their ability to capture fine grained details, integrate multi-scale information, and efficiently process images make them well-suited for various image processing tasks, including semantic segmentation, instance segmentation and image to image translation.

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