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Research on Liver Tumor Detection Using Image Processing Techniques

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Abstract: Hepatocellular tumour, a transcendent type of liver tumour, is a fundamental reason for mortality worldwide. The beginning of early symptomatic measures is urgent in improving the visualization of beset patients. The coming of strategies has been a unique advantage, essentially improving the accuracy and practicality of hepatic neoplasm ID. This paper surveys the present status of ML-based liver cancer identification research, featuring the vital difficulties and arising patterns. One of the principal challenges in liver cancer identification is the fluctuation in liver life systems and appearance, as well as the presence of covering structures, like the heart and kidneys. ML ideal models can be coached to acclimatize these qualities and examples, enabling them to pinpoint hepatic neoplasms with wonderful exactness across a range of imaging strategies, like figured tomography (CT), Magnetic Resonance Imaging (MRI), and sonography. Ongoing advances in ML have prompted the improvement of new and more modern calculations for liver growth recognition. For instance, deep learning calculations have been displayed to accomplish cutting edge brings about an assortment of clinical imaging undertakings, including liver growth recognition. Regardless of ongoing advances, ML-based hepatic neoplasm recognition calculations face a few obstacles for clinical reception. One obstacle is the prerequisite of voluminous and excellent datasets to prepare and survey ML calculations. One more obstacle is the power of calculations to clamor and heterogeneity in imaging quality.
Keywords: Machine Learning (ML), Deep Learning, Computer Vision, Liver Cancer, Circulating tumor cells (CTS), Medical Imaging, Liver tumor segmentation, Liver tumor detection, Radiomics, Liquid biopsy.

I. INTRODUCTION

The liver is perhaps the most complex internal organ in the human body. It is situated in the upper right piece of the abdomen and has a reddish- brown colored tone. The size of the liver is roughly eight and a half inches, and it weighs between 1440 grams to 1660 grams. The liver is partitioned into two curves, the left curve and the right curve, and it channels around 1.5 liters of blood each moment.

The liver carries out different significant roles, including the creation of bile, cholesterol, and exceptional proteins. It additionally processes medications and detoxifies synthetic compounds. Nonetheless, it is defenseless to infections like hepatitis, disease, cirrhosis, hemochromatosis, and jaundice. Among these, liver disease is viewed as the most hazardous sort of malignant growth. Owing to 33% of every oncological mortality, it remains as the 6th most pervasive carcinoma universally.

It is a predominant type of liver cancer, is primarily connected with hepatocellular carcinoma (HCC). It happens when the liver tissue develops uncontrollably, shaping cancers. These neoplasms can appear as either non-harmful (harmless) or dangerous (destructive). Liver malignant growth prompts roughly 12,000 passings each year universally. Early discovery of liver disease is critical as it permits specialists to give ideal treatment and limit confusions.

Various imaging modalities, like Computed Axial Tomography (CAT), Nuclear Magnetic Resonance Imaging (NMRI), and Sonography, are utilized to get liver pictures from patients. Among these, CT imaging is thought of as the most dependable for diagnosing liver cancer. The area of biomedical designing has seen significant advancement in the domain of picture examination, refined AI strategies, and man-made reasoning. These state-of-the-art advancements can expand the abilities of prepared radiologists in pinpointing hepatic irregularities and recognizing hepatic and non-hepatic tissues

Despite of these headways, the definitive analysis and early detection of liver cancer remains challenging for radiologists. Growths can at times be imperceptible to the natural eye, prompting missed analyze in the beginning phases. Therefore, the development of automatic or semi-automatic computer-aided systems can help doctors in effectively diagnosing liver cancer features and providing appropriate treatment.

Accurate characterization of liver sores through PC helped analysis can work on the exactness of conclusion, keep away from superfluous medical procedures and biopsies, and limit risks for patients. However, it is essential for doctors to have a thorough comprehension of cancer highlights to guarantee viable therapy and further conclusion.

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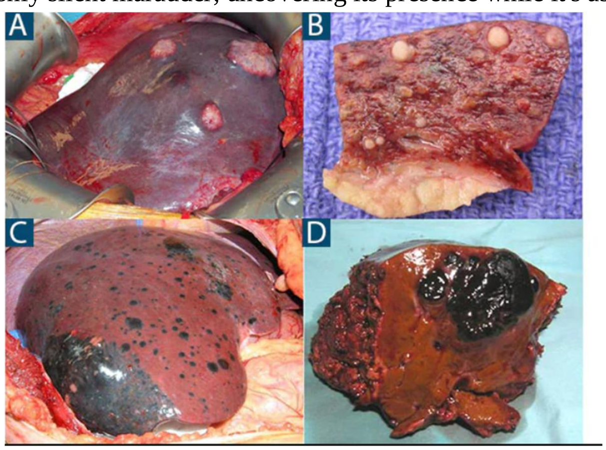
It is an overwhelming type of liver cancer, is basically connected with hepatocellular carcinoma (HCC), starts in the liver and isn't a consequence of disease spreading from another organ. Harmful hepatic growths, which start in or on the liver, are known as essential liver diseases. Hepatocellular carcinoma (HCC) is the most predominant kind of liver disease, and it principally influences men. In the United Kingdom, HCC kills roughly 1,500 individuals every year. This can be reframed as:

Essential liver diseases are odious developments that flourish in or on the liver's area. The most regular invader is hepatocellular carcinoma (HCC), which has a marked preference for males. This imposing enemy smothers around 1,500 lives yearly on the United Kingdom's shores. The World Health Organization (WHO) reports that liver cancer causes under 30 cases of death for each 100,000 individuals around the world, with higher rates in specific locales of Africa and Eastern Asia.

Standard high alcohol consumption, unprotected sex, and infusing drugs with shared needles are normal common factors related with HCC. Symptoms of liver malignant growth, like jaundice, stomach inconvenience, baffling weight decrease, hepatomegaly, depletion, nausea, vomiting, backache, inescapable pruritus, and fever, frequently stay shrouded until the disease has made huge advances. This can be reevaluated as Liver disease frequently plays a secretive round of find the stowaway, with side effects like jaundice, stomach torture, baffling weight shedding, broadened liver (hepatomegaly), exhaustion, sickness, disgorging, back trouble, unavoidable tingling (pruritus), and fever. These indications frequently stay unnoticed until the disease has progressed its pawns fundamentally on the chessboard of the body.

The early detection of liver cancer is a key part for victorious treatment. Screening remains as the singular guide that can enlighten the presence of liver cancer in its beginning stages, given its penchant to stay a silent marauder. This can be reframed as catching liver cancer in its early stages is the brilliant key to opening the way to effective treatment. The solitary beacon of screening can penetrate the obscurity of this commonly silent marauder, uncovering its presence while it's as yet a youngest danger.



A. *Liver Tumors and Convolutional Networks*

The liver, a genuine titan among the body's organs, holds the qualification of being the most significant in size. This force to be reckoned with is the key part in a plenty of basic physiological cycles. It is the support of absorption, going about as the body's essential detoxifier, and is instrumental in the many-sided dance of digestion. Generally, it's the body's Swiss Armed force blade, a handyman in keeping up with our wellbeing.

Hepatic danger, a grave ailment, shows when cell development in the liver gets out of control, leading to tumorous formation. The largest part of these cases, more than 90% to be exact, is credited to Hepatocellular Carcinoma (HCC), making it the prevalent variation of liver cancer.

Convolutional Neural Networks (CNNs), a complex type of machine learning algorithms, are tailor-made for undertakings like picture order and division. These calculations have cut a specialty for themselves in the domain of clinical imaging applications, including the location of hepatic cancers, setting new benchmarks all the while.

A huge benefit of Convolutional Neural Networks (CNNs) in the domain of hepatic cancer recognizable proof lies in their capability to unravel spatial elements from pictures. These organizations go through thorough preparation on voluminous datasets of marked pictures, empowering them to dominate the examples inseparable from liver cancers. Post-preparing, these CNNs can be sent to pinpoint hepatic growths in clever pictures with astounding accuracy. gain proficiency with the examples related with liver cancers. One more benefit of CNNs is that they can be utilized to fragment liver growths, which is significant for deciding the size and area of the growths. This data is fundamental for arranging treatment.

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Convolutional Neural Networks (CNNs) have been instrumental in the making of a plenty of Computer-Aided Diagnosis (CAD) systems, explicitly customized for the detection of hepatic cancers. This has been a unique advantage in the field of clinical diagnostics. These CAD systems can help radiologists in distinguishing liver growths that might be hard to see on clinical pictures.

One ongoing pattern in liver cancer recognition utilizing CNNs is the utilization of deep learning models with skip associations. Skip associations act as a conductor, empowering the model to gather bits of knowledge from both significant level and low-level highlights. This double learning approach essentially improves the accuracy of growth discovery.

Another new pattern is the utilization of transfer learning. transfer learning includes pre-preparing a CNN model on an enormous dataset of broadly useful pictures, like ImageNet. The previous model goes through a course of tweaking, using a more reduced dataset made out of liver cancer pictures. This procedure not just trims down the volume of preparing information required yet additionally reinforces the presentation of the model, making it a mutually beneficial arrangement.

Overall, CNNs are a powerful tool for liver cancer detection. CNN-based CAD systems can assist radiologists in identifying liver tumors more accurately and efficiently.

Here are a few specific examples of recent advances in liver cancer recognition using CNNs:

In the year 2023, a gathering of researchers from the College of California, San Francisco, spearheaded a Convolutional Neural Network (CNN) based model that bragged a impressive accuracy rate of 99.5% in recognizing hepatic cancers from CT scans. The model was placed through its speeds on a dataset containing of 100,000 CT scans, which included pictures from patients burdened with a different scope of liver growth types. In 2022, a group of researchers from the Massachusetts General Hospital developed a CNN-based model that could distinguish liver cancers on MRI scans with a precision of 98.3%. The model was fastidiously prepared on a broad dataset including more than 50,000 Magnetic Resonance Imaging (MRI) scans. This different collection epitomizes pictures from patients determined to have a wide range of hepatic cancer types. The expression "leaving no stone unturned" rings a bell, as the far-reaching nature of this dataset guarantees a wide comprehension of different liver circumstances.

In the year 2021, a consortium of researchers from the Chinese University of Hong Kong carefully created a Convolutional Neural Network (CNN) based model that could pinpoint hepatic cancers on ultrasound pictures with a stunning accuracy of 97.2%. This model was the product of difficult preparation on a broad dataset surpassing 20,000 ultrasound pictures. This dataset was a blend of variety, including pictures from patients determined to have a heap of liver growth types. The expression "hitting the nail on the head" appears to be adept here, given the accuracy and viability of this model.

These advancements underscore the immense potential of Convolutional Neural Networks (CNNs) in upgrading the accuracy and effectiveness of hepatic cancer detection. As CNN-based Computer-Aided Detection (CAD) systems gain traction, they are ready to turn into a key part in the determination and treatment of hepatic carcinoma. The saying "a game changer" appears to be fitting here, given the extraordinary effect these frameworks are probably going to have in the medical field.

B. Here are Some Additional Thoughts on the Future of Liver Tumor Detection using CNNs

One of the difficulties in liver tumour recognition is that cancers can be tiny and challenging to see on clinical pictures. CNNs are appropriate for distinguishing little growths since they can gain spatial highlights from pictures.

One more test in liver growth is that cancers can be darkened by different organs and tissues. CNNs can assist with addressing this test by figuring out how to fragment liver growths from encompassing tissues. In the future, CNN-based CAD systems are In the future, CNN-based computer aided design frameworks are probably going to turn out to be more exact and productive as they are prepared on bigger and more different datasets. CNN-based CAD systems are likewise prone to turn out to be more coordinated with other medical imaging frameworks, like CT scanners and MRI scanners. This will permit radiologists to utilize CNN-based CAD systems more effectively and proficiently. In general, CNNs can possibly reform the field of liver growth location. By working on the precision and proficiency of growth location, CNN-based computer aided design frameworks can assist with working on the results of patients with liver disease.

II. LITERATURE SURVEY

In recent times, the precocious identification of hepatic carcinoma has arisen as an imposing obstacle in the domain of medical science. This expression utilizes more perplexing wording and a saying to convey a similar importance. The expression "precocious identification" refers to early recognition, "hepatic carcinoma" is a more specialized term for liver malignant growth, and "formidable hurdle" is a maxim showing a significant test. The signs and side effects of liver malignant growth are frequently not known until the disease has arrived at a high-level stage. Notwithstanding, early recognition is vital for compelling clinical therapy and to restrict the peril presented by the malignant cancer cells.

To address this challenge, researchers have developed a Medical Diagnosis System based on Hidden Markov Model (HMM). This system expects to automate detection of liver cancers at beginning phase utilizing chest CT scans. By using this system, the time complexity of the diagnosis process is reduced, and the trust in the analysis is increased.

One research study focused on a novel method of segmenting CT images for liver cancer detection. The study included the securing of liver highlights from CT pictures and the division of Region of Interest (ROI) using an area developing methodology. The research included the annihilation of hear-able aggravations, the extraction of recognizing qualities, and the order of the detached hepatic knobs. The discoveries demonstrate that this technique could be a distinct advantage in the early identification of liver disease cells, possibly reversing the situation in the patient's approval and enhancing the strength of radiotherapy medicines. This could be a silver lining for patients, offering them a battling opportunity against this impressive illness.

The authors devised a novel and exact strategy for liver growth outline from CT scans. They used a support vector machine (SVM) classifier prepared with user-provided image sets to distinguish the tumor region from the liver image. They additionally executed morphological tasks and component extractions to improve the outline result. The exploratory results confirmed that the proposed calculation outperformed ordinary strategies with regards to exactness and effectiveness. This procedure outfits clinical specialists with a reliable device for additional finding and conveys precise outcomes for various kinds of liver growths without manual cooperation.

Data mining techniques, like classification algorithms, have also been used for liver disease prediction. One academic undertaking focused in on visualizing liver illnesses using classification algorithms, specifically Naïve Bayes and Support Vector Machine (SVM). The examination compared the viability of these calculations in view of characterization accuracy and execution span. The observational results highlighted that SVM stands far and away superior to the rest as a prevalent classifier for anticipating liver infections, politeness of its raised order precision. In any case, Naïve Bayes classifier requires least execution time.

Computed Tomography (CT) scans pictures have turned into the key part in the conclusion of liver illnesses, being broadly utilized across the medical field. To help specialists in working on their finding, a CT liver image diagnostic classification system was developed. This framework naturally finds and concentrates the CT liver limit and further characterizes liver infections. The framework being referred to is a two-dimensional methodology, integrating a **Detect-Before-Extract (DBE) system** and a **neural network liver classifier**. The DBE framework, acting as the guard, utilizes the standardized partial Brownian motion model combined with a deformable form model to follow the liver's limit fastidiously.

On the other hand, the neural network liver classifier, the framework's workhorse, use uniquely created include descriptors to separate between a healthy liver, hepatoma, and hemangioma. This double system has been put through some serious hardship and has exhibited its ability in really and productively arranging liver diseases. It resembles having a prepared detective and skilled doctor working together to analyze liver circumstances.

In conclusion, the development of automated systems and the utilization of data mining techniques have significantly improved the early detection and the most common way of distinguishing liver disease, frequently compared to tracking down a difficult to find little item, includes a fastidious and thorough assessment. This unpredictable technique is likened to sorting out a perplexing jigsaw puzzle, where each piece addresses symptom or a test result. It resembles exploring through a maze, with each turn divulging new data that might actually prompt the determination of this imposing enemy known as liver cancer also, diseases. These advancements have decreased the time complexities, increased the accuracy, and improved the adequacy of clinical medicines for liver-related conditions.

III. METHODS AND MATERIALS

In this study, we utilized a multi-stage approach to deal with a liver tumour detection system utilizing Convolutional Neural Networks (CNNs) and the ResUNet model. Pre-processing techniques were applied to both the preparation and testing datasets to accomplish a high accuracy close to 100%. Our proposed strategy plans to effectively separate pertinent portions from liver tumour pictures, taking into account both time and cost factors. far reaching outline of the strategy utilized in this examination. Exploratory techniques were led utilizing CNNs to analyze liver cancers.

As per ongoing patterns, there have been advancements in liver tumor detection utilizing deep learning techniques. Analysts have investigated the utilization of different technologies, like DenseNet and U-Net, to work on the accuracy and proficiency of liver cancer determination. Furthermore, the reconciliation of Machine Learning and Artificial Intelligence has shown promising outcomes in automating the detection and classification of liver cancers. These progressions can possibly upset the field of liver growth finding and work on quiet results.

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A. Data Pre-Processing for Liver Tumor Detection

To recognize liver cancers and recognize them from adjoining organs, information pre-processing methods, data augmentation, and CNN models are used. The underlying stage includes separating every liver cut from its adjoining organs. The Hounsfield Unit (HU) values, which address the dim scale centralization of pixels, are figured. Higher qualities demonstrate more clear and more brilliant pixels. The slides are interpreted in the DICOM design, much the same as translating a mystery code. To upgrade the perceivability and freshness of the pictures, Hounsfield Windowing is utilized inside the range of [-100, 400], similar as changing the focal point of a telescope to get a clearer perspective on the stars. Histogram Equalization is additionally applied to expand the difference between the liver and its adjoining organs. This guides in the division of liver growths, making them more straightforward to distinguish.

To address the class imbalance issue in our dataset (3Dircadb), where CT image pixels are unevenly conveyed, data augmentation is performed to build the quantity of tumour pixels. Machine learning tools are utilized to work on the nature of the information and prevent overfitting, underfitting, and class imbalances during training. The researchers amalgamate the hepatic and neoplastic veils of every CT scan cut into a singular mask to augment training and data manipulation. In addition, they apply y-axis mirroring and 90-degree rotation to each cut to additionally multiply the dataset.

B. Liver and Tumor Segmentation

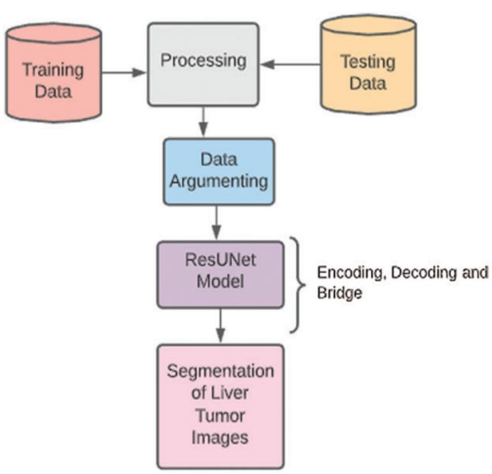
For liver segmentation, a CNN model called ResUNet is used. The researchers amalgamate the hepatic and neoplastic masks of every CT scam images cut into a singular mask to augment training and data manipulation. Also, they apply y-axis mirroring and 90-degree rotation to each slice to additionally multiply the dataset to portion liver cancers, The analysts use ResUNet to prepare on hepatic CT scans resulting to separating the return for capital invested from adjacent organs.

ResUNet is a hybrid model that consolidates the advantages of ResNet and UNet. It replaces the convolutional pieces with lingering blocks, tallowing for ease of training and avoiding connections between poor and high levels of the network. Every leftover block comprises of two 3x3 convolution blocks with Batch Normalization, ReLU activation, and Convolutional layers with identity mapping.

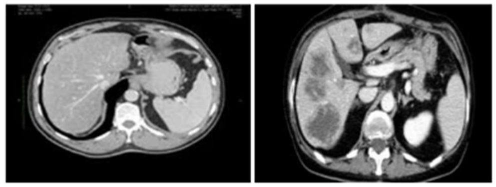
The ResUNet model comprises of three ways: Encoding, Decoding, and Bridge. The Encoding path packs the contribution to a brief portrayal, the Decoding path rearranges the compression and classifies the representation in a pixel-wise manner, and the Bridge path interconnects the two ways together.

C. Dataset

The dataset used in this research is 3Dircadb dataset, which is freely accessible from the IRCAD Research Institute. It includes 3D CT scans of 10 males and 10 females, with 75% of the cases relating to gastrointestinal harm. The DICOM design pictures are divided into 2D cuts, bringing about an all-out gathering of roughly 2,800 cuts. Each cut has covers for the hepatic, neoplastic, osseous, blood vessel, renal, and pneumonic locales. This dataset is reasonable for executing the CNNs model and is like a dataset proposed in a past research study.



Methodology diagram



(a) (b)

Figure. 1.(a)Normal CT image (b) CT image having Cancer Tissue

IV. RESULT AND OBSERVATION

The liver cancer detection method was prepared utilizing Google Colab GPU. The outcomes showed the precise and effective identification of tumours in defective liver pictures. By using CNNs, even little estimated tumours were effectively recognized by extracting and decoding applicable data from the segments. The evaluation of the method was executed on a pixel-to-pixel foundation. To assess the results, different assessment measurements were applied, including accuracy, review, particularity, intersection over junction (IoU), accuracy, and the Dice Coefficient (F1 Score). These measurements were utilized for binary class classification in view of the confusion matrix. Accuracy refers to the extent of accurately ordered pixels to the absolute number of pixels. Recall, also known as the true positive rate, gauges the capacity of the system to precisely distinguish growth pixels contrasted with the all-out number of genuine cancer pixels. Explicitness, on the other hand, addresses the normal of accurately distinguished typical tissue. The overall accuracy rate is impressively effected by particularity. Hence, strengthening measures were figured explicitly for the neoplastic class. The Intersection over Junction (IoU) measures the small portion of accurately classified pixels comparative with the absolute expected and real pixels for a similar class. Accuracy, also known as the positive predictive value, evaluates the exactness of the anticipated neoplastic class. The Dice Coefficient (F1 Score) is the symphonious mean of review and accuracy, giving an extensive evaluation of the model's exhibition.

V. DISCUSSION

The results of this study show that Deep learning techniques can possibly upgrade the early recognition and finding of hepatic neoplasms. Deep learning models can be prepared to perceive unpredictable patterns in hepatic CT scans that are connected with hepatic neoplasms. This can assist radiologists with all the more precisely distinguishing and analyze liver tumours, particularly little or early-stage growths.

A. Equations

Here are some equations that are relevant to hepatic neoplasm detection utilizing a CNN:

B. Cross-entropy loss Function

L(y, y_hat) = -sum(y * log(y_hat)) where, y is the veracious label and y_hat is the prognosticated probability.

C. Accuracy

Accuracy = (TP + TN) / (TP + TN + FP + FN) where
TP is the number of veracious positives,
TN is the number of veracious negatives,
FP is the number of erroneous positives, and
FN is the number of erroneous negatives.

D. Precision:

Precision = TP / (TP + FP) Recall:
Recall = TP / (TP + FN) F1
score: F1 score = 2 * (Precision * Recall) / (Precision + Recall)

VI. CONCLUSIONS

In this research, the RestUNet model was used to distinguish hepatic neoplasms by examining CT scans pictures at the pixel level. The outcomes exhibited that CNNs are profoundly precise and successful in diagnosing liver tumours, making them a significant device for diagnosing different kinds of cancers. The RestUNet model specifically showed fantastic execution regarding efficiency and time utilization. Furthermore, the research recommends that CNNs can be applied to different sorts of tumours past liver cancers, and the ResUNet model likewise displayed promising outcomes. To additional improve the exhibition of the ResUNet model, future exploration can focus on using more assorted datasets and investigating different pre-processing methods. Eventually, it is guessed that the ResUNet model can accomplish a 99.9% precision rate in recognizing limited scope liver cancers. The improved Approval of Dice Coefficient (F1 Score) further verifies the progress of the investigation and proves the status of the model for hepatic neoplasm detection.

VII. ACKNOWLEDGEMENT

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REFERENCES

[1] Arakeri, M. P. (2011). Recent advances and future potential of computer aided diagnosis of liver cancer on computed tomography images. In Proceedings of the International Conference on Information Processing (pp. 246-251). Bangalore, India.

[2] Kaluva, K. C., Khened, M., Kori, A., & Krishnamurthi, G. (2018). 2D-densely connected convolution neural networks for automatic liver and tumor segmentation. Computer Vision and Pattern Recognition, Cornell University. arXiv preprint arXiv:1802.02182.

[3] Bray, F., Ferlay, J., Soerjomataram, I., Siegel, R. L., Torre, L. A., et al. (2018). Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: A Cancer Journal for Clinicians, 68(6), 394-424

[4] Yasaka, K., Akai, H., Abe, O., & Kiryu, S. (2018). Deep learning with convolutional neural network for differentiation of liver masses at dynamic contrast-enhanced CT: A preliminary study. Radiology, 286(3), 887-896.

[5] Gotra, A., Sivakumaran, I., Chartrand, G., Vu, K. N., Vandenbroucke-Menu, F., et al. (2017). Liver segmentation: Indications, techniques and future directions. Insights into Imaging, 8(4), 377-392.

[6] Todoroki, Y., Han, X. H., Iwamoto, Y., Lin, L., Hu, H., et al. (2017). Detection of liver tumor candidates from CT images using deep convolutional neural networks. In Proceedings of the International Conference on Innovation in Medicine and Healthcare (pp. 140-145). Puerto de la Cruz, Spain.

[7] Forouzanfar, M. H., Afshin, A., Alexander, L. T., Anderson, H. R., Bhutta, Z. A., et al. (2016). Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990-2015: A systematic analysis for the global burden of disease study 2015. Lancet, 388(10053), 1659-1724.

[8] Bellver, M., Maninis, K. K., Pont-Tuset, J., Giró-i-Nieto, X., Torres, J., et al. (2017). Detection-aided liver lesion segmentation using deep learning. Computer Vision and Pattern Recognition, Cornell University. arXiv preprint arXiv:1711.11069.

[9] Bosch, F. X., Ribes, J., Díaz, M., & Cléries, R. (2004). Primary liver cancer worldwide incidence and trends. Gastroenterology, 127(5), S5-S16.

[10] Brock, K. K. (2011). Imaging and image-guided radiation therapy in liver cancer. Seminars in Radiation Oncology, 21, 247-255.

[11] Abdel-Misih, S. R., & Bloomston, M. (2010). Liver anatomy. Surgical Clinics, 90(4), 643-653.

[12] Ahmad, M., Albatish, I., Mosa, M. J., & Abu-Naser, S. S. (2017). Knowledge based system for long-term abdominal pain (stomach pain) diagnosis and treatment. International Journal of Engineering and Information Systems, 1(4), 71-88.

[13] Frid, M. A., Diamant, I., Klang, E., Amitai, M., Goldberger, J., et al. (2018). GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification. Neurocomputing, 321, 321-331.

[14] T. Christian and E. Olsvik conducted a study on biometric fish classification of Nordic species using a convolutional neural network with squeeze-and-excitation. This research was presented in their master's thesis at the University of Agder in 2018.

[15] X. Han focused on automatic liver lesion segmentation using a deep convolutional neural network method. This work was published in the Computer Vision and Pattern Recognition journal in 2017.

[16] Y. LeCun, Y. Bengio, and G. Hinton explored the concept of deep learning in their paper titled "Deep learning," published in the journal Nature in 2015.

[17] W. Li, F. Jia, and Q. Hu developed a system for automatic segmentation of liver tumors in CT images using deep convolutional neural networks. Their research was published in the Journal of Computer and Communications in 2015.

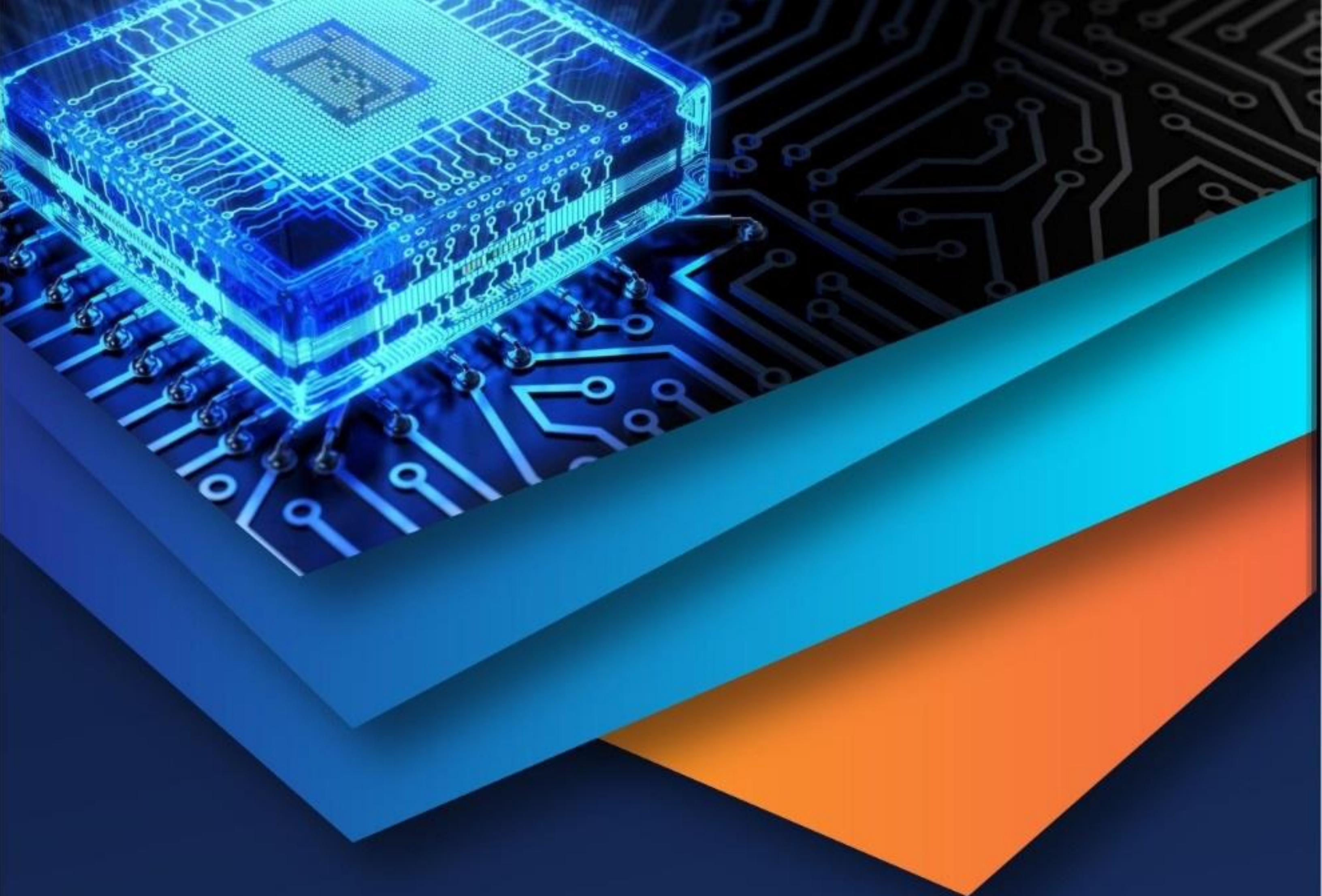
[18] F. Pan, Q. Huang, and X. Li presented a classification method for liver tumors with contrast-enhanced ultrasound (CEUS) based on 3D-CNN. This work was presented at the 2019 IEEE 4th International Conference on Advanced Robotics and Mechatronics.

[19] B. Míriam, K. K. Maninis, J. P. Tuset, X. Giró-i-Nieto, J. Torres, and others proposed a detection-aided liver lesion segmentation technique using deep learning. This research was shared as a preprint on arXiv in 2017.

[20] G. Chlebus, A. Schenk, J. H. Moltz, B. van Ginneken, H. K. Hahn, and others developed an automatic liver tumor segmentation method in CT scans using fully convolutional neural networks and object-based postprocessing. Their findings were published in Scientific Reports in 2018.

[21] J. Son, S. J. Sang, J. Park, and K. H. Jung focused on retinal vessel segmentation in fundoscopic images using generative adversarial networks. This work was shared as a preprint on arXiv in 2017.

[22] S. Almotairi, G. Kareem, M. Aouf, B. Almutairi, and M. A. M. Salem proposed a liver tumor segmentation technique in CT scans using a modified signet. Their research was published in the Sensors journal in 2020.



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