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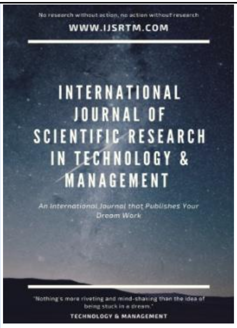

A Review on Automatic Liver Cancer Detection in Digital Image Processing

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***Abstract*— Liver cancer is one of the most important health related problems in the world. Grading diagnosis for liver cancer in liver cancer treatment requires biopsy images diagnosis. Artificial grading system for extracting knowledge to give quantitative and objective results for the physicians and pathologists; it not only saves time but also improving the accuracy of the diagnosis. However, inappropriate vision and complex stroma background affects partition performance. In this paper, a review has been conducted for better analysis of liver cancer diagnosis system. Liver cancer is usually diagnosed by three different tests: blood test, image test and biopsy. To make the task of diagnosing liver cancer simpler and less time consuming, an effective approach is to be adopted. This research puts forward a computer-aided diagnostic system to diagnose liver cancer. Some detection method that researcher uses MRI, CT and USG scan imaging along with various feature extraction method.**

Keywords*— *Liver Cancer Detection, Support Vector Machine, CT Scans, Segmentation, MRI, Edge Detection.

I. Introduction

CT-scans are first used to scan liver cancer images, and tomography is a medical imaging technique that works like a digital x-ray to create a three-dimensional image on an axis where the hard tissue is lighter and softer than the darker tissue [1]. Image processing technology is a field that is widely used in medicine to identify various images or tumors. The majority of liver cancers are 85 to 90% due to alcohol and 10 to 15% due to other causes. These cases are now more frequent due to a combination of genetic factors and asbestos and various types of air pollution. Diagnosing liver cancer is not an easy task and is usually performed by doctors and diagnosed manually. There are various intermediate states for processing the liver image to get any cancerous spots, and if there is a spot the contrast will automatically increase and this will affect the cancer liver image. The system has a high accuracy rate with a low alarm alarm rate. The liver constantly circulates through the body, converting nutrients and drugs absorbed from the gastrointestinal tract into chemicals ready to use. The liver performs many other important functions, such as removing toxins and other chemical contaminants from the blood and preparing them for excretion. Because all the blood in the body has to go through it, the liver enters the cancer cells that normally travel in the bloodstream. Liver cancer is caused by primary liver cancer, cancer of the liver or cancer of other parts of the body. Most liver cancers are secondary or metastatic, meaning they have started elsewhere in the body. Primary liver cancer, which begins in the liver, causes 2% of cancers in the US, but only half of all cancers in some underdeveloped countries. The main reason for this is the spread of hepatitis caused by infectious viruses, which can cause a person to develop liver cancer [2].

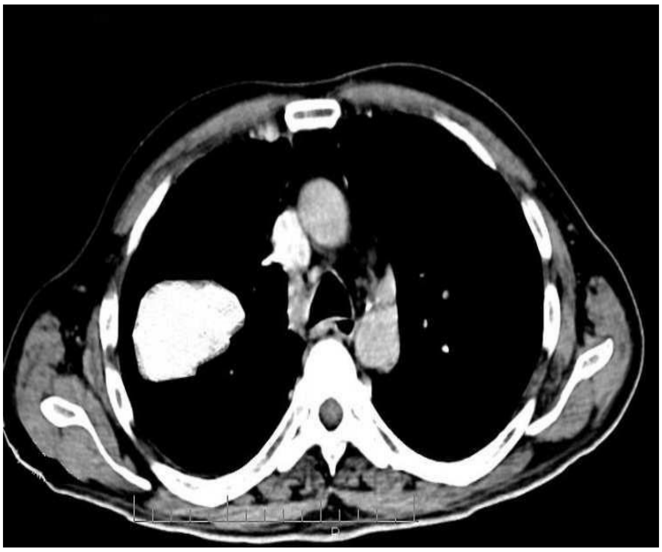

Fig. 1. Liver Cancer Affected Image

Primary liver cancer (hepatocellular carcinoma) is caused by congenital defects in the liver caused by alcohol or hepatitis B, C, hemochromatosis (hereditary disease associated with high iron in the liver) and cirrhosis. More than half of those with primary liver cancer have cirrhosis - alcohol-induced liver scarring. Hepatitis B, C and hemochromatosis cause permanent damage and liver damage. Liver cancer is associated with obese and fatty liver disease. Various carcinogens have been linked to primary liver cancer, some of which include herbicides and chemicals such as vinyl chloride and arsenic. Smoking increases the risk, especially if you abuse alcohol. It also contains plant-type aphrodisiacs that can cause cancer. Aflatoxins contaminate wheat, peanuts, rice, grains and soybeans.

II. RELATED WORKS

A. Related Works

F. P. Romero et al. [3] proposed an approach to capture the effective feature of the Inception V3 by combining the remaining connections from the image and the rest of the trained weight. The potential of the lesion type is that the architecture consists of completely comprehensive classification layers to create the output product. We use an in-clinical clinical bio-bank with 230 liver lesions from 63 patients. With an accuracy of 0.96 and an F1 score of 0.92, the results obtained with the proposed approach surpass the most sophisticated methods. Our work provides the basis for integrating machine learning tools into specialized radiology software to assist physicians in the early detection and treatment of liver injuries.

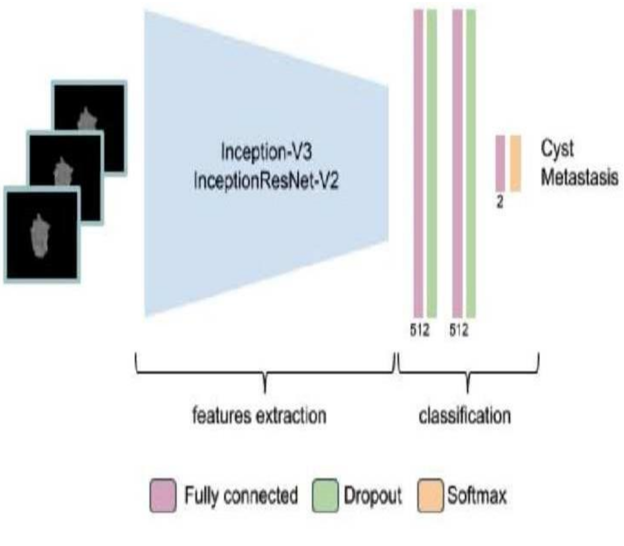

Fig. 2. Frame Work Architecture [3]

Atrayee Dutta et al. [4] proposed a technique for medical applications that use a variety of diagnoses and treatments. It has been used to detect liver cancer cells. The OSTU method is used here to enhance the MRI image, and the watershed method is used to separate the cancer cell from the image.

Fig. 3. Superimposed transparently on original image [4]

B.Lakshmi Priya et al. [5] proposed a channel level set segmentation algorithm with an elastic optimization model with a contrast drive to achieve better partition accuracy. Implemented the Global Visual Accounts approach to detect the boot-up salinity in curve optimization.

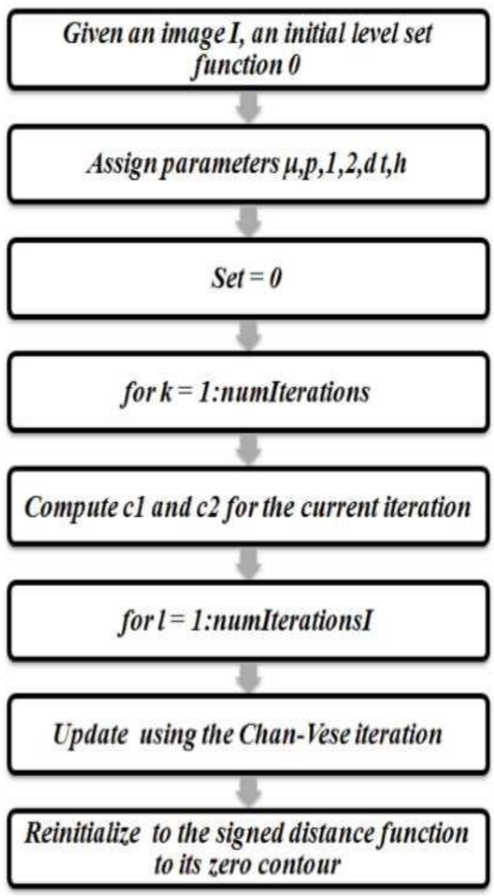

Fig. 4. Existing Chan-Vese segmentation model flow diagram [5]

The solitude map and weighted coefficient technique are measured using an average shift filter, which improves the salience detection accuracy. Specific partitioning technology can have accurate results compared to current partitioning technology. The separation method used here allows medical practitioners to analyze the main object of the image. This type of separation clearly cuts the desired object from the image and gives good results even in an image with border conditions. Priority and background; any type of image can be categorized using a project with a single color intensity level.

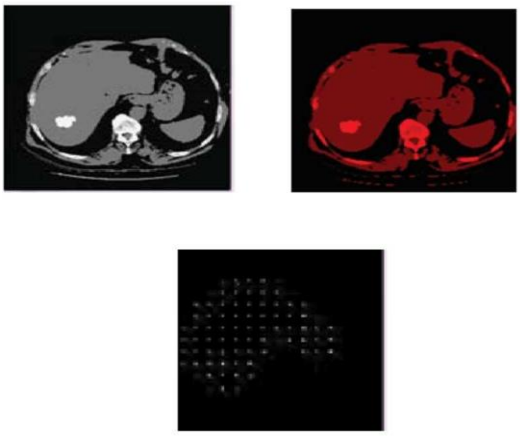

Fig. 5. Saliency mapping [5]

Mohamed Yaseen Jabarulla et al. [6] proposed a work that is enumerated by the Anisotropic Diffusion Filter (SRAD) Five Image Filtering Techniques for Evaluation and Performance Analysis, which reduces quantum, frost, fish, median and speckles from the spatial filtration process for liver US data. U.S. Application of Hepatic Liver Cancer Image Selected and U.S. Selected algorithms are applied to assess the effect on the scapular image signal. Experiments are based on peak signal-to-noise ratio (PSNR), fish structural similarity (MSIM) and fish square error (MSE). The result shows that the SRAD filter is better than other denominating filters with PSNR = 31.11 dB, MSE = 31.07 and MSSIM = 0.895. Hong Zhou et al. [14] proposed a method where the biosensor 20 ng / ml AFP detection was experimentally tested using a staphylococcal protein A (SPA) binding reagent. Since the sample detects the electromagnetic field directly, the system is unlabeled, direct and indestructible. This work provides an approach to flexible, low-cost, fast and unlabeled biological innovation that will benefit BIOS development. Shao-Kuo Tai et al.

[15] proposed a system that uses artificial intelligence to provide quantitative and objective results to physicians and pathologists; This not only saves time, but also improves the accuracy of the diagnosis. In the grading process, the main task is to grade the nucleus separated from the cancer biopsy images. However, inappropriate vision and complex stroma background affect the performance of the segmentation. If we can estimate the separation of the nucleus and avoid a failed separation from the grading system, this will significantly improve the accuracy of the grading. In this paper, we propose a method of in-depth study to estimate the separation of the liver nucleus, proving that the efficiency of our method with test results is 90.5%.

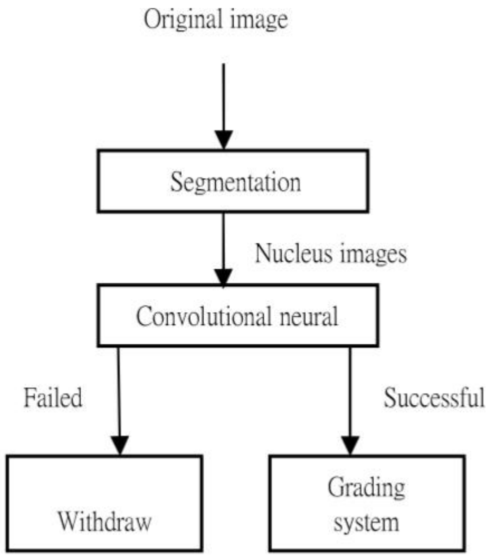

Fig. 6. Evaluation Process [6]

Amita Das et al. [7] proposed a system which is based on watershed transform and Gaussian mixture model. In this work author proposed a new system called the Watershed Gaussian Based Deep Learning (WGDL) technique to effectively describe cancerous lesions in computed tomography (CT) images of the liver.

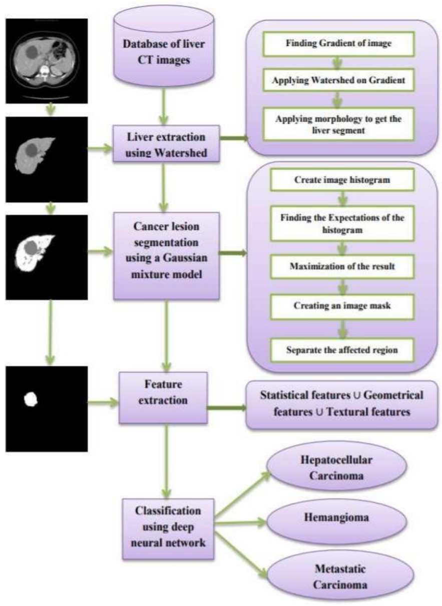

Fig. 7. CAD System [7]

A total of 225 images were used in this work to develop the specific design. Initially, the liver was isolated using a marker-controlled watershed separation process and finally the cancerous lesions were classified using the Gaussian Composite Model (GMM) algorithm. After tumor division, various morphological features were isolated from the divided area. The Deep Neural Network (DNN) classification for autoimmune classification of three types of liver cancer is classified in this category: hemangioma (HEM), hepatocellular carcinoma (HCC) and metastatic carcinoma (MET). Samy A Azer et al. [8] proposed a system which is based on deep learning with convolutional neural network that have been used in the interpretation of artificial intelligence images and in the diagnosis of hepatocellular carcinoma (HCC) and liver mass. The machine learning algorithm, similar to the in-depth study, demonstrated the ability to detect CNN and specific features that can detect pathological lesions. Systematically searched for PubMed, Embassy, Web Science and Research books using related keywords. Studies that analyze the pathological anatomy, cellular and radiological images of HCC or liver mass according to a study protocol used to detect cancer or to differentiate cancer from other lesions or to manage tumors. Data were collected according to a predetermined extraction. Analyzed the accuracy level and function of CNNs in detecting cancer or early stages of cancer. The primary outcome of the study was to analyze the type of cancer or liver mass and identify the type of images that show the most accuracy in cancer detection. Shi-hui Zhen et al. [18] proposed a system which is based on Deep learning method. Author used CNN to develop an in-depth study system (DLS) to classify liver tumors based on clinical data, including improved MR images, improved MR images, and text and laboratory test results. Using data from 1,210 patients with liver tumors (N = 31,608 images), we trained CNLs to obtain seven-way classification, binary classification, and three-way malignant-classification (Model-A-Model G). Samples were validated in an externally independent extended group of 201 independent patients (N = 6,816 images). The receiver operating character (ROC) curve (AUC) area is compared to different models. We compared the sensitivity and specificity of the models with the performance of three experienced radiologists.

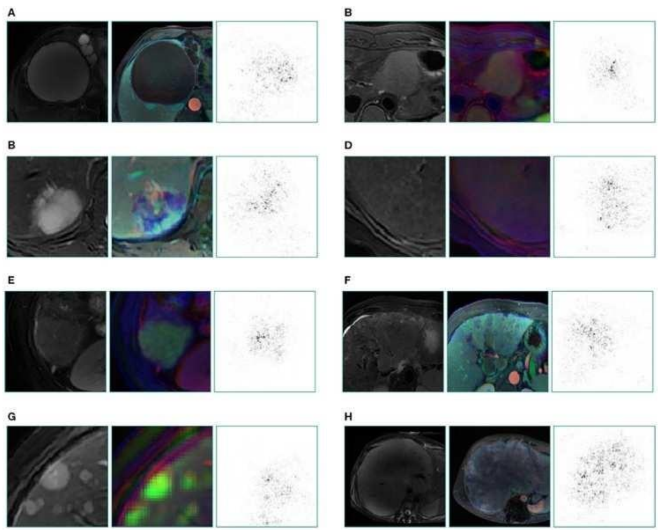

Fig. 8. (A) cyst, (B) FNH, (C) hemangioma, (D) benign nodule, (E) HCC,
(F) primary adenocarcinoma, (G) metastatic malignancy originating from pancreas, (H) malignant fibrous histiocytoma [8]

DLS, trained with data under different acquisition conditions, can be used as an accurate and time- saving assay-analysis strategy for liver tumors in clinical settings even in the absence of contrast agents. Therefore, DLS has the potential to prevent contrast-related side effects for liver tumor patients and reduce the financial costs associated with current standard MRI screening procedures. Rajesh G et al. [9] proposed a system which is based on PeSOA and PNN classifier. Detecting and dissecting liver abnormalities is a testing and important step in a treatment plan that extends the patient's survival. Liver cancer increases mortality because side effects cannot be detected because cancer is also in its progression. Early diagnosis and regular monitoring are the best ways to control the development of heart disease and save lives. Ultrasound imaging is one of the most widely used diagnostic tools for the diagnosis and classification of liver disorders. Traditional liver cancer detection strategies have high computational time and versatility. We suggest a new optimal hierarchical feature fusion based on the Penguin Search Optimization Algorithm (PESOA) to reduce the complexity of the computational process and increase the analytical accuracy in this paper. The probabilistic neural network (PNN) that classifies liver cancer tissue uses the resulting properties of PESOA.

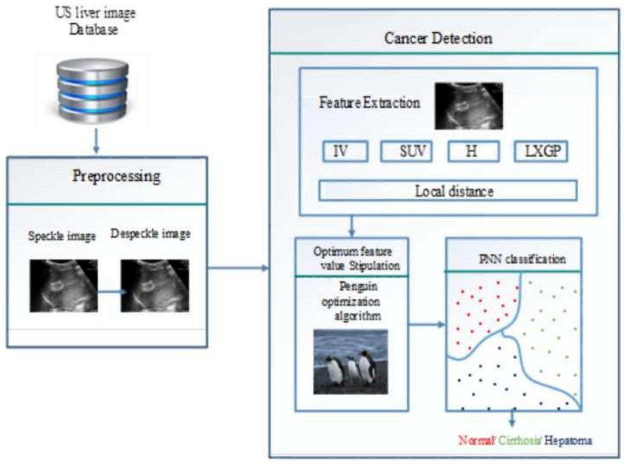

Fig. 9. Schematic overview of the proposed system [9]

Namrata Ghuse et al. [10] proposed a system which is based on wavelet transform. This research puts forward an image processing system to detect liver cancer. The specific identification method uses MRI and CT. The area is adopting increasing technology to classify images to capture the area of interest. Then, the wavelet conversion is calculated to calculate the limit values for the area of interest. It gives the correct result in an effective time period after processing and measuring. Wavelet conversion plays an important role in image compression. For image compression applications, wavelet conversion is a more convenient technology compared to Fourier conversion. Fourier conversion is not practical for calculating spectral information, as it requires past and future information about the signal in the full-time domain, and since Fourier conversion is operation time, it is not possible to observe the variables of frequencies changing over time. -Possible activity. Wavelet conversions, on the other hand, depend on the wavelengths of different frequencies of a given frequency over a limited period of time. Due to the practicality of wavelet conversion, this research paper is written to explore the features and improvements that can be made to improve wavelet conversion performance.

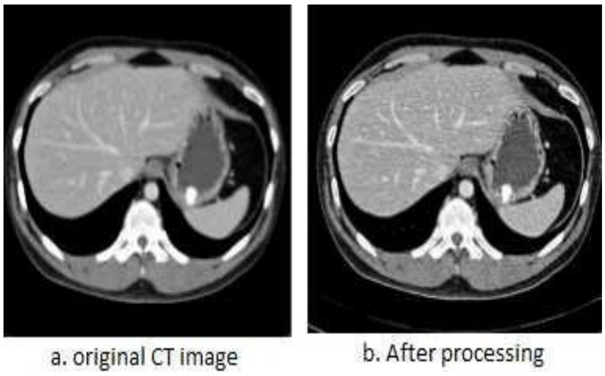

Fig. 10. Noise removal process [10]

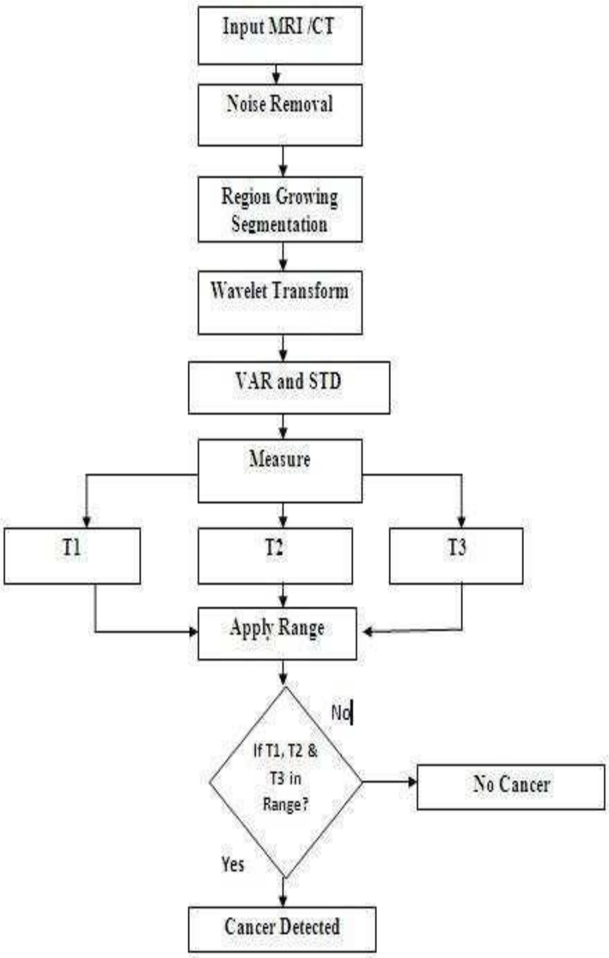

Fig. 11. System Overview [10]

Yamini Upadhyay et al. [11] proposed a system which is based on Genetic Algorithm. The purpose of this paper is to simplify the ugly learning problems associated with the study of MR images. It is difficult to study MR images related to the detection of cancer in the liver or abdominal area. This is due to the complexity of the shape and the lapping of the liver with other organs. The watershed technique was used as a basic technique to compare a genetic algorithm with a specific technique. A comparative analysis of the table is provided based on the results of both methods. Sound the picture and find the ROI considering the problem and objectives of the paper. To examine the patient's data sets for liver cancer, its size, size and shape; The structure of its vessels; and positions are important. The purpose of this paper is therefore to demonstrate a technique that can be used to produce image sound and calculate the area of interest. To achieve this goal, technology must be developed that can analyze patient data prior to treatment.

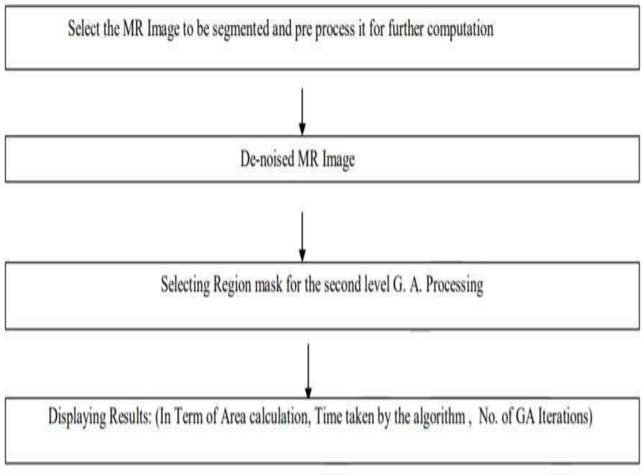

Fig. 12. Work Flow of the System [11]

The proposed technology is based on GA and for dataset comparison, the watershed technique was used as the base technology. Diagnosis and Comparison The area of the tumor, the time taken for analysis, depends on the frequency and pixel variation of the genetic algorithm determined by the two methods. The goal is to implement a technology that can analyze the data set based on the area of the tumor and deliver results that will take some time compared to current technology.

Table No. I Result Comparison

	Method	Accuracy in %
B.Lakshmi Priya [5]	Chan-Vese Method	87.22
Shao-Kuo Tai [14]	CNN	90.5
D Santhosh ReddY [15]	CNN	90.6
Amita Das [7]	Fuzzy	95.02

III. CONCLUSION & FUTURE SCOPE

This paper reviewed various implemented systems that extract liver lesion using CNN, DNN, Wavelet Transform, Watershed Filtration and many more. Most of the system uses CNN and a training model for creating templates that later match for nearest classification. But there is no appropriate model for liver lesion feature extraction, instead of that it can be achieved through edge detection techniques along with various pre-processing models. The system can be enhanced in future by implementing it with different techniques and filters, which may acquire good accuracy and minimal false alarm rate. Because as per the ideal system, accuracy is an important parameter, that is why accuracy of system can be enhanced in future with different techniques or filters. In this paper a new automatic segmentation method was developed to detect liver cancer. The new proposed strategy is based on a genetic algorithm. From the results and analyzes produced, it can be concluded that the genetic algorithm is considered a new breakthrough in the detection of liver cancer. Furthermore, the results obtained from this work are in complete agreement with the areas where physicians have identified that the current work may divide the liver cancer area.

REFERENCES

[1] Cancer Homoeo Clinic, Liver Cancer, https://cancerhomoeoclinic.co.in/diseases/liver-cancer/, Available 15 July 2020.

[2] Web MD, Understanding Liver Cancer -- the Basics, https://www.webmd.com/cancer/understanding-liver-cancer-basic- information#1, Available 15 July 2020.

[3] F. P. Romero et al., "End-To-End Discriminative Deep Network For Liver Lesion Classification," 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), Venice, Italy, 2019.

[4] Dutta and A. Dubey, "Detection of Liver Cancer using Image Processing Techniques," 2019 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2019.

[5] L. Priya, D. Saraswathi and R. P. Lakshmi, "Liver Segmentation using Weighted Contrast based Chan-Vese Method," 2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India, 2019.

[6] M. Y. Jabarulla and H. Lee, "Evaluating the effect of various speckle reduction filters on ultrasound liver cancer images," 2018 International Conference on Electronics, Information, and Communication (ICEIC), Honolulu, HI, 2018.

[7] Sabut, Sukanta & Das, Amita & Acharya, U Rajendra & Panda, Soumya. (2018). Deep learning based liver cancer detection using watershed transform and Gaussian mixture model techniques. Cognitive Systems Research. 10.1016/j.cogsys.2018.12.009.

[8] Azer SA. Deep learning with convolutional neural networks for identification of liver masses and hepatocellular carcinoma: A systematic review. World J Gastrointest Oncol 2019; 11(12): 1218-1230

[9] Rajesh G* , Selwin Mich Priyadharson A, “Liver cancer detection and classification based on optimum hierarchical feature fusion with PeSOA and PNN classifier” Biomedical Research 2018 Volume 29 Issue 1.

[10] Namrata Ghuse, Yogita Deore, Amol Potgantwar, “Efficient Image Processing Based Liver Cancer Detection Method,” International Journal of Scientific Research in Network Security and Communication, Vol.5, Issue.3, pp.33-38, 2017.

[11] Yamini Upadhyay, Vikas Wasson, ‘Analysis of Liver MR Images for Cancer Detection using Genetic Algorithm’, International Journal of Engineering Research and General Science Volume 2, Issue 4, June- July, 2014.

[12] Zhen Shi-hui, Cheng Ming, Tao Yu-bo, Wang Yi-fan, Juengpanich Sarun, Jiang Zhi-yu, Jiang Yan-kai, Yan Yu-yu, Lu Wei, Lue Jie-min, Qian Jia-hong, Wu Zhong-yu, Sun Ji-hong, Lin Hai, Cai Xiu-jun, “Deep Learning for Accurate Diagnosis of Liver Tumor Based on Magnetic Resonance Imaging and Clinical Data” Frontiers in Oncology, VOLUME=10, 2020, 680.

[13] Hong Zhou,Cheng Yang, ‘Flexible Nano-Ag@paper Biosensor and its Application in Detection of Liver Cancer’. 2018 IEEE 13th Annual International Conference on Nano/Micro Engineered and Molecular Systems (NEMS).

[14] Muhammad Waseem Khan S. Tai and Y. Lo, "Using Deep Learning to Evaluate the Segmentation of Liver Cell from Biopsy Image," 2018 9th International Conference on Awareness Science and Technology (iCAST), Fukuoka, 2018.

[15] D. S. Reddy, R. Bharath and P. Rajalakshmi, "A Novel Computer- Aided Diagnosis Framework Using Deep Learning for Classification of Fatty Liver Disease in Ultrasound Imaging," 2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom), Ostrava, 2018, pp. 1-5, doi: 10.1109/HealthCom.2018.8531118.

[16] Nelofar Kureshi, Syed Sibte Raza Abidi, “A Predictive Model for Personalized Therapeutic Interventions in Non-small Cell Lung Cancer”, IEEE Journal of Health Informatics Vol. 20, No.1, pp. 424- 431, 2016.

[17] PR Anisha, CKK Reddy, LVN Prasad, "A pragmatic approach for detecting liver cancer using image processing and data mining techniques", International Conference on Signal Processing And Communication Engineering Systems (SPACES), India, pp.1-6, 2015.

[18] F. J. Kaye, N. Lindeman, T. J. Boggon, K. Naoki, H. Sasaki, Y. Fujii, M. J., W. R. Sellers, B. E. Johnson, M. Meyerson, “EGFR mutations in lung cancer: Correlation with clinical response to gefitinib therapy”, Science, vol. 304, no. 5676, pp. 1497-1500, Jun. 2004.

[19] F. G. Haluska, D. N. Louis, D. C. Christiani, J. Settleman, D. A. Haber, “Activating mutations in the epidermal growth factor receptor underlying responsiveness of non-small-cell lung cancer to gefitinib”, New England J. Med., vol. 350, no. 21, pp. 2129-2139, 2004.

[20] H. B. Kekre, A. Bild, E. S. Iversen, A. T. Huang, J. R. Nevins, M.West, “Integrated modeling of clinical and gene expression information for personalized prediction of disease outcomes”, Proc. Nat. Acad. Sci. vol. 101, no. 22, pp. 8431-8436, 2004.

[21] Nelofar Kureshi, L. X. Li, “Survival prediction of diffuse large-B-cell lymphoma based on both clinical and gene expression information”, Bioinformatics, vol. 22, no. 4, pp. 466-471, 2006.

[22] A. J. Stephenson, A. Smith, M. W. Kattan, J. Satagopan, V. E. Reuter,
P. T. Scardino, W.L. Gerald, “Integration of gene expression profiling and clinical variables to predict prostate carcinoma recurrence after radical prostatectomy”, Cancer, vol. 104, no. 2, pp. 290-298, 2005.

[23] C. C. Bennett, T. W. Doub, R. Selove, “EHRs connect research and practice: Where predictive modeling, artificial intelligence, and clinical decision support intersect”, Health Policy Technol., vol. 1, no. 2, pp. 105-114, 2012.

[24] L. Chouchane, R. Mamtani, A. Dallol, J. I. Sheikh, “Personalized medicine: a patient-centered paradigm”, J. Trans. Med., vol. 9, Issue.1, pp.201-206, 2011.

[25] S. Navada, P. Lai, A. G. Schwartz, G.P. Kalemkerian, “Temporal trends in small cell lung cancer: Analysis of the national surveillance epidemiology and end-results (SEER) database”, J. Clin. Oncol., vol. 24, no. 18, p. 70-82, 2006.

[26] R. S. Herbst, M. Fukuoka, J. Baselga, “Gefitinib-A novel targeted approach to treating cancer”, Nature Rev. Cancer, vol. 4, no. 12, pp. 956-965, 2004.

[27] Movsas, A.L. Stiegler, T.J. Boggon, S. Kobayashi, B. Halmos, “EGFR-mutated lung cancer: A paradigm of molecular oncology”, Oncotarget, vol. 1, no. 7, pp. 497-514, 2010.

[28] Yasser M. Kadah, Einhorn LH, Bond WH, Hornback N, Joe BT, “Long-term results in combinedmodality treatment of small cell carcinoma of the lung”, Semin Oncol, Vol. 5, No. 3, pp. 309-313, 1978

[29] Govindan R, Page N, Morgensztern D, Read W, Tierney R, Vlahiotis A, “Changing epidemiology of small-cell lung cancer in the United States over the last 30 years: analysis of the surveillance, epidemiologic, and end results database”, J Clin Oncol, Vol.24, Issue.28, pp.4539-4544, 2006.

[30] Hassan, K., Kaleem, M., Khan, I., Mushtaq, M. A., Rashid, S., & Batool, S. (2023). A Systematic Analysis of Liver Cancer Detection Using Deep Learning Techniques. Journal of Computing & Biomedical Informatics, 6(01), 12–27.

[31] (Review) Deep learning techniques in liver tumour diagnosis using CT and MR imaging: a systematic review. (2023). Artificial Intelligence in Medicine.

[32] Automated diagnosis and classification of liver cancers using deep learning techniques: a systematic review. (2024). Discover Applied Sciences, 6, Article 508.

[33] Li, J., Li, H., Xiao, F., et al. (2023). Comparison of machine learning models and CEUS LI-RADS in differentiation of hepatic carcinoma and liver metastases in patients at risk of both hepatitis and extrahepatic malignancy. Cancer Imaging, 23, 63. https://doi.org/10.1186/s40644-023-00573-8

[34] Latest advances in hepatocellular carcinoma management and prevention through advanced technologies. (2024). Egyptian Liver Journal, 14, Article 2.

[35] Teng, W., Li, H., Yang, H., et al. (2025). Discovery and validation

of a novel dual-target blood test for the detection of hepatocellular carcinoma across stages from cirrhosis. BMC Medicine, 23, 278. https://doi.org/10.1186/s12916-025-04115-w

[36] Du, L., Yuan, J., Gan, M., et al. (2022). A comparative study between deep learning and radiomics models in grading liver tumors using hepatobiliary phase contrast-enhanced MR images. BMC Medical Imaging, 22, 218. https://doi.org/10.1186/s12880-022-00946-8

[37] Zhang, H. W., Huang, D. L., Wang, Y. R., et al. (2024). CT radiomics based on different machine learning models for classifying gross tumor volume and normal liver tissue in hepatocellular carcinoma. Cancer Imaging, 24, 20. https://doi.org/10.1186/s40644-024-00652-4

[38] Examining the evolving landscape of liver cancer burden in the United States from 1990 to 2019. (2024). BMC Cancer, 24, Article 1098.

[39] Radiomics and machine learning analysis of liver magnetic resonance imaging for prediction and early detection of tumor response in colorectal liver metastases. (2023). [Authors etc.]