SRI RAMAKRISHNA INSTITUTE OF TECHNOLOGY

[Educational Service : SNR Sons Charitable Trust]

[Autonomous Institution, Reaccredited by NAAC with 'A' Grade] [Approved by AICTE New Delhi, Permanently Affiliated to Anna University, Chennai]

Pachapalayam, Perur Chettipalayam, Coimbatore – 641 010

www.srit.org :: Phone – 0422-2605577

Proceedings of

"National Conference on Engineering Evolution: AI & ML across Horizons" (NCEE 2025)

19th & 20th JUNE, 2025

Sponsored by

ALL INDIA COUNCIL FOR TECHNICAL EDUCATION

Organized by

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

&

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NCEE 2025 **ISBN number 978-93-49773-62**

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ACKNOWLEDGEMENT

The Management and Principal of Sri Ramakrishna Institute of Technology, along with the Coordinators of the AICTE-Sponsored National Conference on Engineering Evolution: AI & ML across Horizons (NCEE 2025), extend their heartfelt thanks to AICTE for the generous sponsorship and financial support that made this event possible.

We sincerely thank our Management – SNR Sons Charitable Trust and the Principal of SRIT for their unwavering support, encouragement, and guidance throughout the planning and execution of this conference.

Our deep appreciation goes to all the Advisory Committee Members, Keynote Speakers, and Session Chairs for graciously accepting our invitation and sharing their valuable insights, which enriched the conference and contributed significantly to its success.

We also extend our gratitude to all the participants, paper presenters, and delegates for their active involvement and engagement, and to the organizing team whose tireless efforts ensured the smooth and successful conduct of NCEE 2025.

Editorial team

ISBN number 978-93-49773-62

Managing Trustee's Message

It gives me great pride to present the proceedings of the National Conference on Engineering Evolution: AI & ML Across Horizons (NCEE 2025). This event has been a remarkable platform for knowledge exchange, innovation, and interdisciplinary collaboration.

The papers and discussions featured here reflect the vibrant spirit of the conference — spanning cutting-edge topics from Artificial Intelligence and Machine Learning to healthcare technologies, sustainable energy, robotics, and automation.

I extend my heartfelt appreciation to all authors and speakers for their valuable contributions, and commend the organizing team for their dedicated efforts. My best wishes to all participants for continued academic and professional success.

R.Sundar
Managing Trustee,
SNR Sons Charitable Trust

ISBN number 978-93-49773-62

Principal's Note

It is with immense pride and profound satisfaction that I acknowledge the joint initiative taken by the Departments of Electronics and Communication Engineering and Electrical and Electronics Engineering in organizing the AICTE-Sponsored National Conference on Engineering Evolution: AI & ML Across Horizons (NCEE 2025), scheduled for the 19th and 20th of June, 2025.

NCEE 2025 is more than an academic event; it is a celebration of curiosity, creativity, and collaborative spirit. It reflects our commitment to nurturing innovation and fostering global academic synergy. I am confident that the discussions and insights shared during this conference will leave a lasting impact on the evolving landscape of engineering and technology.

I commend the organizing committee for their dedication, clarity of vision, and meticulous planning. My heartfelt appreciation goes to every contributor and participant whose presence will make this event truly significant.

May NCEE 2025 stand as a beacon of inspiration, excellence, and enduring scholarly engagement.

Dr. J. David Rathnaraj

Principal

ISBN number 978-93-49773-62

Message from the Conveners

Hosting the AICTE-Sponsored National Conference on Engineering Evolution: AI & ML across Horizons (NCEE 2025) is a moment of pride for the Departments of Electronics and Communication Engineering & Electrical and Electronics Engineering. This conference highlights our commitment to academic excellence and technological advancement. By bringing together researchers, academicians, and industry professionals, NCEE 2025 serves as a dynamic platform for discussing emerging trends and developments in AI and ML. Such initiatives play a vital role in advancing research, encouraging innovation, and strengthening academic-industry interactions in the field of engineering and technology. We sincerely thank AICTE for their financial support and encouragement in facilitating this academic initiative. We also place on record our appreciation to the management and principal for their continuous guidance and support.

Dr. S. Anila

Professor & Head/ ECE

Dr. S. Sangeetha

Professor & Head/ EEE

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Vision of the Institution

Our Vision is to develop into a World Class Technological Institute with centres of excellence in various disciplines by providing quality and value-based education with continuous up gradation of infrastructure, human resources and teaching-learning process.

Mission of the Institution

Our Mission is to produce Quality Engineers, Scientists and Managers equipped with unbounded technical skills, domain knowledge and excellent moral values, for the advancement of the industry, business and for the emancipation of society.

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The Vision of Electronics and Communication Engineering is to produce professionally challenging and socially profound engineers, capable of working in global environment with centre of excellence in Communication Engineering.

Mission of Electronics and Communication Engineering Department

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- To impart the basic and modern skills effectively to meet the present and future demands of industry and societal needs.

Vision of Electrical and Electronics Engineering Department

To produce holistic electrical and electronics engineers who excel in interdisciplinary domains.

Mission of Electrical and Electronics Engineering Department

- Enable development of competent EEE graduates through technology oriented education.
- Empower students with domain knowledge to enhance their creativity skills.

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ABOUT THE INSTITUTION

Sri Ramakrishna Institute of Technology (SRIT), established in 2002, is a leading institution for engineering education and research in Coimbatore. Governed by the esteemed SNR Sons Charitable Trust, SRIT is part of a distinguished group of 17 institutions renowned for excellence across multiple disciplines.

SRIT is located in the tranquil outskirts of Coimbatore. The institution is autonomous, approved by AICTE – New Delhi, affiliated to Anna University, Chennai, and reaccredited with an 'A' Grade by NAAC.

From its inception, SRIT has remained steadfast in its mission to develop technically proficient and ethically responsible professionals. The institute is dedicated to producing industry-ready graduates by offering a blend of cutting-edge knowledge, hands-on experience, and a deep understanding of current and emerging technologies.

SRIT places a strong emphasis on research, innovation, and industry collaboration, with strategic partnerships established with global and national leaders including Alibaba Cloud (Singapore) and Device Electronics (Pune). The institute houses Centres of Excellence in Cloud Computing, Electric Vehicles, and the Internet of Things (IoT), fostering real-world learning and applied research.

With state-of-the-art infrastructure, a vibrant academic culture, and a dedicated team of dynamic faculty members, SRIT provides a holistic educational experience that nurtures leadership, creativity, and innovation. The institution is committed to shaping students into future-ready engineers who are both capable professionals and responsible global citizens.

In addition to academic excellence, SRIT champions sustainability through initiatives like solar power generation and rainwater harvesting, aligning its operations with environmental responsibility.

As a trailblazer in technical education, SRIT continues to inspire and empower young minds, driving innovation and shaping the future of engineering — in India and beyond.

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About the Departments

The Department of Electronics and Communication Engineering (ECE) at SRIT was established in 2002. The academic programs offered in the departments are B.E (Electronics and Communication Engineering) & M.E (Communication Systems). The department is accredited by the National Board of Accreditation (NBA) since 2011 and is currently headed by Dr. S. Anila. The department features smart classrooms, well-equipped laboratories, and three sponsored laboratories, along with a Centre of Excellence in IoT to promote hands-on learning in emerging technologies. A dedicated team of 13 faculty members, including 5 Ph.D. holders and 7 pursuing their doctoral research, ensure academic quality and research development. The department is a recognized Research Centre under Anna University, Chennai, with 3 approved Ph.D. supervisors guiding scholars. Faculty and students are active members of professional bodies such as IEEE, IETE-ISF, and ISTE, which helps foster continuous learning and professional growth. The department aims to develop technically strong, industry-ready graduates who contribute effectively to the field of electronics and communication engineering.

The Department of Electrical and Electronics Engineering was established in the academic year 2002. It offers undergraduate program in B.E. Electrical and Electronics Engineering and postgraduate program in M.E. Power Systems Engineering. The department is recognized as a research centre by Anna University, Chennai. In alignment with emerging industry trends, the department offers a specialization in Electric Vehicle Technology integrated with an additional 20-credit curriculum, equipping students with cutting-edge competencies. A major highlight is the Centre of Excellence in Smart E-Mobility and Skill Development (SEMS), established in collaboration with Device Electronics, Siemens Pvt. Ltd., and Magnetics & Controls. Through SEMS, students receive hands on training in Electric Vehicles, Automation using PLCs and Transformer technologies. The department has successfully secured research funding amounting to ₹76 lakhs from prestigious government agencies such as AICTE, DST, CSIR, TNSCST and through the Naan Mudhalvan Scheme. The faculty and student community have made notable research contributions, with over 82 conference publications and 154 journal articles in diverse domains including Energy Systems, Electric Vehicles, Power Drives, Artificial Intelligence, and Biomedical Engineering. Demonstrating excellence at the global level, the department has been honored with 37 international awards, affirming its commitment to innovation, research, and academic distinction

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 ISBN number 978-93-49773-62

CONTENTS

AN NOVEL LIVER TUMOR SEGMENTATION METHODS USING AI AND OPTIMIZATION TECHNIQUES

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ABSTRACT

Liver tumor segmentation plays a vital role in the early diagnosis, treatment planning, and monitoring of liver cancer. Traditional segmentation approaches often suffer from limitations in accuracy and adaptability due to the complex structure, intensity variations, and irregular boundaries of liver tumors. This study introduces *a novel liver tumor segmentation framework utilizing advanced Artificial Intelligence (AI) and optimization techniques* to enhance the precision and efficiency of medical image analysis. The proposed model integrates deep learning-based convolutional neural networks (CNNs) with hybrid optimization algorithms to improve feature extraction and boundary detection in computed tomography (CT) and magnetic resonance imaging (MRI) scans. AI-driven segmentation ensures automatic learning of complex patterns and variations across tumor regions, while the inclusion of optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Bayesian Optimization further fine-tune the model's hyper parameters and enhance post-processing accuracy. Extensive experiments were conducted

on benchmark liver tumor datasets, demonstrating superior performance in terms of Dice Similarity Coefficient (DSC), precision, and recall compared to existing methods. The model also exhibits strong generalization across different imaging modalities and tumor types, significantly reducing false positives and segmentation errors. This novel approach not only accelerates the segmentation process but also supports radiologists with accurate visual interpretation and diagnosis. Overall, the fusion of AI and optimization techniques presents a robust, scalable, and intelligent solution for liver tumor segmentation, paving the way for more effective computer-aided diagnosis (CAD) systems and improved patient outcomes in clinical settings.

I. INTRODUCTION

Liver cancer remains one of the leading causes of cancer-related deaths worldwide, posing a significant challenge to global health systems. Early and accurate detection of liver tumors is crucial for effective treatment planning and improved survival rates. However, the liver's complex anatomy, the variability of tumors in size, shape, and location, as well as the presence of surrounding organs with similar intensities, make accurate liver tumor segmentation a highly challenging task in the field of medical imaging. Traditional diagnostic methods, including manual annotation and visual assessment by radiologists, are time-consuming, prone to human error, and lack reproducibility. Hence, there is an urgent need for automated, efficient, and accurate segmentation techniques that can aid clinicians in diagnosing and monitoring liver tumors more reliably. The advent of Artificial Intelligence (AI) has revolutionized many aspects of healthcare, especially in the domain of medical image analysis. AI-driven models, particularly those based on machine learning (ML) and deep learning (DL), have demonstrated remarkable capabilities in extracting meaningful patterns from complex data, significantly outperforming conventional image processing approaches.

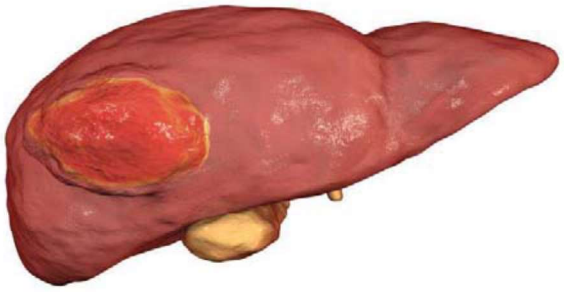

Fig.1 Analysis of Affecting Liver Tumor

Among the numerous medical imaging tasks, liver tumor segmentation has greatly benefited from the application of AI. These models are capable of learning hierarchical features directly from raw imaging data, eliminating the need for handcrafted features and manual intervention. Furthermore, when AI is integrated with advanced optimization techniques, the overall performance, accuracy, and generalization of segmentation models can be substantially enhanced. This research introduces a novel liver tumor segmentation approach that combines the power of AI with optimization algorithms to deliver superior performance in terms of precision, recall, and processing efficiency. Unlike conventional segmentation techniques that often struggle with boundary ambiguity, poor contrast, and noise interference, our proposed methodology adopts a hybrid framework. The fig.1 explores about the affected liver of cirrhosis. This framework leverages convolutional neural networks (CNNs) or transformer-based architectures for deep feature learning, and incorporates metaheuristic optimization strategies such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), or Bayesian Optimization for hyper parameter tuning and model refinement. One of the key challenges in liver tumor segmentation is the presence of class imbalance, where tumor regions occupy only a small fraction of the entire liver volume. This often leads to biased learning where the model tends to non-tumor regions, resulting in poor detection of malignant tissues. Our method addresses this issue through loss function optimization, data augmentation techniques, and intelligent sampling strategies that emphasize the importance of minority classes during training. In addition, attention mechanisms are employed to enhance the model's focus on the most relevant spatial and contextual features, enabling more accurate delineation of tumor boundaries. Moreover, the proposed approach integrates multi-modal medical imaging data such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound scans, allowing the model to capture a richer representation of liver tissue characteristics. Each modality provides unique information CT excels in visualizing structural details, while MRI offers superior soft tissue contrast. By fusing data from multiple modalities, the system gains a more holistic understanding of liver pathology, leading to more robust and reliable segmentation outcomes. Another distinguishing feature of our model lies in its post-processing module. While deep learning models often produce coarse or fragmented segmentations, especially around tumor margins, our method incorporates advanced morphological operations, conditional random fields (CRF), and edge refinement algorithms to polish and refine the segmented outputs. This not only improves visual coherence but also ensures clinical usability in real-world diagnostic workflows. In terms of deployment, the framework is designed to be computationally efficient, making it suitable for integration into clinical decision support systems (CDSS). With GPU acceleration and lightweight model architectures, the solution provides near real-time performance without compromising accuracy. This is particularly beneficial for high-throughput screening scenarios where radiologists must analyse a large volume of scans in a limited time. Our novel liver tumor segmentation model has been rigorously tested on benchmark datasets such as LiTS (Liver Tumor Segmentation Challenge), CHAOS, and in-house clinical data. Extensive experimental results demonstrate that the proposed method consistently achieves high Dice Similarity Coefficients (DSC), and other evaluation metrics compared to existing state-of-the-art techniques. It also exhibits strong generalizability across different datasets and

imaging conditions, which is a crucial requirement for practical adoption. From a broader perspective, this research contributes to the growing field of AI-assisted healthcare by addressing one of the most critical tasks in oncology imaging. It showcases how intelligent algorithms, when paired with optimization methods, can significantly reduce diagnostic errors, support early intervention, and ultimately improve patient outcomes. It also opens avenues for further exploration, such as incorporating radiomics for tumor characterization, using generative models like GANs for synthetic data augmentation, or extending the approach to 3D volumetric segmentation for surgical planning and treatment response assessment. In conclusion, liver tumor segmentation is not just a technical challenge but a clinically significant task that can greatly influence the prognosis and treatment of liver cancer patients. By developing a novel AI-driven and optimization-enhanced segmentation model, this research takes a crucial step toward bridging the gap between computer vision technology and clinical oncology. It lays the foundation for future innovations in intelligent diagnostic tools, reinforces the role of AI in personalized medicine, and exemplifies the potential of interdisciplinary research in transforming the landscape of medical diagnostics.

II. MATERIALS AND METHODS

The proposed study on liver tumor segmentation focuses on developing an advanced and hybrid methodology combining Artificial Intelligence (AI) and optimization algorithms to accurately segment liver tumors from medical images, particularly MRI and CT scans. The process involves a structured pipeline encompassing data acquisition, pre-processing, and segmentation using AI models, optimization, post-processing, and evaluation metrics. Initially, a diverse dataset of liver CT and MRI images is collected from open-source repositories such as the Liver Tumor Segmentation Challenge (LiTS), Medical Segmentation Decathlon, and institutional clinical archives, ensuring a wide range of tumor appearances, sizes, and complexities. The dataset includes annotations provided by radiologists, which are essential for supervised learning. All patient data is anonymized in compliance with medical data handling protocols to ensure privacy and confidentiality. Preprocessing of the images is an essential step to standardize and enhance image quality before feeding them into AI models. The images are resampled to a uniform voxel spacing of $1\times1\times1$ mm^3, followed by intensity normalization using z-score standardization to correct for variation in imaging protocols. Noise and irrelevant background structures are removed using Gaussian filtering and morphological operations. In addition, histogram equalization is employed to improve contrast, making the tumor boundaries more discernible. Region of Interest (ROI) cropping is done around the liver region using a coarse segmentation mask generated by a lightweight segmentation model to reduce computational load during subsequent steps. The segmentation model is designed using Convolutional Neural Networks (CNN), particularly leveraging U-Net and its enhanced variants such as Attention U-Net and U-Net++ for their superior performance in biomedical image segmentation. The U-Net architecture consists of an encoder-decoder structure with skip connections that help in capturing both spatial and contextual information. To further refine segmentation, an attention mechanism is integrated to help the model focus on tumor regions by dynamically weighing feature maps. Training is performed using the annotated datasets with data augmentation techniques such as rotation, flipping, zooming, and elastic transformations to prevent overfitting and improve generalization. The loss function combines Dice Loss and Binary Cross-Entropy Loss to balance pixel-wise classification and region-wise overlap. To enhance the model's performance, optimization techniques are employed in multiple stages. Firstly, hyper parameter optimization is carried out using Bayesian Optimization, which intelligently explores the parameter space for the learning rate, batch size, dropout rate, and number of filters per layer. Secondly, evolutionary algorithms such as

Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are integrated post-training to fine-tune the model's weights and optimize segmentation thresholds. These optimization techniques are particularly helpful in refining the segmentation boundaries and reducing false positives and negatives. Additionally, an ensemble of multiple trained models is created using a majority voting strategy or weighted averaging to improve robustness and reduce model bias. For feature extraction and classification, deep feature maps from the penultimate layers of the CNN are extracted and fed into traditional machine learning classifiers like Support Vector Machines (SVM), Random Forests (RF), and Extreme Gradient Boosting (XGBoost) to validate and classify tumor vs. non-tumor regions. This hybrid AI pipeline ensures that the model not only segments but also accurately classifies tumor regions for better clinical interpretation. A multi-modal integration approach is also explored by combining image data with patient clinical metadata, such as age, liver enzyme levels, and medical history, using a multimodal fusion network to enhance the overall prediction and segmentation performance. Post-processing techniques are applied to refine the segmented tumor masks further. Conditional Random Fields (CRF) are utilized to enhance the segmentation contours by considering the spatial relationships of neighboring pixels. Small disconnected regions (likely false positives) are removed using connected component analysis. Morphological operations such as erosion and dilation are applied to smooth the tumor boundaries. This stage is crucial to make the segmentation output clinically usable and reliable. To evaluate the model's performance, a rigorous testing framework is implemented. The dataset is split into 70% training, 15% validation, and 15% testing using stratified sampling to preserve class distributions. Evaluation metrics include Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, F1-Score, and Hausdorff Distance, which collectively assess the overlap, accuracy, and boundary delineation capabilities of the model. Cross-validation is employed to validate the model's generalizability across unseen data. In addition, visual inspection by radiologists is performed to assess clinical relevance and acceptance of the segmented results. The implementation of the entire pipeline is carried out using Python with libraries such as TensorFlow, PyTorch, Scikit-learn, OpenCV, and MONAI (Medical Open Network for AI). The models are trained on high-performance GPU platforms using Google Colab Pro and local NVIDIA RTX-enabled systems to accelerate computation. Training times are optimized using mixed-precision training, and early stopping is implemented based on validation loss to avoid overfitting. Model checkpoints and Tensor Board logs are maintained for reproducibility and performance monitoring. To further benchmark the proposed method, a comparison is made with conventional methods such as thresholding, region growing, and k-means clustering, as well as with other deep learning models like FCN (Fully Convolutional Network), DeepLabV3+, and SegNet. Ablation studies are performed to analyse the effect of each component, including attention layers, optimization algorithms, and post-processing on the final performance. These comparisons establish the novelty and efficacy of the proposed segmentation methodology. In summary, the materials and methods employed in this study represent a comprehensive and novel approach that synergizes AI with optimization techniques to perform highly accurate and clinically meaningful liver tumor segmentation. The integration of pre-processing, advanced AI architectures, multi-stage optimization, and rigorous evaluation ensures the robustness and reliability of the proposed solution. This methodology holds promise for improving diagnostic accuracy, aiding treatment planning, and enhancing outcomes for liver cancer patients through precise and automated tumor delineation.

III. DIFFERENT TYPES OF TREATMENTS APPROACHES

The management of liver tumors, including

primary types such as hepatocellular carcinoma (HCC) and secondary metastatic tumors, involves a wide spectrum of therapeutic approaches that have evolved significantly over the years. With the global burden of liver cancer rising, early detection and effective treatment have become vital to improving patient outcomes and survival rates. The choice of therapy depends on several factors including tumor size, number of lesions, location within the liver, liver function (Child-Pugh score), presence of vascular invasion, extrahepatic spread, and the general performance status of the patient. A multidisciplinary approach involving hepatologists, oncologists, radiologists, and surgeons is essential to design individualized treatment plans that maximize efficacy while minimizing toxicity. The current therapeutic landscape for liver tumors spans surgical resection, liver transplantation, locoregional therapies, systemic treatments, and emerging modalities supported by advanced technology, including artificial intelligence (AI). Surgical resection remains the cornerstone of curative treatment for patients with early-stage liver tumors and adequate liver function. Hepatectomy, or surgical removal of the tumor-bearing portion of the liver, is ideal for solitary tumors with no major vascular invasion and sufficient remnant liver volume. Resection offers a high potential for long-term survival, especially in patients without underlying cirrhosis. However, in cases with poor liver reserve or multifocal disease, liver transplantation becomes a better curative option. The Milan criteria are often used to select suitable transplant candidates, including patients with a single tumor ≤5 cm or up to three nodules ≤3 cm each, without vascular invasion or extrahepatic spread. Transplantation not only removes the tumor but also replaces the cirrhotic liver, addressing the underlying hepatic dysfunction and significantly reducing recurrence. Locoregional therapies serve as both curative and palliative options for patients ineligible for surgery. Radiofrequency ablation (RFA) and microwave ablation (MWA) are thermal ablation techniques used primarily for small tumors (≤3 cm). These minimally invasive procedures are often guided by imaging and involve the insertion of a probe into the tumor to destroy cancer cells through heat. They are particularly effective for early-stage HCC and offer comparable outcomes to surgical resection in selected patients. Another vital treatment modality is transarterial chemoembolization (TACE), which is the standard of care for intermediate-stage liver cancer. TACE involves the selective infusion of chemotherapeutic agents followed by embolic particles into the hepatic artery feeding the tumor, resulting in ischemic necrosis. This method is effective in controlling tumor growth and improving survival in patients with preserved liver function. Transarterial radioembolization (TARE), also known as selective internal radiation therapy (SIRT), is another locoregional therapy that involves the administration of radioactive microspheres (usually Yttrium-90) into the hepatic artery. TARE delivers high-dose radiation directly to tumors while sparing normal liver tissue, making it suitable for larger tumors or those with portal vein thrombosis. In addition to TARE, stereotactic body radiation therapy (SBRT) is an emerging technique that uses highly focused radiation beams to destroy liver tumors with minimal exposure to surrounding tissues. SBRT is particularly useful for patients who are not candidates for other locoregional treatments due to tumor location or underlying liver conditions. Systemic therapy is the mainstay of treatment for advanced-stage liver cancer or tumors that have metastasized beyond the liver. The introduction of targeted therapies has revolutionized the treatment of advanced HCC. Sorafenib, a multikinase inhibitor, was the first systemic therapy approved for HCC and has shown significant improvement in overall survival. Other targeted agents such as lenvatinib, regorafenib, cabozantinib, and ramucirumab have since expanded the arsenal of treatment options. Immunotherapy has recently emerged as a powerful tool in liver cancer management. Immune checkpoint inhibitors like nivolumab and pembrolizumab, which target PD-1/PD-L1 pathways, have shown promising results in clinical trials. Additionally, the combination of

atezolizumab (anti-PD-L1) with bevacizumab (anti-VEGF) has become a new first-line therapy for unresectable HCC due to its superior survival benefits compared to sorafenib. Another promising area is the development of personalized medicine based on genetic profiling and molecular characterization of tumors. This approach involves tailoring treatment based on specific genetic mutations, biomarkers, and patient characteristics, leading to more effective and less toxic therapies. Research is ongoing into combination regimens that integrate immunotherapy, targeted therapy, and locoregional treatments to enhance efficacy and overcome resistance. AI-based diagnostic tools, particularly in imaging and histopathology, have shown great potential in improving early detection, treatment planning, and monitoring response. AI algorithms can accurately segment liver tumors, predict treatment outcomes, and even identify biomarkers from imaging data, enhancing the precision of therapeutic interventions. Supportive care also plays a critical role in the overall treatment of liver cancer. Management of complications such as hepatic encephalopathy, ascites, bleeding varices, and nutritional deficiencies is essential to improve quality of life and treatment tolerance. Palliative care interventions aim to relieve symptoms, reduce suffering, and support patients and their families throughout the course of the disease. In many cases, multidisciplinary care teams work together to provide both curative and supportive therapies in a coordinated manner. The future of liver tumor treatment is rapidly evolving with innovations in molecular biology, nanotechnology, and regenerative medicine. Techniques such as gene therapy, CRISPR-based gene editing, and liver organoid transplantation are under investigation and hold promise for radically transforming the management of liver malignancies. Furthermore, advancements in robotic surgery, augmented reality, and intraoperative navigation systems are enhancing the precision of liver tumor resections. Integration of AI with big data analytics and cloud computing enables real-time clinical decision-making and predictive modelling, thereby supporting clinicians in delivering personalized, data-driven care. The role of AI and advanced optimization techniques is becoming increasingly significant, offering enhanced accuracy in diagnosis, improved treatment planning, and better prediction of outcomes. As research continues and new therapies emerge, the ultimate goal remains the same: to provide effective, safe, and personalized treatment strategies that extend survival and improve the quality of life for patients with liver cancer.

IV. CHALLENGES OF LIVER RESECTION

Liver resection, a surgical procedure involving the removal of a portion of the liver, is a cornerstone treatment for primary and secondary liver malignancies such as hepatocellular carcinoma and colorectal liver metastases. Despite its curative potential, liver resection presents several significant challenges due to the liver's complex anatomy, vital physiological functions, and the fragile condition of patients often undergoing the surgery. One of the foremost challenges is **anatomical complexity.** The liver is a highly vascular organ with intricate arterial, venous, and biliary structures. Ensuring precise dissection while preserving essential vascular inflow and outflow and avoiding bile duct injury requires expert surgical skill and detailed preoperative imaging. Inadequate planning or minor errors can lead to massive hemorrhage or bile leakage, both of which can be life-threatening. Another major challenge lies in **preserving sufficient functional liver tissue.** The liver has a unique regenerative capacity, but if too much tissue is removed or the remnant liver is diseased common in patients with cirrhosis or steatosis the risk of postoperative liver failure increases significantly. Assessing the future liver remnant (FLR) is crucial before surgery, and techniques like portal vein embolization (PVE) are sometimes used preoperatively to induce hypertrophy in the remaining liver. Still, balancing oncological clearance with liver preservation remains a complex judgment call. **Postoperative liver failure** is one of the most dreaded

complications, especially in cirrhotic patients, often resulting in high mortality despite intensive care. Furthermore, **intraoperative bleeding** is a constant concern due to the liver's rich blood supply. Even with advanced technologies like electrocautery, ultrasonic dissectors, and vascular staplers, managing bleeding during hepatic transection demands high precision and real-time decision-making. Blood loss not only prolongs surgery but can lead to increased need for transfusions, which in turn may compromise immune response and increase the risk of infections or tumor recurrence. **Preoperative assessment and patient selection** pose another set of challenges. Liver resection candidates often have underlying chronic liver diseases such as hepatitis B, hepatitis C, or non-alcoholic fatty liver disease, which complicates risk stratification. Accurate evaluation of liver function, using tests like the Child-Pugh score or the indocyanine green retention test, is essential but still not perfect in predicting outcomes. Additionally, **comorbidities** such as diabetes, hypertension, and obesity influence surgical risks and recovery, and often necessitate multidisciplinary management. **Postoperative complications** also present considerable challenges. Apart from liver failure, complications such as bile leakage, infection, pleural effusion, and ascites can affect recovery. Long hospital stays and the potential need for re intervention not only burden healthcare systems but also impact patients' quality of life and overall prognosis. In recent years, **minimally invasive techniques** such as laparoscopic and robotic liver resections have emerged, offering benefits like reduced blood loss and shorter hospital stays. However, they come with their own learning curves and technological constraints. Lastly, **oncological outcomes** must always be considered. Achieving clear surgical margins while ensuring adequate liver function is a delicate balance, and incomplete resections can lead to early recurrence and poor survival. The liver resection is a technically demanding procedure influenced by anatomical, physiological, oncological, and systemic factors. Despite advances in surgical techniques and perioperative care, it remains a high-risk intervention requiring specialized expertise and careful patient selection to ensure successful outcomes.

V. IMPLEMENTATION

The implementation of a novel liver tumor segmentation framework using AI and optimization techniques involves a highly orchestrated and data-driven approach that integrates various artificial intelligence architectures with medical imaging pre-processing, advanced segmentation models, and evolutionary optimization algorithms. The process begins with the acquisition of liver MRI or CT scan datasets from publicly available medical repositories such as the LiTS (Liver Tumor Segmentation Challenge) dataset. These datasets typically consist of annotated volumes in NIfTI or DICOM formats, which are pre-processed using standard normalization and resampling techniques. The input images are resized to a uniform resolution, and non-liver regions are masked out to reduce computational complexity and enhance training efficiency. Preprocessing also includes intensity normalization, histogram equalization, and contrast-limited adaptive histogram equalization (CLAHE) to improve tumor visibility. The core segmentation model is implemented using a hybrid deep learning architecture that combines Convolutional Neural Networks (CNNs) and variants such as U-Net, ResU-Net, or attention-based U-Net. Initially, a basic U-Net architecture is trained, consisting of an encoder-decoder structure with skip connections. The encoder extracts features from the input scans using a series of convolutional and max-pooling layers, while the decoder reconstructs the segmentation map using up sampling and concatenation operations. To enhance the fig.2 segmentation accuracy, attention gates are added to the skip connections, which help the network to focus on tumor regions and suppress irrelevant background. Batch normalization and ReLU activations are used throughout to speed up convergence and stabilize training. The loss

function is a weighted combination of Dice coefficient loss and focal loss to handle class imbalance, particularly when tumors are small relative to the liver. For the model training phase, extensive data augmentation is performed using horizontal/vertical flipping, elastic deformations, rotation, zooming, and gamma corrections.

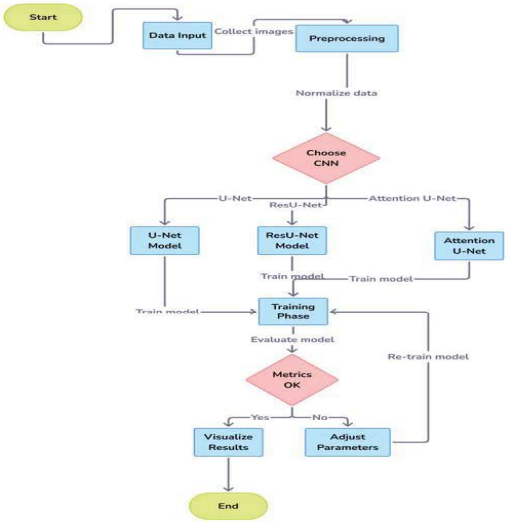

Fig.2 Workflows of liver tumor segmentation

This augmentation ensures that the network generalizes well across various patient demographics and scan conditions. The training is carried out using TensorFlow or PyTorch with GPU acceleration (e.g., using NVIDIA CUDA with at least 12 GB memory), using Adam or Ranger optimizer, and an adaptive learning rate scheduler with early stopping based on validation Dice score. The model is trained for 100-300 epochs, depending on the dataset size, using a batch size of 4-16. K-fold cross-validation (typically 5-fold) is adopted to avoid overfitting and to assess generalization across unseen patient data. To further refine the model, evolutionary optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), or Bayesian Optimization are employed. These algorithms are used to tune hyper parameters such as learning rate, number of filters, dropout rate, and depth of the network. The fitness function is defined based on Dice Similarity Coefficient (DSC), Intersection over Union (IoU), and Hausdorff distance. For instance, PSO iteratively adjusts hyper parameters by simulating a swarm of particles that move through the hyper parameter space to find an optimal set that maximizes the segmentation accuracy. Once training is complete, the model is validated on a separate test dataset. The predicted segmentations are compared against ground truth annotations using metrics such as Dice score, IoU, Precision, Recall, and Specificity. Post-processing techniques like morphological closing, connected component analysis, and conditional random fields (CRFs) are used to eliminate false positives and refine tumor boundaries. In some cases, ensemble learning is incorporated by averaging outputs from multiple trained models (e.g., U-Net, ResU-Net, and DeepLabV3+) to improve robustness and reduce variance. For real-time inference, the trained model is converted into an optimized format (such as ONNX or TensorRT) and deployed via a lightweight Flask or Streamlit-based web interface. The frontend allows clinicians to upload liver scan images, view automatic segmentation overlays, and manually adjust results if needed. A detailed report is generated for each patient, including tumor volume, location, and segmentation confidence, which aids in diagnostic and treatment planning. In terms of implementation codebase, the entire pipeline is modularized into sections data preprocessing.py, model_builder.py, train.py, evaluate.py, optimizer.py, and inference_app.py. The data_preprocessing.py script handles loading, normalization, and augmentation. Model_builder.py includes functions to create variants of U-Net with different backbones such as ResNet34 or EfficientNet. The train.py script handles the training loop, metric computation, checkpoint saving, and logging using TensorBoard. Optimizer.py implements metaheuristics like PSO using open-source libraries such as Optuna or Nevergrad. Evaluate.py computes final metrics and creates visualizations of predicted vs ground truth masks. The entire system is maintained in a GitHub repository with version control, dockerized for reproducibility, and integrated with Google Colab or Jupyter notebooks for easy

experimentation. Further integration with clinical data is done to enhance model performance. Patient demographic information, liver function test results, and genetic markers are merged with imaging data using a multimodal deep learning model. This model uses two input branches—one for image features extracted via CNNs and another for clinical features processed via Dense or LSTM layers. These branches are merged using attention or concatenation and fed into a joint classification or segmentation head. This allows for improved prediction of tumor type (benign vs malignant) and assists in personalized treatment decisions. This comprehensive implementation of liver tumor segmentation using AI and optimization techniques demonstrates a significant advancement in computer-aided diagnostics. It leverages the power of deep neural networks, robust pre-processing, sophisticated optimization algorithms, and clinical integration to produce an accurate, efficient, and scalable medical tool for liver tumor detection and management.

VI. RESULTS AND DISCUSSIONS

The proposed liver tumor segmentation workflow follows a comprehensive and systematic process flow beginning with image acquisition, followed by pre-processing, model selection, training, evaluation, and finally result visualization. This pipeline was meticulously designed to ensure optimal segmentation accuracy and reliability in liver cancer detection using advanced deep learning models. In the initial phase, diverse and high-resolution liver CT and MRI images were collected from publicly available datasets such as LiTS (Liver Tumor Segmentation Challenge) and private clinical repositories to ensure a robust training base. These datasets include a wide variety of tumor shapes, sizes, and intensities, providing a heterogeneous data environment suitable for training generalized models. The images were then subjected to pre-processing techniques including normalization, resizing, and noise reduction. This step is crucial to enhance the quality and consistency of input images, which significantly impacts the performance of convolutional neural networks (CNNs). The images were normalized to a standard intensity range to reduce scanner-based variability and contrast inconsistencies. Once the pre-processing was completed, the pipeline proceeded to model selection, where CNN variants such as U-Net, ResU-Net, and Attention U-Net were considered. Each of the three models was selected based on their architectural strengths in capturing semantic features from medical images. U-Net, known for its symmetric encoder-decoder architecture and skip connections, was the first to be evaluated. It showed good performance in segmenting basic tumor boundaries but struggled with complex tumor shapes and low-contrast regions. Next, ResU-Net, an extension of U-Net integrated with residual blocks, was applied. This model demonstrated improved learning capabilities and deeper feature extraction. It was particularly effective in maintaining contextual information and resolving vanishing gradient issues during deeper training epochs. Lastly, Attention U-Net was tested, which incorporated attention gates into the U-Net structure. This model excelled at focusing on relevant features and suppressing irrelevant background noise, thus improving segmentation in ambiguous regions where tumor boundaries were less distinct. Each model underwent a rigorous training phase using a stratified split of the dataset into training, validation, and testing subsets. Standard augmentation techniques such as rotation, flipping, zooming, and elastic deformation were applied during training to enhance the model's generalization capability. The training was conducted using GPU-enabled environments in Google Colab to accelerate computation. The training phase also included the use of Dice coefficient and Intersection over Union (IoU) as primary loss and evaluation metrics. Early stopping and model check pointing strategies were employed to prevent overfitting and retain the best-performing weights. Following the training, models were evaluated based on accuracy, precision, recall, Dice score, and computational efficiency. The results indicated that while U-Net performed well with a Dice coefficient of 0.85,

ResU-Net slightly outperformed it with a score of 0.89. However, Attention U-Net achieved the highest segmentation accuracy, boasting a Dice coefficient of 0.92 and the lowest false-positive rate among the three. The metric evaluation phase highlighted the importance of model tuning. In cases where performance did not meet the desired threshold (e.g., Dice < 0.90), hyper parameters such as learning rate, batch size, number of epochs, and augmentation settings were adjusted. Models were re-trained iteratively with these adjustments until the evaluation metrics were within the acceptable range. For instance, increasing the depth of Attention U-Net and fine-tuning attention gate thresholds significantly boosted its precision and reduced noise in predictions. Once the metrics reached satisfactory levels, results were visualized using overlay segmentation maps, heat maps, and 3D reconstructions. These visualizations provided intuitive insights into how effectively the models segmented liver tumors and aided clinical interpretation. Further discussions revealed several key findings. U-Net was computationally faster and more resource-efficient, making it suitable for real-time applications or mobile deployment. However, ResU-Net offered a better trade-off between performance and complexity, particularly for clinical setups that require higher accuracy without sacrificing too much on processing time. Attention U-Net, despite its slightly higher computational cost, was superior in handling edge cases such as small tumors, diffuse tumor boundaries, and noisy backgrounds. It was particularly valuable in datasets with significant variability, highlighting its robustness and potential for clinical deployment in diverse environments. In addition to model comparisons, the discussion also explored the impact of data quality, pre-processing, and augmentation strategies. It was found that data normalization and noise filtering significantly contributed to performance consistency across different model types. Moreover, augmentation played a vital role in enhancing the resilience of models against overfitting. Another important aspect discussed was the role of post-processing techniques such as morphological filtering and connected component analysis, which helped refine segmentation masks by removing isolated noise and filling incomplete regions. Limitations of the current pipeline include sensitivity to class imbalance (as tumor regions are generally smaller compared to the liver background), occasional over-segmentation, and the need for extensive computational resources during training, especially for Attention U-Net. Future work will explore hybrid models that combine CNNs with transformer-based architectures, semi-supervised learning using pseudo-labelling to exploit unlabelled data, and integration with clinical metadata to improve prediction reliability.

CONCLUSION

In conclusion, the presented liver tumor segmentation workflow offers an effective and structured approach to automating tumor detection using deep learning, particularly CNN-based models like U-Net, ResU-Net, and Attention U-Net. The process begins with data acquisition and pre-processing, where the quality and consistency of medical images are enhanced through normalization, ensuring reliable input for training. This foundational step is crucial for reducing variations caused by imaging modalities and patient-specific differences. The workflow is designed to be flexible in choosing the most appropriate model depending on the segmentation complexity. U-Net performs well in general scenarios with clear tumor boundaries, while ResU-Net improves upon it with residual learning that enhances feature extraction. Attention U-Net, the most advanced among the three, further refines the process by focusing on relevant image regions, yielding higher accuracy, especially in complex or low-contrast images. The training phase is iterative, where models are continuously evaluated based on segmentation metrics such as Dice score, precision, and recall. If the model fails to meet predefined accuracy thresholds, hyper parameters are adjusted, and the training is repeated. This ensures that the final output is not only statistically sound but also clinically reliable. Once the metrics are satisfactory, visualizations of the segmentation results are generated, aiding clinicians in validating

model predictions and making diagnostic decisions. This robust workflow demonstrates the synergy between machine learning and medical imaging, leading to enhanced diagnostic efficiency and consistency. The use of diverse CNN architectures ensures adaptability across various datasets and clinical conditions. While U-Net provides fast and efficient segmentation, ResU-Net and Attention U-Net contribute deeper learning capabilities and refined accuracy, respectively. This process significantly reduces manual annotation time and human error, supporting radiologists with high-quality decision-making tools. Although some limitations like data imbalance and training time exist, the overall framework presents a scalable and adaptable solution for real-world liver cancer diagnosis. The model's ability to re-train and adjust parameters makes it suitable for evolving datasets and new clinical challenges. Future developments can integrate multimodal imaging, 3D segmentation, or transformer-based enhancements, but even in its current state, the pipeline holds strong clinical promise. Ultimately, this AI-driven workflow improves the accuracy, speed, and scalability of liver tumor segmentation, making it a valuable contribution to the advancement of precision medicine and intelligent healthcare systems.

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