Liver Tumor Detection Using Deep Learning

BABU G[1], ARUN M[2], ASWIN KUMAR S[3], BHADRIPRASATH B J[4], DHARSHINIPRIYA V[5]
[1]*Assistant Professor, Dept. of Computer Science and Engineering, Knowledge Institute of Technology, Salem, India.*
[2,3,4,5]*UG students, Dept. of Computer Science and Engineering, Knowledge Institute of Technology, Salem, India.*

***Abstract-* Liver tumor poses a significant global health challenge, requiring accurate and cost-effective diagnostic solutions. In this study, we propose leveraging Deep Learning algorithms to streamline Liver Tumor diagnosis, aiming for improved efficiency and reduced costs. Traditional liver tumor diagnostic methods are complex and expensive, hindering accessibility to healthcare. This study addresses the need for more efficient and accurate diagnostic approaches, particularly in identifying early-stage tumor cases. We present a novel approach using Deep Learning algorithms for automated liver tumor diagnosis. By the use of these technology, our model aims to provide timely and cost-effective solutions, revolutionizing liver tumor diagnosis. As we compare our solution with the existing system, we make use of MRI scan instead of CT scan and provides more accuracy and reduces false alarms. By using these technologies, we can reduce the human biasness in detecting the tumor in a cost- efficient manner.**

***Indexed Terms-* Liver tumor, Deep Learning, Cost-effectiveness, MRI scan.**

I. INTRODUCTION

"Liver Tumor Detection Using Deep Learning" revolutionizes medical imaging by automating the identification of liver tumors. Traditional methods are time-consuming and prone to errors, necessitating a shift towards more advanced solutions. This project harnesses deep learning, specifically convolutional neural networks (CNNs), to analyze liver imaging scans automatically.

A diverse dataset is meticulously curated and annotated to train the model, which learns to recognize tumor patterns through iterative training. Techniques like transfer learning optimize its performance and generalization ability. Validation ensures reliability across different imaging conditions and patient demographics. Deployed in clinical settings, this deep learning model seamlessly integrates with existing systems, aiding radiologists and clinicians in interpreting liver scans efficiently and accurately.

II. LITERATURE SURVEY

1)A REVIEW ON LIVER CANCER DETECTION TECHNIQUES (BHAWANA MAURYA, DR. SAROJ HIRANWAL, MANOJ KUMAR, 2020)
This study offers information of many ways that show how hybrid intelligence approaches are applied to various categories of cancer detection and treatments. A thorough evaluation of liver cancer detections has been conducted. This review's main objective is to highlight the most often used features, classifiers, approaches, important ideas, and their accuracy. Many machine learning algorithms, including decision trees, support vector machines (SVM), neural networks, random forests, computer-aided detection, genetic algorithms, etc., are employed in cancer diagnosis strategies. These approaches have varying degrees of accuracy and have a major impact on liver image characterization. This manuscript includes all the long-short solutions discussed strategies and explores them up to different execution measures.

2) LIVER CANCER DETECTION USING HYBRIDIZED FULLY CONVOLUTIONAL NEURAL NETWORK BASED ON DEEP LEARNING FRAMEWORK (XIN DONG, YIZHAO ZHOU, LANTIAN WANG, JINGFENG PENG, YANBO LOU, AND YIQUN FAN, 2020)
Liver cancer is a leading cause of mortality worldwide, with homemade identification of cancer towel in CT reviews posing a challenge. The Hybridized Completely Convolutional Neural Network(HFCNN) has been proposed for liver excrescence segmentation, abetting in treatment

planning and response monitoring. Distinguishing between cancerous and non-cancerous lesions is pivotal, and HFCNN facilitates this through semantic segmentation. also, an end- to- end literacy strategy has been explored to separate benign excrescencies from colorectal cancer metastases in liver CT reviews. This approach merges residual and pre-trained weights with features uprooted from Inception, effectively representing original image voxel features in point charts. The system illuminates decision- making stages of deep neural networks and analyzes inner layers to enhance prognostications.

3) AUTOMATIC LIVER CANCER DETECTION USING DEEP CONVOLUTION NEURAL NETWORK (KIRAN NAPTE, ANURAG MAHAJAN, SHABANA UROOJ, 2021)

Since the liver is the largest organ in the body and is essential to both metabolism and toxin excretion, automatic liver cancer detection (ALCD) is a critical component of automatic biomedical image analysis diagnostics. Using computed tomography (CT) scans, several machine learning and deep learning techniques have been studied for autonomous ALCD throughout the past ten years. Liver segmentation is a crucial task that can lead to both under- and over-segmentation of the organ due to noise, complex structures in abdominal computed tomography (CT) images, and textural changes throughout the CT images. These factors make ALCD in CT images difficult. In order to prevent the u-seg and o-seg of the liver in CT images, this study offers liver segmentation based on the suggested Edge Strengthening Parallel UNet (ESP-UNet). Additionally, it provided ALCD based on sequential Deep Convolution Neural Networks (DCNN) that are lightweight. The evaluation of the effects of ESP-UNet DCNN-based ALCD is done by looking at F1-score, accuracy, recall, and precision. When compared to the conventional state of the arts, the proposed method offers a significant improvement in ALCD.

4) DETECTION OF LIVER TUMOUR USING DEEP LEARNING BASED SEGMENTATION WITH COOT EXTREME LEARNING MODEL, (KALAIVANI SRIDHAR, KAVITHA C, WEN-CHENG LAI, BALASUBRAMANIAN PRABHU KAVIN, 2023)

Multimodal intelligence-based systems are crucial for medical analytics and decision-making in healthcare. Liver cancer, a common form of cancer, requires early detection for successful treatment. Tumor segmentation in the liver involves two stages: liver identification and tumor segmentation. Conventional segmentation techniques face challenges with uneven tumor forms and low contrast in liver tumor images. A novel deep learning-based segmentation method is proposed in this study, combining the Coot Extreme Learning Model for efficient tumor identification from publicly available liver image data. The approach minimizes user input by incorporating a geodesic distance encoding approach for improved segmentation. An Extreme Learning Model is utilized for classification, optimized by the Coot Optimization algorithm (COA). Evaluation on the 3D-IRCADb1 dataset demonstrates superior performance in terms of segmentation quality measures like DICE and accuracy, particularly in liver-colored and tumor separation.

5) AUTOMATED VISION-BASED SURVEILLANCE SYSTEM TO DETECT DROWNING INCIDENTS IN SWIMMING POOLS (ALSHBATAT ET AL, 2020)

This paper proposed a system which will track swimmers in a pool using machine learning techniques and prevents drowning accidents is projected. The system consists of a Raspberry Pi with the Raspbian software, a Pixy camera, associate degree Arduino Nano board, stepper motors, associate degree device, and motor drivers. The projected system relies on the color-based algorithm to position and rescue swimmers are drowning. The device then sends alarm to the lifeguards. To verify the implemented, and tested. The results from experiments indicate that the system incorporates a distinctive capability to watch and track swimmers, thereby sanctionative it to mitigate and curb the quantity of deaths by drowning.

III. PROBLEM STATEMENT

Liver tumor is a significant global health issue with diverse causative factors. Early detection of liver infections is critical for effective treatment. Current diagnostic methods for CLD are costly and complex. Deep Learning algorithms are proposed to reduce the high cost of CLD diagnosis through accurate prediction.

IV. PROPOSED SOLUTION

In the proposed solution we use MRI (Magnetic Resonance Imaging) to detect a liver tumor instead of CT scan. By using MRI scan to detect a tumor first we need to do a segmentation process on the image. Then graphing the tumor counter and c-label alongside its boundary provides valuable insights into its dimensions, shape and size. The utilization of MRI scans offers enhanced soft tissue contrast compared to CT scans, potentially leading to more precise tumor detection and characterization. The segmentation process facilitates the delineation of tumor boundaries, aiding in the accurate measurement of tumor dimensions and assisting clinicians in treatment planning and monitoring.

V. TECHNICAL ARCHITECTURE

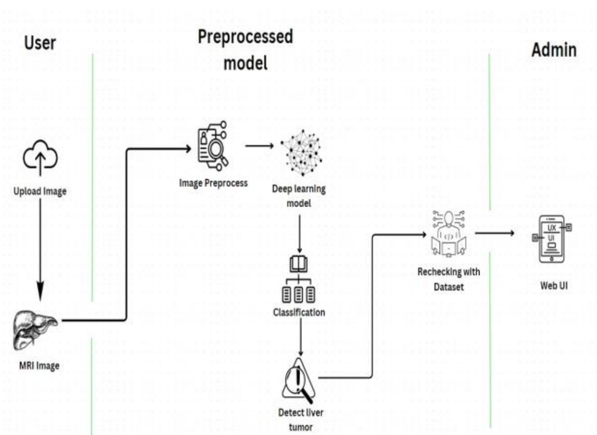

FIG.NO.5.1 TECHNICAL ARCHITECTURE

VI. MODULES

1.Data pre-processing: Data preprocessing is essential for preparing raw input data for deep learning models. Key tasks include cleaning data to remove noise, standardizing or normalizing to ensure consistency, and augmenting the dataset for diversity and size. Proper preprocessing significantly enhances model performance and generalization ability.

2. Model Creation: Model creation entails designing the architecture of the deep learning model, involving the selection and configuration of appropriate neural network layers. Tailoring the model architecture to the specific task and dataset is crucial, considering factors such as problem complexity, dataset size, and available computational resources. Techniques like transfer learning can be employed to leverage pre-trained models and adapt them to the target task, enhancing efficiency and performance.

3.Model training: Model training optimizes parameters to minimize prediction errors using algorithms like stochastic gradient descent. It iteratively processes batches of training data, adjusts parameters to reduce errors, and continues until satisfactory performance is achieved based on predefined metrics.

4.Model evaluating/Testing: Model evaluation assesses the performance of the trained deep learning model on unseen data by using a separate test dataset not encountered during training. Evaluation involves comparing model predictions with true labels or ground truth, using metrics like accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).The primary goal of model evaluation is to gauge the model's ability to generalize to new data and to detect issues like overfitting or underfitting.

5.Detection: Detection utilizes a trained deep learning model to identify objects or patterns in input data, such as liver tumors in medical imaging scans. In liver tumor detection, the model locates and delineates suspected tumor regions from the scans, with detection performed at different granularities like pixel-level segmentation or bounding box detection. The output of detection aids clinical diagnosis and treatment planning by providing accurate identification and characterization of liver tumors, empowering healthcare professionals with valuable information.

VII. CONCLUSION AND FUTURE ENHANCEMENT

In conclusion, this study underscores the pressing global need for a cost-effective diagnostic solution for liver tumors, given their significant health implications. By leveraging Deep Learning algorithms, we propose a novel approach to streamline liver tumor detection, with a focus on enhancing efficiency and reducing costs. Traditional diagnostic methods for liver tumors are often intricate and costly, limiting accessibility to healthcare, particularly in identifying early-stage tumor cases. Our proposed solution harnesses the power of Deep Learning algorithms to automate liver tumor diagnosis, offering timely and cost-effective solutions that have the potential to revolutionize the field. Through the utilization of MRI scans instead of CT scans, our model strives for enhanced accuracy and reduced false alarms, thus mitigating human bias in tumor detection in a cost-efficient manner. The future enhancement of this proposed solution is giving accurate size and shape of the tumor.

REFERENCES

[1] Dietterich TG.(2000), Ensemble methods in machine learning. In: Proceedings of Multiple Classifier System, vol. 1857, Springer (2020), pp. 1–15.

[2] Zhi-Hua Zhou, Ensemble Methods: Foundations and Algorithms, Machine Learning & Pattern Recognition Series, 2022.

[3] Yongjun Piao, Minghao Piao, Keun Ho Ryu, Multiclass cancer classification using a feature subset-based ensemble from microRNA expression profiles, Computers in Biology and Medicine 80 (2021) 39– 44.

[4] Manjeevan Seera, Chee Peng Lim, A hybrid intelligent system for medical data classification, Expert Systems with Applications 41 (2022) 2239– 2249.

[5] Michael J Sorich. An intelligent model for liver disease diagnosis. Artificial Intelligence in Medicine 2021.