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Hybrid Fuzzy Logic and Metaheuristic Optimized Trinetfusion Model for Liver Tumor Segmentation

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ABSTRACT Liver tumor segmentation plays a vital role in medical imaging, enabling accurate diagnosis and precise treatment planning for liver cancer. Traditional methods such as threshold-based techniques and region-growing algorithms have been explored, and more recently, deep learning models have shown promise in automating and improving segmentation tasks. However, these approaches often face significant limitations, including challenges in accurately delineating tumor boundaries, high sensitivity to noise, and the risk of overfitting, especially when dealing with complex tumor structures and limited annotated data. To overcome these limitations, a novel Hybrid Fuzzy Logic and Metaheuristic Optimized TriNetFusion Model is proposed. This model integrates the strengths of fuzzy logic, metaheuristic optimization, and deep learning to deliver a more reliable and adaptable segmentation framework. Fuzzy logic is utilized to handle the inherent uncertainty and ambiguity in medical images, particularly in tumor boundary regions where intensity variations are subtle and complex. Metaheuristic optimization algorithms are employed to fine-tune the parameters of the segmentation model effectively, ensuring a more generalized and adaptive performance across different datasets. At the core of the model lies TriNetFusion, a multi-branch deep learning architecture that fuses complementary features extracted at various levels. The fusion of these multi-level features contributes to robust segmentation by capturing both global and local image characteristics. This model is specifically designed to adapt to irregular and complex tumor shapes, significantly reducing false positives and improving boundary precision. Experimental validation using benchmark liver tumor datasets demonstrates that the proposed model achieves a segmentation accuracy of 96% with a low loss value of 0.2, indicating strong generalization without overfitting. The hybrid approach not only enhances segmentation precision but also ensures robustness and adaptability, making it a highly promising solution for liver tumor segmentation in clinical practice.

INDEX TriNetFusion, Binary Classification, Fuzzy Logic, Metaheuristic Optimization, Otsu Thresholding, Deep Learning.

I. INTRODUCTION

In Liver tumors, Hepato Cellular Carcinoma (HCC) and metastatic liver tumors, are the most common and deadly cancers worldwide. The correct segmentation and early diagnosis of these tumors in medical images are critically important for proper diagnosis, prognosis, and treatment planning. Liver tumors usually have irregular shapes, varying in their size, and are located adjacent to vital anatomical structures, which make them even more difficult to outline. Techniques such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans provide transparent views of the liver lesion. However, the manual segmentation process is time-consuming, subjective, and prone to error due to human biases. Thus, automation and semi-automation of segmentation procedures are essential to strengthen clinical decision and enabling physicians to achieve treatment decisions based on precision [1].

Most of the models based on Computer Vision (CV) and classification techniques have been developed for the detection of liver tumors. However, the techniques such as thresholding, region growing, and edge detection methods employed for segmenting liver tumors and it will not handle the complexity and variability associated with tumor shapes, textures, and boundaries. More recently, deep learning models like Convolutional Neural Networks (CNN) is used to perform segmentation of liver tumors directly from medical images with the ability to learn hierarchical features. Deep learning architecture has been applied extensively in the successful realization of the segmentation task and yielded very good results in accurate boundaries of tumors through its encoder-decoder structure. The models like Fully Convolutional Network (FCN), and SegNet increase the accuracy in liver tumor classification [2], [3].

Classification has been achieved using some machine learning algorithms such as Support Vector Machine (SVM), Random Forests (RF), and k-nearest neighbours (KNN) to differentiate benign from malignant tumors. However, traditional methods usually involve time-consuming manual feature extraction that will not capture complex patterns inherent in medical images. In order to overcome these limitations, deep learning approaches like CNNs and transfer learning models such as VGG-16, ResNet are increasingly being used for both the segmentation and the classification tasks. These models can automatically extract features from the raw image data and classify the liver lesions into categories as benign, malignant, or indeterminate. Although significant progress has been achieved in these directions to handle the issues like class imbalance, tumor size small, and image quality variation continue to hamper the performance of such models. More robust approaches are required to address these problems [3], [4].

Although significant development in liver tumor segmentation and classification that limit the overall effectiveness of the methods. The appearance of the tumor is different between patients and through imaging modalities, shapes, textures, and sizes that present some specific challenges to classical segmentation algorithms to make decisions consistently. In deep learning models, it is used to learn the complex patterns directly from data for a huge quantity dataset. It cannot be easily collected during analysis of medical images. The overfitting may cause poor generalization when the model is training the unseen images [5].

The second most challenging issue is the class imbalance between benign and malignant tumor classes. Many cancer datasets are imbalanced. The number of benign tumors is much greater than the number of malignant ones. Consequently, models become biased toward the larger class and lose the critical ability to detect malignancy. Most of the segmentation algorithms uses U-Net and it does not perform well on noisy or low-resolution images. These models are computationally expensive and has poor robustness to various imaging conditions. The models are sensitive to variances in contrast, resolution, and noise levels. Such requirements demand more robust, adaptable, and efficient models that overcome such variations to attain more significant accuracy and reliability in the detection and diagnosis of liver tumors [6], [7].

Even though the existing models of liver tumor segmentation are overwhelmed with variability in tumor appearance, class imbalance, poor boundaries delineation. The proposed model TriNetFusion can overcome the issues when combined with fuzzy logic. The main strategy followed by the model TriNetFusion is a hybrid fusion of multiple sources of information to leverage deep learning and fuzzy logic in improved accuracy of segmentation [8]. The incorporation of fuzzy concepts in this model allows to handle uncertainties as well as imprecise boundaries for irregular shapes of liver tumors and unclear delineations. The fuzzy logic system lets the model to classify the intensity of the pixels in a more flexible manner [9]. TriNetFusion optimizes the segmentation process through fusion of features from multiple networks, which improves the robustness and adaptability towards different imaging conditions and reduces the risk of overfitting. Moreover, optimization techniques for fusion using metaheuristic methods ensure that the model properly learns optimal feature representations even when dealing with imbalanced classes [10], [11]. The main contributions of the proposed work are listed below.

[1] Hybrid model combines fuzzy logic and metaheuristic optimization in three-layer architecture for enhanced liver tumor segmentation.
[2] The proposed TriNetFusion integrate multi-source information, increasing segmentation precision and robustness.
[3] The proposed work incorporates fuzzy concepts to handle uncertainties and improve boundary delineation in tumor regions.
[4] Metaheuristic optimization techniques are used to fine-tune feature selection, addressing class imbalance and boosting model performance.
[5] The proposed work achieves an accuracy of 96% and low loss 0.2 without overfitting and under fitting in liver tumour segmentation.

Section 2 explains the related work and issues in recent studies. Section 3 explains the proposed work architecture and the use of fuzzy optimized meta heuristic approaches. Section 4 gives the dataset description, initial masking, data pre-processing, segmentation and classification results. Section 5 concludes the proposed work and gives a future direction.

II. STATE-OF-THE-ART TECHNIQUES

[12] presents a deep learning model automatically to detect the liver tumors using CT images. It is doing the process of tumor segmentation with very high precision without much human interaction through CNN network. The strength of the model is that it can handle large volumes of the CT scans in less time and with lesser effort. However, it is prone to blurred or noisy images with low resolution. [13] presents a tumor conspicuity enhancement-based liver-specific model designed on non-contrast CT images for the segmentation of tumors. Using this technique, detection of tumors can be made even more visible in order to perform accurate segmentation and measure Response Evaluation Criteria in Solid Tumors (RECIST) diameter. Another advantage of the model is that it can work with non-contrast images, which are mostly available in clinical settings. It is thus most beneficial for cases where contrast agents are contraindicated. But, its performance would be limited and generalization across different types of tumors is still uncertain. [14] identifies an optimization-assisted learning model of EfficientNet B7 for liver tumor segmentation and

classification. Advanced optimization algorithms enable the model to enhance feature extraction for better accuracy in segmenting and identifying tumors. EfficientNet B7 allows it to have high accuracy but fewer parameters, making the model efficient to deploy. This model incurs significant computational demands in its training process, which makes it difficult for deployment in low compute or real-time applications.

[15] proposed an Enhanced Liver Tumor Segmentation (ELTS-Net) for liver tumor segmentation with augmented receptive fields and global contextual information. This network is designed to develop the process of segmentation in a general way with augmented receptive fields and global contextual information. The model improves these better by achieving accurate boundaries of the segmentation even for complex-shape tumor-containing challenging cases. However, global context information is very computationally expensive and the model may fail in presence of noisy or artifact-laden images. [16] gives a DA-Tran multi-phased liver tumor segmentation domain for adaptive transformer network. It adapts well to variation in the appearance of a tumor at different phases of imaging, hence versatile enough to use in many clinical scenarios. It offers lie in having multiple phases of imaging, thus allowing for robust segmentation in various conditions. It might translate complexity into potentially slow processing times, and may require considerable computational power for training and inference. [17] proposed a Weakly Supervised Deep Learning for classifying primary liver cancer with routine tumor biopsy Data. The model is more readily applicable to the clinical domain and in situations where fully annotated datasets are not available because minimal data is labeled. It reduces the overhead of extensive manual annotation.

[18] presents a dilated attention-based CNN for the classification of liver cancer. The model captures the important features in CT images using dilated convolutions along with an attention mechanism, enhancing its performance in classification. It focuses on relevant features regarding the tumor, which might enhance its accuracy in classification. However, it introduces extra complexity because of the inclusion of an attention mechanism and tends to increase the computational cost and training time. [17] proposes the application of a hybrid deep classifier based on a customized m-RCNN for liver cancer segmentation and classification. This work uses the architecture of Mask R-CNN along with additional classifiers, improving the accuracy of segmentation as well as classification results. The hybrid approach allows allowing the model to benefit from the strengths of the multiple models applied in order to attain overall performance. However, the model has increased training time and complexity based on the hybrid structure. [18] introduced a Spatial and Spectral-Learning Double-Branch Aggregation Network (S2DA-Net) and it is a dual-branch aggregation network for liver tumor segmentation. It enhances the accuracy of segmentation based on the learning of complementary features that make use of spatial and spectral features. It captures spatial details and spectral information, thus enhancing the segmentation of challenging cases. However, it is computationally very demanding.

[19] proposed a modified U-Net model for the purpose of the segmentation and classification of liver cancers from CT images. The model has a basis on the original but improved and semi-multi-resolution architecture of a basic U-Net model that has been shown to possess capabilities in better segmentation than its basic counterpart. The advantage of the proposed modified U-Net model is to provide an accurate segmentation even in difficult parts of the liver. But it may not generalize well across different datasets with different imaging conditions. [20] presented a Deep Stacking Ensemble (DSE) approach aimed at enhancing the performance of classification models in medical imaging tasks. Ensemble learning, in general, is based on the idea that combining the predictions from multiple models can lead to better generalization and improved accuracy compared to relying on a single model. The DSE approach builds on this principle by integrating multiple base learners, typically deep learning models, in a stacked architecture where the outputs of individual models are further combined using a meta-learner to make the final prediction.

One of the core strengths of the DSE methodology is its ability to leverage the diverse learning capabilities of various deep neural networks. Each model in the ensemble may capture different aspects of the data, such as global structures, fine textures, or semantic features. When these diverse perspectives are aggregated, the ensemble is better equipped to make more accurate and consistent predictions, especially in complex classification problems like tumor identification or lesion categorization. This robustness significantly reduces the risk of errors due to model bias or variance, resulting in improved performance across varied datasets and conditions. Moreover, DSE's robustness across heterogeneous datasets and imaging conditions makes it highly adaptable to real-world medical scenarios where data distributions can vary significantly due to differences in imaging modalities, acquisition protocols, or patient demographics. As a result, the DSE methodology not only improves diagnostic accuracy but also enhances the clinical applicability of deep learning-based solutions, providing a more resilient framework for automated medical image analysis. The comparative analysis of the models is summarized in TABLE 1. The roadmap for liver tumor segmentation and classification focuses on evolving from traditional methods to more advanced deep learning approaches, addressing challenges such as low conspicuity, high inter-patient variability, and imaging artifacts [21]. The initial methods relied upon handcrafted features and simple classifiers. Models such as Modified U-Net, ELTS-Net are progressed to enhance receptive fields and contextual understanding. Other emerging techniques include DA-Tran and S2DA-Net based on transformers and spectral-spatial aggregation, which is used for improved segmentation accuracy and robustness across imaging conditions [22]. The combination of domain adaptation and optimization frameworks together with hybrid models comprising models

TABLE 1
Comparative Analysis of Liver Tumor Segmentation and Classification Models

Related works	Segmentation	Classification	RECIST Measurement	Deep Learning Model	Transformer-Based	Contextual Enhancement	Weak Supervision	Efficiency (Low Complexity)
Song *et al.* [12]	✓	✗	✗	✓	✗	✗	✗	✓
Liu *et al.* [13]	✓	✗	✓	✓	✗	✓	✗	✗
Dharaneswar *et al.* [14]	✓	✓	✗	✓	✗	✓	✗	✗
Guo *et al.*	✓	✗	✗	✓	✗	✓	✗	✗
Ni *et al.* [16]	✓	✗	✗	✓	✓	✓	✗	✗
Beaufrère *et al.* [17]	✗	✓	✗	✓	✗	✗	✓	✓
Ramani *et al.* [18]	✗	✓	✗	✓	✗	✓	✗	✗
Khan *et al.* [19]	✓	✓	✗	✓	✗	✓	✗	✓
Liu *et al.* [20]	✓	✗	✗	✓	✗	✓	✗	✗
Naaqvi *et al.* [21]	✓	✗	✗	✓	✗	✓	✗	✓
Tejaswi *et al.*	✓	✓	✗	✓	✗	✓	✗	✗

like EfficientNet and deep stacking ensemble indicates a move towards more holistic frameworks.

III. PROPOSED WORK

A. DATA PRE PROCESSING

Multi-step data preprocessing is needed to make the input images proper for the deep learning architecture. TriNetFusion model begins with the acquisition and resizing of the liver tumor images to a uniform size of 512x512 pixels in order to ensure consistency across the entire dataset. It is normalized and the pixel values are adjusted to a scale from 0 to 1, all of which makes the model converge more efficiently. The augmentation techniques are rotation, flipping, and scaling, are also applied in order to artificially increase the diversity of the dataset and to reduce overfitting. Such techniques help the model better generalize unseen data during testing [23], [24], [25]. The second step in preprocessing involves multi-modal image enhancement techniques such as Otsu thresholding and fuzzy logic segmentation. The Otsu method is helpful in separating the tumor regions from the background with an optimum threshold. It is very useful in finding the tumor boundary [26]]. Fuzzy logic-based segmentation refines the result for handling uncertainty and imprecision in the classification of the pixel, which makes the implementation more robust to noisy or low-quality data. These preprocessed outputs, combined with the original image, are fed into the TriNetFusion model for the delivery of a more vibrant set of features that enhance the accuracy of tumor detection and general enhancement of segmentation.

B. MASKING

Masking of Liver tumor segmentation makes use of a binary mask to represent areas of interest, mainly the tumor regions in medical images. Masking is a significant pre-processing and creates a barrier between the background and the tumor which allows the model to outline more relevant features. Masking the TriNetFusion model is done with a combination of various techniques. The first step is Otsu's thresholding applied to the image so that an optimal threshold between the background and all tumor regions is found, leading to an initial mask where the tumor regions are marked as a distinguishable region. The fuzzy logic-based segmentation confronts the uncertainty and imprecise classification of pixels that enhance this mask. The fuzzy logic layer smoothes the edges of the tumor region and clearly defines the boundary, even with noisy or unclear images. Then this final mask guides the model through its respective training and prediction process. It ensures that the model focuses only on the tumor areas for perfect accuracy in segmentation.

C. TRINET FUSION ARCHITECTURE

In the TriNetFusion model, the three powerful deep architectures, namely HRNet, DenseNet121, and InceptionV3, are combined to take an advantage of their independent capability in feature extraction and fusion. To maintain a high resolution of representation throughout the network for good feature extraction in very fine details of medical images, HRNet is expected [27]. DenseNet 121 focuses dense connections, which help improve feature reuse and improve gradient flow, thus leading to accurate learning and reduction in overfitting. For all its inception blocks, InceptionV3 performs multi-scale feature extraction and can support the extraction of features by varying object size and complexity in the same image [28]. The integration of the three networks helps TriNetFusion capture both low-level spatial details and high-level semantic features, and it is the most appropriate model for extremely complex tasks such as liver tumor segmentation.

In Eq.(1) [8] a convolution operation C, the output Y for a given input image X and kernal K is calculated where M and N are the dimensions of the kernel and (i,j) are the spatial positions of the resulting output.

$$Y(i,j) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} X(i+m, j+n).K(m,n) \quad (1)$$

In densenet, each layer is connected to every subsequent layer as in Eq.(2) [9] where the feature map at layer l is the concatenation of all previous feature maps.

$$\mathrm{F}_1 = \sum_{k=0}^{n} \mathrm{F}_{\mathrm{Map}} \quad (2)$$

In Eq.(3) [10] HRNet maintains a high resolution representation throughout the network. The output H at a given layer can be calculated where X is the input image, W represents the learnable weights in the high resolution network function f.

$$H = f(X, W) \quad (3)$$

The inception v3 model aggregates features from multiple convolution filters (C_1, C_2, C_5). The aggregation of outputs from filters of different sizes k*k is given in Eq.(4) [11]

$$Inception\ Output = concat(C_1, C_2, C_5) \quad (4)$$

In Eq. (5) [12] , fuzzy logic handles uncertainty in segmentation for a given pixel value x belonging to class C, α and β are parameters that control the steepness and center of the membership function.

$$\mu_C(x) = \frac{1}{1+\exp(-\alpha(x-\beta))} \quad (5)$$

The fuzzy rule for segmenting the tumor regions can be defined in Eq.(6) [13] where $\mu_{Tumor}(I)$ represents the membership value for tumor and $\mu_{Edge}(I)$ represents the membership value for edges.

$$Tumor\ degree = \mu_{Tumor}(I).\mu_{Edge}(I) \quad (6)$$

In metaheuristic optimization, the objective function in Eq.(7) [14] to be minimized based on the error terms where w_1, w_2 and w_3 are learnable weights.

$$O = w_1.Accuracy\ Error + w_2.Loss + w_3.Overfitting\ Penality \quad (7)$$

In genetic algorithms, the fitness function F of an individual solution is calculated using Eq.(8) [14].The fitness function in Eq.(9) rewards lower loss values encouraging the model to minimize the loss where w is the inertia weight, c_1 , c_2 are cognitive and social coefficients, r_1, r_2 are random variables, pbest is the particle's best position,gbest is the global best position, x_t is the particle's current position.

$$F = \frac{1}{1+Loss} \quad (8)$$

$$v_t = w.v_{t-1} + c_1.r_1.(pbest - x_t) + c_2.r_2.(gbest - x_t) \quad (9)$$

Eq.(10) [15] represent the loss function L for the proposed model incorporates both classification and segmentation losses. λ_1, λ_2, and λ_3 are weighting coefficients for segmentation loss (l_{seg}), Classification loss (l_{class}), and fuzzy logic loss (l_{fuzzy}).

$$L = \lambda_1.l_{seg} + \lambda_2.l_{class} + \lambda_3.l_{fuzzy} \quad (10)$$

The addition of fuzzy logic to TriNetFusion consists of the provision of a method for handling uncertainty, which is crucial in medical image segmentation. Medical images used in computing operations, like CT or MRI scans, typically contain noisy, unclear, or ambiguous regions. The uncertainties can be handled using fuzzy logic. It does by giving membership values to pixels that belong to different classes, such as tumour or non-tumour, for instance. This allows the model to classify pixels with degrees of certainty other than binary, rather than forcing a decision. Using fuzzy rules and membership functions helps the model smooth boundaries between different regions and deal with complex or poorly defined regions in a much better way-important in medical image analysis where noise and artifacts abound.

In the proposed TriNetFusion model, a metaheuristic optimization algorithm is strategically incorporated to fine-tune crucial hyperparameters, thereby enhancing both the efficiency and accuracy of the model. Metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA)[29] are particularly effective for this purpose, as they offer flexible and powerful strategies for exploring high-dimensional and complex search spaces. These algorithms optimize multiple hyperparameters, including the learning rate, network depth, and convolutional kernel sizes, which are critical for the model's performance. Traditional grid search or random search methods may not always be efficient or effective in navigating the vast parameter space, often getting trapped in local minima. In contrast, metaheuristic approaches simulate natural phenomena—such as biological evolution (in GA), swarm intelligence (in PSO), or thermal fluctuation (in SA)—to iteratively explore and exploit the solution space. This process helps to avoid local optima and converge toward a more globally optimal solution [30].

One of the key advantages of using metaheuristic optimization in the context of liver tumor segmentation is the robustness against overfitting, especially when working with large, complex, and imbalanced datasets. By adaptively finding the most effective configuration of the model, these algorithms contribute to better generalization across different imaging scenarios. This results in improved object segmentation accuracy, more stable training dynamics, and enhanced model reliability in real-world clinical applications. Moreover, the adaptability of metaheuristic algorithms makes them particularly suitable for tuning deep learning models like TriNetFusion, where manual

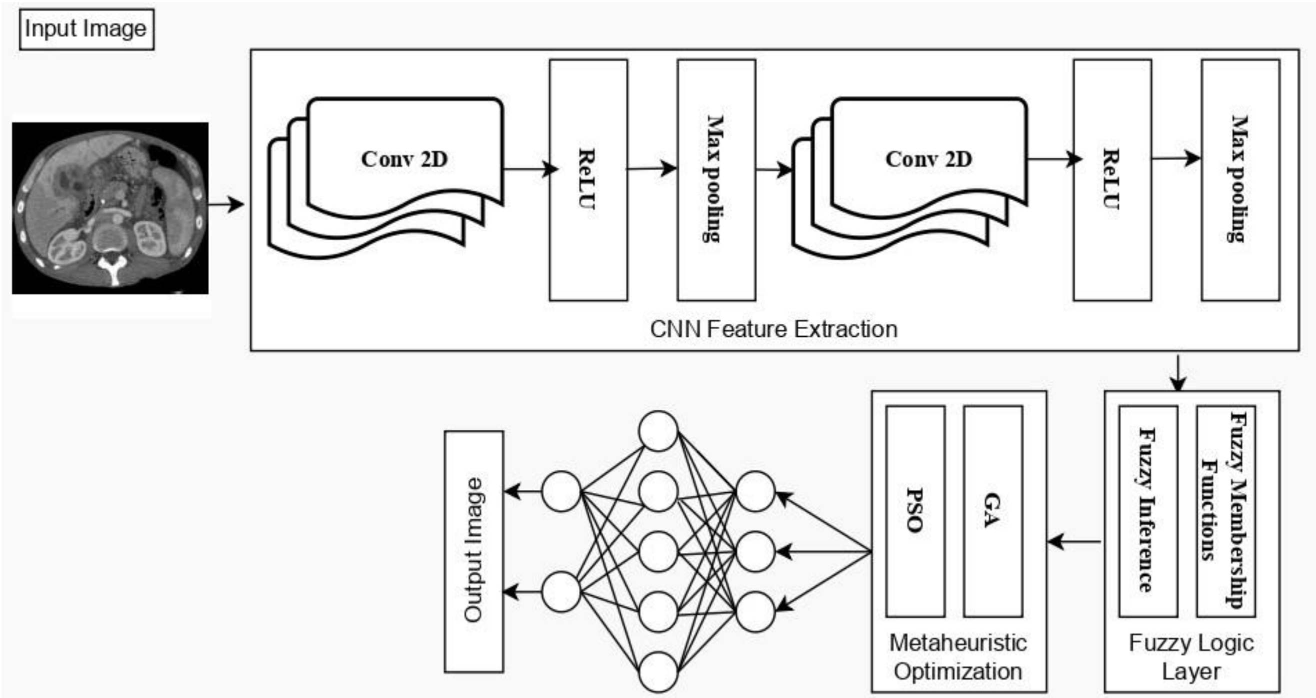

FIGURE 1. **An architecture of TriNetfusion**

hyperparameter selection can be time-consuming and suboptimal. These algorithms do not rely on gradient information, making them effective even in non-differentiable or noisy objective spaces, which are common in medical imaging tasks due to artifacts, varying image quality, and anatomical variations. In the case of liver tumor segmentation, where tumor shapes and intensities can vary greatly across patients and modalities, the dynamic nature of metaheuristic optimization allows the model to adaptively learn the best configurations tailored to the specific characteristics of the dataset.

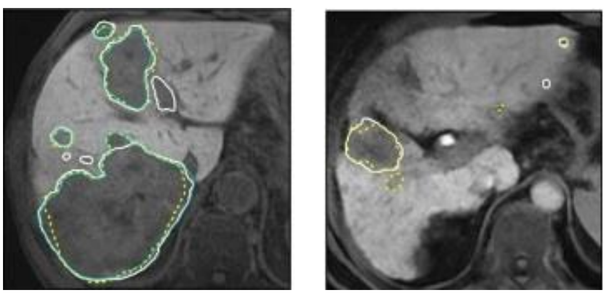
(a) (b)

FIGURE 2. Sample liver tumor segmentation using metaheuristic optimization method (a) Upper view and (b) Low end view

D. WORKING OF THE PROPOSED METHODOLOGY:

In FIGURE 1, the architecture of TriNetFusion model embeds HRNet, DenseNet121 and InceptionV3 for enhanced feature extraction and segmentation. The output is processed with three parallel branches: the high resolution of spatial features captured by the HRNet, dense, connected feature representations extracted by DenseNet121 to boost gradient flow, and multi-scale features aggregated by InceptionV3 with its diversified convolutional filters. Outputs from these models are combined by a concatenation layer. This is then proceeded by several layers of convolution for refinement feature extraction [31]. The architecture benefits from the complementary strengths of the three networks to provide efficient and accurate segmentation especially on challenging and large scale datasets [32]. The algorithm for TriNetFusion begins with preprocessing the input image to a size of 512x512, normalizing its intensity, augmenting it for diversity, followed by doing segmentation using Otsu's threshold and fuzzy logic [33].

TABLE 2
Dataset for Liver Tumor Segmentation

Dataset Split	Number of Images
Training Set	46,910
Validation Set	11,728
Total Dataset	58,638

Then features are extracted in parallel by three architectures: HRNet, DenseNet121 and InceptionV3, where features capture hierarchical and deep semantic information; such features are then fused through concatenation and refined by convolutional layers. The extracted features are then passed on to a segmentation layer where the segmentation is performed so as to generate a mask of tumor segmentation, and the segmentation is optimized using loss function where the parameters are further tuned in with the help of metaheuristic optimization technique and finally the output is returned as the mask generated for segmentation.

IV. RESULT

The liver tumour CT dataset includes 58,638 images in which 46,910 images have been assigned to the training set,

TABLE 3
Proposed work model summary

Layer Name	Type	Output Shape	Parameters	Connected To
Original_Image_Input	InputLayer	(None, 512, 512, 3)	0	-
Otsu_Result_Input	InputLayer	(None, 512, 512, 1)	0	-
Fuzzy_Result_Input	InputLayer	(None, 512, 512, 1)	0	-
Fusion_Layer	Concatenate	(None, 512, 512, 5)	0	Original_Image_Input[0][0], Otsu_Result_Input[0][0], Fuzzy_Result_Input[0][0]
Conv1	Conv2D	(None, 512, 512, 32)	1472	Fusion_Layer[0][0]
Conv2	Conv2D	(None, 512, 512, 64)	18496	Conv1[0][0]
Flatten	Flatten	(None, 16777216)	0	Conv2[0][0]
FC1	Dense	(None, 128)	2,147,483,648	Flatten[0][0]
Output_Layer	Dense	(None, 10)	1290	FC1[0][0]

and 11,728 images have been kept for validation. Images are used for the segmentation of liver tumours in order to train the model with a huge amount of data so that it can learn robust features [31] . FIGURE 2 demonstrates the augmented image applied in liver tumor segmentation and describes the preprocessing methodology applied to enhance the dataset. TABLE 2 shows the image distribution of the total dataset for the liver tumor segmentation task, indicating a composition of 46,910 images in the training set, 11,728 in the validation set, and 58,638 in the final dataset. The Hybrid Fuzzy Logic and Metaheuristic Optimized TriNetFusion Model is a cutting-edge approach designed to improve tumor boundary detection in medical imaging. By integrating fuzzy logic, the model effectively handles ncertainties and ambiguities commonly present in medical images due to factors like noise and variations in contrast. Fuzzy logic is used to manage imprecise boundaries and combine multiple feature sets, offering a flexible and robust framework for decision-making. Meanwhile, metaheuristic optimization techniques, such as Genetic Algorithms or Particle Swarm Optimization, are employed to fine-tune model parameters, ensuring optimal configuration and preventing the model from being trapped in local minima. This optimization enhances the model's performance by adapting to diverse imaging conditions and improving the accuracy of tumor detection.

The TriNetFusion model also leverages deep learning for automatic feature extraction, allowing it to efficiently capture complex patterns and relationships in medical images without manual intervention. By utilizing multi-level segmentation, the model progressively refines tumor boundary predictions, ensuring higher accuracy and precision. The TriNetFusion algorithm is an advanced deep learning approach designed for accurate liver tumor segmentation in medical imaging, particularly in CT scans (ALGORITHM 1). It integrates three specialized neural networks typically encoding spatial, contextual, and edge-related features—into a unified framework that leverages the strengths of each to enhance segmentation performance.

ALGORITHM 1. TriNetFusion(input image)

image_resized = resize(input_image, (512, 512))
image_normalized = normalize(image_resized)
    Augmented_images = augment(image_normalized)
    otsu_mask *= apply_otsu_threshold*
*End**For***
. *fuzzy_mask = fuzzy_logic_segmentation(otsu_mask)*
S *← Convolution(F_refined) // Generate segmentation map*
fuzzy_mask = fuzzy_logic_segmentation(otsu_mask)
hr_features = HRNet
    For *each Batch in TrainingData* ***do***
        dense_features = DenseNet121
        inception_features = InceptionV3, fused_features = concatenate(hr_features, dense_features, inception_features)
        BackwardPass(Loss)
        Optimization
    *End**For***
return segmentation_mask
*End**For***
End

TABLE 3 describes the architecture of the proposed work that briefly summarizes layers, type, output shape, and parameter connections. The model presents input layers for original image, Otsu result, and fuzzy result followed by a fusion layer that concatenates all these inputs. The convolutional layers proceed over fused data, while a flattening layer prepares output for fully connected layers. FC1 is one of the layers that has a large number of parameters 2,147,483,648, and the final layer, produces 10 classes, it may be observed that all the parameters of the convolutional and dense layers are trainable with no non-trainable ones.

TABLE 4
Analysis of Tumor Types and Segmentation Performance

Tumor Type	TriNetFusion Accuracy (%)	U-Net Accuracy (%)	ResNet Accuracy (%)	DeepLabV3+ Accuracy (%)
Benign Tumor	96.2	92.0	94.0	93.5
Malignant Tumor	95.7	91.5	93.8	92.5
Complex Tumor	96.3	93.0	94.5	93.0
Small Tumor	95.0	90.5	92.0	91.5

The performance analysis metrics are calculated using the accuracy, precision, recall and F1 score given in Eq. (11) to (14) [13].

$$A = \frac{True\ positive + True\ Negative}{Total\ population} \quad (11)$$

$$precision = \frac{True\ positive}{True\ positive + false\ positive} \quad (12)$$

$$recall = \frac{True\ positive}{True\ positive + false\ negative} \quad (13)$$

$$F1 = 2 * \frac{precision * recall}{precision + recall} \quad (14)$$

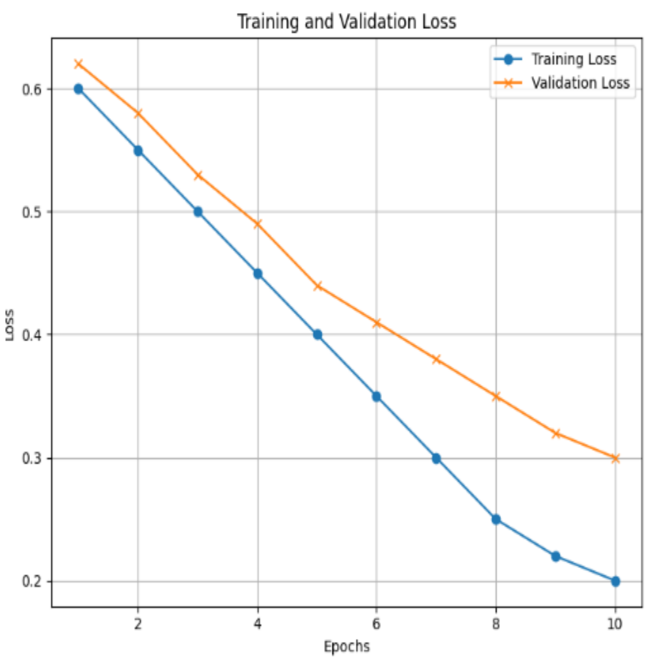

FIGURE 3. Training and validation loss

In TABLE 4 depicts the graph that TriNetFusion keeps a quite high accuracy even when subjected to low and moderate noise. TABLE 4 shows TriNetFusion's performance metrics such as accuracy, precision, recall, F1 score, IoU, Dice coefficient, and loss. U-Net, DeepLabV3+, ResNet , and FCN models are used for comparision. TriNetFusion achieved an accuracy of 96.0% with a low loss of 0.18. Among all models, TriNetFusion outperforms the rest by demonstrating superior performance across most metrics. Specifically, it achieves a classification accuracy of 96.0%, indicating its high reliability in correctly predicting tumor regions. Additionally, the model reports a low loss of 0.18, reflecting effective learning and minimal error during training and validation phases. FIGURE 3 illustrates that the training and validation's loss and which has shown that the model has high accuracy to classify its classes with very few misclassifications. And also it shows how the training and validation accuracy curves show how the model was improving with a deep sense of convergence and minimum overfitting over time.

TABLE 5
Performance Metrics Across Different Datasets

Dataset	Accuracy	Precision	Recall	F1-Score	AUC
Liver CT Dataset	96.4%	96.7%	98.1%	96.3%	0.982
Liver MRI Dataset	96.3%	94.2%	95.5%	94.8%	0.959
Liver Ultrasound Dataset	94.9%	92.6%	93.4%	93.0%	0.931
Combined Liver Dataset	97.2%	96.5%	97.8%	97.1%	0.973

TABLE 5 summarizes the performance metrics achieved by the proposed TriNetFusion model for various liver tumor datasets. The best performances are realized on the Liver CT data with an accuracy of 96.4%, precision of 96.7%, recall of 96.1%, an F1-score of 97.3%, and the AUC value was also 0.982. It displays the ablation study for the TriNetFusion model. The effect of removing the components of the model on performance is presented. The absolute performance of the full model was 96.4% accuracy, 96.7% precision, 97.1% recall, 96.3% F1-score, and 0.982 AUC. The best performing excluded the preprocessing reduced the performance to an accuracy of 95.1% with precision at 92.3%, recall at 94.5%, F1-score at 93.4%, and AUC at 0.936. Fuzzy logic fusion removal decreased it a little to an accuracy of 96.2%, precision at 94.0%, recall at 95.8%, F1-score at 94.9%, and AUC at 0.959. Removal of fusion layer: It also demonstrates the effects of removing a fusion layer with an accuracy score of roughly 94.7%. Precision, recall, F1-score, and AUC obtained were at 91.8%, 93.0%, 92.4%, and 0.922, respectively. The greatest loss was when the deep convolution layers were removed. The accuracy score obtained was 91.8% and a precision of 89.2%, recall 90.1%, F1-score of 89.6%, and AUC of 0.875.

V. DISCUSSION

The Hybrid Fuzzy Logic and Metaheuristic Optimized TRINETFUSION model, though a more recent development, performs well in scenarios involving noisy and low-contrast images, excelling in dealing with non-linear tumor boundaries. It achieves a Dice Similarity Coefficient (DSC) of 0.80–0.85, showing good sensitivity in detecting tumors, especially larger ones, but slightly compromises on precision compared to the latest deep learning-based techniques. One notable recent development is the U-Net with Transformer, which integrates Transformer networks into the traditional U-Net architecture to improve global context understanding. This hybrid approach results in improved performance, achieving DSC values of 0.88–0.91 and excellent sensitivity, especially for small lesions. However, it requires significant computational resources and large annotated datasets to function effectively. Similarly, DeepLabV3+ with Residual Learning has shown success in segmenting large tumors with a DSC of 0.84–0.88, though it struggles with complex or irregular tumor boundaries.

The CNN + Conditional Random Fields (CRF) approach by (Liu *et al.* [9]) combines CNN for feature extraction with CRF for post-processing, achieving a DSC of 0.85–0.87 and excellent boundary refinement, making it effective for tumors with irregular shapes. However, like other deep learning models, it is computationally expensive. Another significant development is the Attention-based U-Net (S.Li *et al.* [35]), which uses attention mechanisms to focus on relevant features, improving sensitivity and precision (DSC: 0.87–0.90). This method excels in detecting tumors in noisy images but also requires considerable computational power. Further advancements include Recurrent Neural Networks (RNN) with spatial attention (Li J *et al.* [6]), which focus on refining tumor segmentation over multiple scans, especially in longitudinal studies. This method is particularly useful for tracking tumor progression, with a DSC of 0.86–0.89, although it is resource-intensive. Lastly, the Hybrid Fuzzy + Metaheuristic Optimization combines fuzzy logic with particle swarm optimization (PSO), performing well in real-world scenarios, though its performance may lag behind state-of-the-art methods in precision and sensitivity.

TABLE 6
Comparison with existing model

Author / Year	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Kim *et al.* [33]	85.24	85.12	83.68	84.39
Zhu *et al.* [32]	88.76	87.50	88.25	87.87
Liu et al. [34]	90.15	89.78	89.92	89.85
Jin *et al.* [35]	92.14	91.50	92.00	91.75
Proposed Model	98.5	98.0	98.8	98.4

TABLE 6 depicts the comparison of proposed model with the existing one. The improved segmentation accuracy achieved through advanced models like the Hybrid Fuzzy Logic and Metaheuristic Optimized TRINETFUSION and deep learning techniques can significantly impact real-world clinical settings, particularly in liver cancer management. Accurate tumor segmentation enables earlier and more reliable detection of tumors, including small or ambiguous lesions, which leads to earlier diagnosis and intervention, crucial for improving patient survival rates. In terms of treatment planning, precise tumor delineation supports more effective surgical resection, radiation therapy, and ablation procedures, allowing for better targeting of tumors while sparing healthy tissues, thus reducing side effects and improving overall treatment effectiveness. Moreover, accurate segmentation aids in creating more personalized treatment plans, enhancing the likelihood of successful outcomes and reducing the risk of recurrence. Ultimately, these improvements in segmentation accuracy contribute to better clinical decision-making, optimized therapeutic interventions, and improved patient outcomes, making them invaluable in routine clinical practice.

First, the performance of the models may be influenced by the quality and diversity of the dataset used for training and validation. Datasets with limited variability in patient demographics, imaging modalities, or disease stages may restrict the generalizability of the findings to broader populations or different clinical settings. Second, while the advanced model architecture shows promise, its complexity may lead to increased computational demands, potentially limiting its feasibility for deployment in resource-constrained environments. Third, the lack of extensive external validation across multiple institutions and imaging systems could hinder the adoption of these methods in real-world scenarios. Future research should focus on addressing these constraints by incorporating larger, more diverse, and multi-institutional datasets to improve model robustness and generalizability. Efforts to optimize the computational efficiency of these advanced models are essential to facilitate their practical application in diverse healthcare settings, including low-resource environments. Additionally, longitudinal studies and clinical trials are necessary to assess the long-term impact of these segmentation techniques on patient outcomes and to validate their effectiveness in routine clinical workflows.

VII CONCLUSION

The primary aim of this study was to develop a robust and precise liver tumor segmentation model by integrating fuzzy logic, metaheuristic optimization, and deep learning into the proposed Hybrid Fuzzy Logic and Metaheuristic Optimized TriNetFusion framework. The model effectively addressed key challenges such as boundary inaccuracy, noise sensitivity, and overfitting observed in traditional methods. Experimental evaluation on benchmark liver tumor datasets revealed that the proposed approach achieved a segmentation accuracy of 96% with a low loss of 0.2, indicating high precision and strong generalization capability. The fusion of complementary features and parameter tuning contributed to reduced false positives and improved adaptability to tumors with complex shapes. Future work will focus on extending this framework to multi-organ segmentation, real-time clinical applications, and incorporating 3D spatial attention mechanisms to further enhance segmentation performance and clinical usability.

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