Grenze International Journal of Engineering and Technology, June Issue

A Novel Investigation about the Deep Learning Techniques for Liver Diseases Identification

Asha Chandran S[1] and Dr. Jeyaraj Jane Rubel Angelina[2]
[1-2]Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Srivilliputtur,Tamilnadu,India
Email: ashachandran848@gmail.com, jane.angelina@gmail.com

***Abstract*— Deep learning segmentation techniques have been created recently to enhance the identification of liver illnesses, which have demonstrated tremendous promise for increasing precision and effectiveness in diagnosis. Here discuss and evaluate recent studies on deep learning segmentation techniques for the liver utilizing MRI, CT, and ultrasound data. This review concentrates on methods for segmenting the pancreas, biliary tract, liver and gallbladder precisely since they are crucial for clinical diagnosis. Here aim to highlight the major trends and problems in this field through our examination of the literature, and to offer insights into the possibilities and difficulties for additional study and research in this sector.**

***Index Terms*— CNN, GAN, TL.**

I. INTRODUCTION

The liver is a dark red, reddish brown organ located on the right side of the abdomen. It is responsible for controlling most of the chemical levels in your blood. The liver gets its oxygenated blood supply from the liver artery and nutrient rich blood from the liver portal vein. The liver holds approximately 13% of body's blood supply. It is made up of two major lobes connected by the common liver duct. The liver processes blood coming from your stomach or intestines, breaks down nutrients, and metabolizes drugs into non-toxic forms. Liver functions include bile production, protein production, cholesterol production, glucose conversion, amino acid metabolism, haemoglobin processing, and urea conversion. The liver also clears your blood of drug and other toxic substances, controls blood clotting and fights infections. inflammation, liver parenchyma damage, and regeneration. Toxins, excessive drinking, infections, autoimmune diseases, hereditary, and metabolic abnormalities are a few examples of etiologies.[1] The alteration of the liver's architecture occurs in the last stage, cirrhosis. Computed tomography pictures are employed during the expensive and difficult diagnostic process. In this paper, recent studies related to liver disease identification and classification using deep learning are introduced.
This paper is arranged in the following manner

1. Methods in deep learning to identify the liver diseases
2. Similar works associated
3. Conclusion

II. METHODS IN DEEP LEARNING

Deep learning is a technique for learning data representations and patterns that has made strides in areas like

Grenze ID: 01.GIJET.10.2.178_1

natural language processing (NLP) and computer vision (CV). This section focuses on and provides a thorough description of the deep learning techniques utilized in liver research.

A.CNN

A CNN is a deep learning method that specializes in the processing and recognition of images. It consists of the following layers:

• convolutional layers
• pooling layers
• completely connected layers

The first layer of a CNN is called the convolutional layer. In a CNN, filters are applied to the input image to extract characteristics such as edges, textures, forms, etc. The output of a CNN is sent through the pooling layers. Pooling layers are used to down-sample feature maps and keep the most important data while reducing the spatial dimension. The output of pooling layers is then used to predict or classify the image.[3]

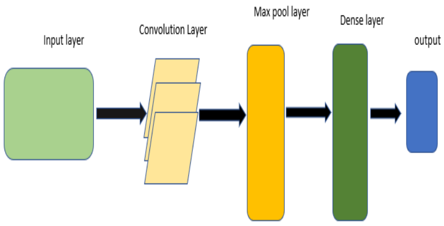

Fig1: Basic Architecture of CNN

B. RNN

Recurrent neural network (RNN) is a neural network where the output of one phase is used as an input for the next phase. In traditional neural networks, the inputs and outputs are independent of each other. For example, if you want to predict the next word of a phrase, you need to remember all the previous words in the phrase. RNN solves this problem by using a Hidden Layer. The Hidden state is the primary and most important characteristic of RNN. It stores some information about the sequence. This state, which remembers the previous input, is also called memory state. It uses the same parameters for every input as it does the same task for every input or hidden layer to generate the output. Unlike other neural networks, the complexity of the parameters is reduced. [2]

C. Transformer/attention

The attention mechanism is based on human visual system research and was first used in machine translation. The attention mechanism has now become an important part of the neural net and has achieved high performance in Natural Language Processing (NLP) and Computer Comprehension (CV). The transformer model uses the encoder decoder structure in the RNN. However, the attention mechanism replaces the sequential structure in the transformer model. The attention mechanism allows the transformer model to have global information while overcoming the long distance dependency problem. In addition, the transformer model can achieve parallel training and significantly increases running efficiency. The transformer was originally used in NLP. The bidirectional encoder representation from transformers (BERT), based on the transformer network, has yielded surprising results.

D.GCN

The convolution in GCN is the same as a convolution in convolutional neural networks.[7] It multiplies neurons with weights (filters) to learn from data features. It acts as sliding windows on whole images to learn features from neighbouring cells. The filter uses weight sharing to learn various facial features in image recognition system Now transfer the same functionality to Graph Convolutional networks where a model learns the features from neighbouring nodes. The major difference between GCN and CNN is that it is developed to work on non-Euclidean data structures where the order of nodes and edges can vary.

There are two types of GCNs:

• *Spatial Graph Convolutional Networks* -It uses spatial features to learn from graphs that are located in spatial space.

• *Spectral Graph Convolutional Networks* -It uses Eigen decomposition of graph Laplacian matrix for information propagation along nodes. These networks were inspired by wave propagation in signals and systems.

E.U-Net

The U-Net architecture also called fully convolutional network. The main idea is to supplement a usual contracting network by successive layers, where pooling operations are replaced by up sampling operators. Hence these layers increase the resolution of the output.[6] A successive convolutional layer can then learn to assemble a precise output based on this information. One important modification in U-Net is that there are a large number of feature channels in the up-sampling part, which allow the network to propagate context information to higher resolution layers. As a consequence, the expansive path is more or less symmetric to the contracting part, and yields a u-shaped architecture. The network only uses the valid part of each convolution without any fully connected layers.[2] To predict the pixels in the border region of the image, the missing context is extrapolated by mirroring the input image. This tiling strategy is important to apply the network to large images, since otherwise the resolution would be limited by the GPU memory

F.GAN

The generative adversarial network (GAN) provides an approach to learn deep representations without extensively annotated training data. The model learns to produce an excellent output through the mutual game between the generative model and discriminative model in the framework. GAN uses two neural networks to compete with each other to become more accurate predictions, pitting one against the other (hence "adversarial") to generate new synthetic data instances that can pass for real data. GANs use a cooperative zero-sum game framework to learn. They are widely used in image, video, and voice generation. There are three main steps in GAN training:

1. Select several real images from the training set.
2. Generate several fake images by sampling random noise vectors and creating images from them using the generator.
3. Train the discriminator for one or more epochs using fake and real images.

G. Transfer learning

One of the effective Deep Learning technique is transfer learning. Training deep neural networks with little or no data has become possible because to transfer learning, which makes use of the models' capacity to be reused and their understanding of novel challenges. By transferring information from various but related source domains, transfer learning (TL) seeks to improve target learners' performance on target domains. Therefore, building target learners can eliminate the need for a significant amount of target domain data. TL has emerged as a prominent and exciting field in deep learning due to its broad range of interesting prospective applications. A link between two learning activities is necessary for the transfer to occur; for instance, a person with violin instruction can pick up the piano more quickly than someone without it. TL can be further separated into homogeneous and heterogeneous categories based on the disparity between domains. The scenario where domains share the same feature space is taken into account by homogeneous TL techniques. When domains have distinct feature spaces, the process of knowledge transfer is referred to as heterogeneous TL.

III .SIMILAR WORKS ASSOCIATED

There are lot of works happening in the area of liver disease identification. Main mode of data modality is CT, Transfer Learning, U-net, CNN etc.In this survey the techniques used in 2022 is evaluated and the identified technique and application is included in the following table.

IV. INFERENCES FROM SIMILAR WORKS

The three most popular deep learning methods are U-Net, CNN and Transformer. Most of the deep learning methods used in medical image segmentation are based on these three methods. As the Transformer has been developed in the field of Computer Vision, there are more and more studies on how to use the Transformer to search the liver. However, there are several issues that limit the use of the liver deep learning method store. For most liver research, standard datasets are not available. In many of the studies, researchers are using non-public data which makes it very challenging to evaluate the deep learning methods. For all the topics, liver tumors only have publicly available datasets. These datasets have a limited amount of data and are not updated for a long period of time. For the same topic, researchers have different data modalities for searching; however, for most of the deep learning liver research, researchers are only using one data modality which limits the practicability

TABLE I: TABLE OF TECHNIQUES AVAILABLE IN LIVER RESEARCH

Title	Technique	Application
Efficient liver segmentation with 3D CNN using computed tomography scans [14] (2022)	CNN,Data Modality: CT	Liver tumor segmentation
Liver fat assessment in Multiview sonography using TL with CNN [11] (2022)	Transfer learning Data Modality: US	Liver fat assessment
Deep transfer learning for automated liver cancer gene recognition using spectrogram images of digitized DNA sequences [10] (2022)	Transfer learning, CNN Data Modality: DNA	Liver cancer gene recognition
Distance Measurement by Neural Network Learning of Near-Field Microwave Reflection Spectra (2022)	U-Net, attention, LSTM Data Modality: CT	Liver transplantation Automatic volume estimation
FireNet-MLstm for classifying liver lesions by using deep features in CT images [13] (2022)	LSTM Data Modality: CT	Hepato cellular carcinoma
Automatic Hepatocellular Carcinoma Diagnosis using Graph Convolutional Network [12] (2022)	GCN Data Modality: BLOOD TEST RECORDS	Hepato cellular carcinoma diagnosis
AI-DRIVEN Novel Approach for Liver Cancer Screening and Prediction Using Cascaded Fully Convolutional Neural Network [15] (2022)	FCN Data Modality: CT, MRI	Liver cancer screening
Transformer Based Generative Adversarial Network for Liver Segmentation (2022)	Transformer, AN Data Modality: CT	Automatic liver segmentation
Detection of Liver Cancer through Computed Tomography Images using Deep Convolutional Neural Networks (2022)	U-Net, CNN Data Modality: CT	Liver cancer detection
Liver Fat Assessment in Multiview Sonography Using Transfer Learning with Convolutional Neural Networks (2022)	Transfer learning Data Modality: US	Non-alcoholic fatty liver
Performance of a generative adversarial network using ultrasound images to stage liver fibrosis and predict cirrhosis based on a deep-learning radiomics nomogram (2022)	GAN Data Modality: US	Liver fibrosis, predict cirrhosis

V. CONCLUSION

Deep learning is a promising direction in liver research. Although deep learning models have achieved excellent performance, there are still some problems to be solved. Moreover, because of the particularity of the liver field, deep learning methods need more experimental demonstrations before they can be applied to clinical practice and recognized by patients and the medical community. However, we believe that with the advancement of deep learning technology, deep learning methods can make break throughs in the diagnosis and treatment of liver diseases.

REFERENCES

[1] Manjunath RV, Ghanshala A, Kwadiki K. Deep learning algorithm performance evaluation in detection and classification of liver disease using CT images. Multimed Tools Appl. 2023 May 15:1-18. doi: 10.1007/s11042-023-15627-z. Epub ahead of print. PMID: 37362702; PMCID: PMC10183675.

[2] N. M. Rezk, M. Purnaprajna, T. Nordström and Z. Ul-Abdin, "Recurrent Neural Networks: An Embedded Computing Perspective," in IEEE Access, vol. 8, pp. 57967-57996, 2020, doi: 10.1109/ACCESS.2020.2982416.
[3] Jiuxiang Gu, Zhenhua Wang, Jason Kue n, et al.Recent advances in convolutional neural networksPattern Recogn, 77 (2018), pp. 354-377
[4] SherifRZ. Abdel Misih, Mark Bloomston Liver anatomy Surgical Clinics, 90 (4) (2010), pp. 643-653
[5] GeorgeN. Ioannou, Weijing Tang, Laure n A. Beste, et al.Assessment of a deep learning model to predict hepatocellular carcinoma in patients with hepatitis c cirrhosisJAMA Netw Open, 3 (9) (2020), p. e2015626e2015626
[6] Olaf Ronneberger, Philipp Fischer, Tho mas Brox U-net: convolutional networks for biomedical image segmentation International conference on medical image computing and computer-assisted intervention, Springer (2015), pp. 234-241
[7] Si Zhang, Hanghang Tong, Jiejun Xu, et al.Graph convolutional networks: a comprehensive review Computational Social Networks, 6 (1) (2019), pp. 1-23
[8] Sidra Gul, Muhammad Salman Khan, Asima Bibi, et al. Deep learning techniques for liver and liver tumor segmentation: a review
[9] Samy A. Azer Deep learning with convolutional neural networks for identification of liver masses and hepatocellular carcinoma: a systematic review
[10] Das Bihter,ToramanSuat.Deeptransferle arningforauto-matedlivercancergene recognition Using Spectrogram images of digitized DNA sequences.BiomedSignal ProcessControl2022;72:103317.
[11] ByraMichal,HanAiguo,BoehringerAndr ewS,etal.Liverfatassessment in multi views on ography using transfer learning with convolutional neural networks. JUltrasoundMed2022;41(1):175–84.
[12] KimYushin,KimJaehyeon,LeeSejong,et al.Automatic hepatocellular carcinoma diagnosis using graph convolutional network. 2022BMCBiomedicalEngineering 2021;3(1):1–13. InternationalConferenceonElectronics, Information,and Communication(ICEIC),pages1–4. IEEE,2022
[13] KashalaKabe Gedeon,SongYuqing,LiuZhou.Firenetmlstmforclassifying liver lesions by using deep features in CT images.MultimedToolAppl2022;81(2): 1607–23
[14] HumadyKhaled,AlSaeedYasmeen,EladawiNabila,etal.Efficie nt liver segmentation with 3dcnnusing computedtom ographyscans.arXivpreprint arXiv:2208.132712022.
[15] ShuklaPiyushKumar,ZakariahMohamm ed,HatamlehWesamAtef,etal.Aidrivennovelapproac hfor liver cancer screening and prediction us in gcascaded fullyconvolutionalneuralnetwork.JournalofHealthcare Engineering2022: 2022.
[16] DemirUgur,ZhangZheyuan,WangBin,et al.Transformer based generative adversarial network forliversegmentation.ar XivpreprintarXiv:2205.10663 2022.
[17] NaaqviZunaira,AkbarShahzad,HassanS yedAle,etal.Detectionof livercancer through computed tomography images using deep convolutional neuralnetworks. In:20222ndinternationalconferenceondigit al futures and transformative technologies(ICoDT2). IEEE;2022.p.1–6.
[18] Byra Michal, HanAiguo, BoehringerAndr ewS,etal. Liverfat assessment in Multiview sonography using transfer learning with convolutional neural networks. JUltrasoundMed2022;41(1):175–84.
[19] DuanY-Y, QinJ, QiuWQ, etal.Performance of a generative adversarial network using ultrasound images to stage liverfibrosis and predict cirrhosis based on a deeplearningradiomicsnomogram.ClinRadiol20 22;77(10):e723–31.
[20] JeongJinGyo, ChoiSangtae,KimYoungJ ae,etal.Deep3DattentionCLSTMunetbased automated liver segmentation and volumetry for the liver transplantation in abdominal CT volumes. Sci Rep2022;12(1):1–9. helhamer E, Long J, Darrell T (Nov 2014). "Fully Convolutional Networks for Semantic Segmentation". IEEE Transactions on Pattern