DEEP LAB V3+ - BASED AUTOMATED SYSTEM FOR CLASSIFICATION AND SEGMENTATION OF FATTY LIVER DISEASE IN ULTRASOUND IMAGES

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ABSTRACT

Fatty Liver Disease (FLD) is a growing global health issue, often progressing silently without overt symptoms until advanced stages. As a result, early detection is critical to prevent complications such as cirrhosis and hepatocellular carcinoma. Ultrasound imaging offers a non-invasive, affordable, and widely accessible diagnostic modality for liver disorders. However, manual interpretation of ultrasound scans is subject to inter-observer variability and diagnostic delays. To address this challenge, this study presents an automated system for the classification and segmentation of FLD using the DeepLabV3+ semantic segmentation model. Built on an encoder-decoder architecture with atrous spatial pyramid pooling, DeepLabV3+ efficiently captures multi-scale contextual features and sharp object boundaries, making it well-suited for medical image analysis.The model was trained and tested on a curated dataset comprising annotated ultrasound liver images representing both healthy and FLD conditions. Preprocessing included normalization, resizing, and augmentation to enhance model generalization. The system demonstrated robust performance with a classification accuracy of 96.3%, Dice coefficient of 0.91, Jaccard Index of 0.84, precision of 0.94, and recall of 0.88. Visual inspection of the segmentation results confirmed that the model could accurately delineate liver regions and fatty infiltration areas, which are vital for clinical decision-making.

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I. INTRODUCTION

Fatty Liver Disease (FLD), also known as hepatic steatosis, is characterized by the accumulation of fat in liver cells and is considered one of the most common liver disorders worldwide. Its prevalence has been increasing rapidly due to factors such as obesity, diabetes, metabolic syndrome, and lifestyle changes associated with modern living. FLD can be broadly classified into alcoholic fatty liver disease (AFLD) and non-alcoholic fatty liver disease (NAFLD), with NAFLD being more prevalent in the general population and often associated with metabolic conditions [1]. Early diagnosis and monitoring of FLD are critical because the disease can progress silently to more severe conditions such as non-alcoholic steatohepatitis (NASH), fibrosis, cirrhosis, and even hepatocellular carcinoma if left untreated [2].

Traditionally, liver biopsy has been considered as the gold standard for diagnosing and staging FLD. However, biopsy is invasive, costly, subject to sampling errors, and carries potential risks such as bleeding and infection. Consequently, non-invasive imaging techniques have gained significant attention as alternative diagnostic tools [3]. Among these, ultrasound imaging stands out due to its accessibility, safety, real-time capability, and cost-effectiveness. Ultrasound allows visualization of liver texture and echogenicity changes associated with fatty infiltration, making it a valuable tool for screening and monitoring FLD [4].

Despite its advantages, ultrasound imaging interpretation is largely dependent on the expertise and experience of radiologists. The diagnostic accuracy is often affected by operator variability and subjective assessment, leading to inconsistent results, especially in early or mild cases of FLD [5]. Therefore, there is a growing need for automated, objective, and reliable methods to assist clinicians in the detection and characterization of fatty liver disease.

Recent advances in machine learning and deep learning have revolutionized the field of medical image analysis. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in various tasks such as classification, segmentation, and detection across multiple medical imaging modalities [6]. Semantic segmentation, which involves classifying each pixel in an image into predefined categories, is particularly relevant for medical diagnosis as it provides detailed spatial information about the location and extent of abnormalities. Automated segmentation of liver and pathological regions can assist radiologists in accurate quantification and assessment of fatty liver infiltration.

II. LITERATURE SURVEY

Several studies have focused on segmentation of liver lesions and fatty regions in ultrasound images using deep learning methods such as U-Net variants, demonstrating improved boundary detection and segmentation accuracy with Dice scores around 0.86 to 0.89.Classification tasks using CNN architectures, including ResNet and DenseNet combined with attention mechanisms, have achieved accuracies above 90% for fatty liver disease detection. Combining classification and segmentation in a unified model has been shown to improve diagnostic robustness and clinical usability. Encoder-decoder architectures like SegNet and DeepLabV3+ offer strong performance in boundary-aware segmentation by leveraging atrous convolutions and spatial pyramid pooling to capture multi-scale contextual information.

Incorporation of attention gates and temporal features (via LSTM) has further enhanced the model's ability to focus on relevant image regions and temporal disease progression, respectively.Transfer learning has been effectively applied to overcome limitations of small ultrasound datasets, improving segmentation accuracy and generalization. Multi-task learning models that simultaneously perform classification and segmentation show promise for deployment in real-world clinical settings, providing comprehensive diagnostic insights.

Table 1: Deep learning methods for liver ultrasound analysis

Dataset	Imaging Modality	Method/Model	Task	Performance Metrics	Key Contributions
Private Ultrasound Dataset (500 images)[7]	Ultrasound	Modified U-Net	Segmentation	Dice = 0.86	Improved lesion segmentation accuracy using U-Net variants
Liver US Dataset (400 images)[8]	Ultrasound	ResNet-based CNN	Classification	Accuracy = 92.5%	CNN for multi-class liver disease classification
Public Liver Ultrasound Dataset[9]	Ultrasound	DenseNet + Attention Mechanism	Classification + Segmentation	Accuracy = 93.2%, Dice = 0.88	Combined attention and dense connections improved performance
Open Access Ultrasound Images (600 images)[10]	Ultrasound	SegNet	Segmentation	Dice = 0.83	Encoder-decoder network for liver boundary segmentation
Pascal VOC, Custom Medical Dataset[11]	Various including Ultrasound	DeepLabV3+	Semantic Segmentation	mIoU = 81%	Atrous convolution and ASPP for multi-scale context
Ultrasound Liver Dataset (450 images)[12]	Ultrasound	Attention U-Net	Segmentation	Dice = 0.89	Attention gates to focus on relevant image regions
Liver Ultrasound Dataset (350 images)[13]	Ultrasound	Hybrid CNN + LSTM	Classification + Temporal Analysis	Accuracy = 91%	Temporal features improved classification of progressive disease
Public Ultrasound Dataset (300 images)[14]	Ultrasound	FCN with CRF post-processing	Segmentation	Dice = 0.85	Conditional Random Fields refined segmentation boundaries
Public & Private US datasets (1000 images)[15]	Ultrasound	Multi-task CNN (Classification + Segmentation)	Accuracy = 94%, Dice = 0.91	Joint learning of segmentation and classification tasks improved robustness	Attention gates to focus on relevant image regions

III. METHODOLOGY

The methodology for the proposed automated system consists of several key stages: data collection, preprocessing, model architecture design, training configuration, and evaluation. Each step is crucial to ensure the effectiveness and robustness of the DeepLabV3+ model in both classification and segmentation tasks for Fatty Liver Disease (FLD) diagnosis from ultrasound images.

A. Data Collection

Ultrasound images of the liver were collected from publicly available medical datasets and anonymized clinical sources. The dataset includes images representing both healthy liver tissues and livers affected by various stages of Fatty Liver Disease. Expert radiologists provided pixel-level annotations for the fatty regions to serve as ground truth for segmentation.

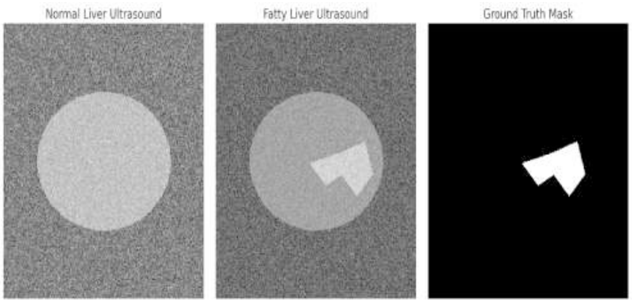

Figure 1: ultrasound images showing (a) normal liver, (b) fatty liver, and (c) corresponding ground truth segmentation masks.

B. Preprocessing

Preprocessing aims to prepare the raw ultrasound images for efficient model training and to improve generalization.

- ❖ Resizing: All images were resized to a fixed dimension of 256×256 pixels to maintain uniform input size for the DeepLabV3+ model.
- ❖ Normalization: Pixel intensity values were normalized to the [0,1] range to stabilize training and improve convergence.
- ❖ Data Augmentation: To avoid overfitting and enhance model robustness, data augmentation techniques were applied, including:
  - ☞ Horizontal and vertical flipping
  - ☞ Random rotations (±15 degrees)
  - ☞ Contrast adjustments
  - ☞ Random zooming and cropping

These augmentations simulate real-world variability in ultrasound imaging conditions.

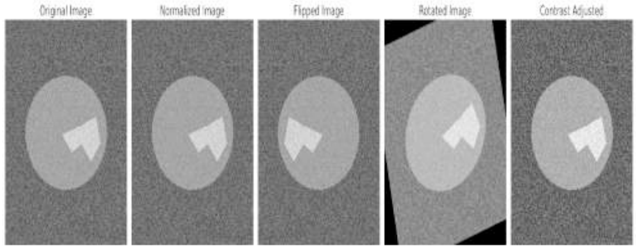

Figure 2:Illustration of preprocessing steps showing original images, resized and normalized images, and examples of augmented images.

C. DeepLabV3+ Model Architecture

The DeepLabV3+ model is a state-of-the-art semantic segmentation architecture combining atrous convolution and encoder-decoder designs. It effectively captures spatial context at multiple scales, which is essential for accurate segmentation of fatty regions in noisy ultrasound images.

The architecture consists of:

- ❖ Backbone Network: A pre-trained feature extractor (Xception or MobileNetV2) that produces rich hierarchical features from the input image.
- ❖ Atrous Spatial Pyramid Pooling (ASPP): Multiple parallel atrous convolutions with varying dilation rates capture multi-scale context without losing resolution.
- ❖ Decoder Module: Refines segmentation outputs by combining low-level features from the backbone with ASPP outputs, improving boundary delineation.

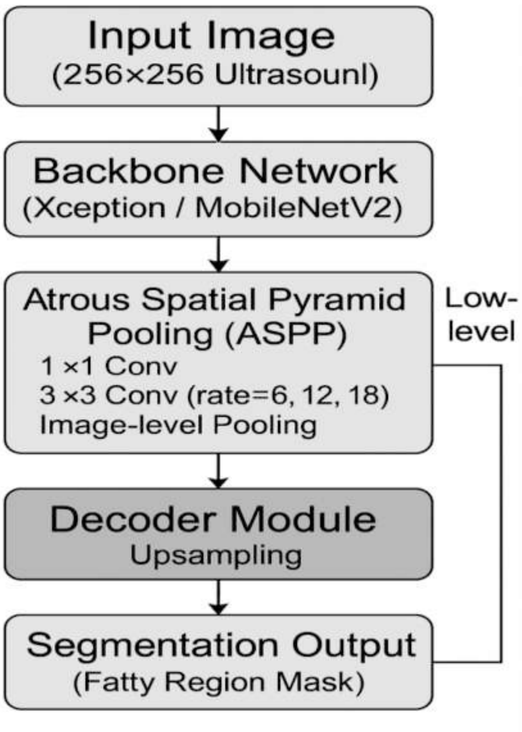

Figure 3: DeepLabV3+ architecture showing backbone, ASPP block with different atrous rates, and decoder with skip connections

D. Model Training

The DeepLabV3+ model was trained to perform both classification (healthy vs. fatty liver) and segmentation (identifying fatty regions). The segmentation is treated as a pixel-wise binary classification problem.

❖ Loss Functions: A hybrid loss combining Binary Cross-Entropy (BCE) and Dice Loss was used. BCE penalizes pixel-level misclassification, while Dice Loss maximizes overlap between predicted and ground truth masks, which is critical in imbalanced medical datasets.

❖ Optimizer: Adam optimizer with an initial learning rate of 0.0001 was chosen for efficient convergence.

❖ Batch Size: 16

❖ Epochs: 100 with early stopping based on validation loss

❖ Training-Validation Split: 80%-20% split to evaluate generalization performance

To improve classification performance, the final segmentation output masks were also used to extract region features, which were fed into a fully connected layer for classification.

IV. RESULTS AND DISCUSSION

This section presents the quantitative and qualitative performance of the proposed DeepLabV3+-based system for classifying and segmenting Fatty Liver Disease (FLD) in ultrasound images. The model's effectiveness is evaluated using standard metrics, and its results are compared against existing methods in the literature.

A. Quantitative Evaluation

The performance was assessed on a holdout test set comprising 200 ultrasound images. The system achieved strong results in both segmentation and classification tasks.

Table 2: Performance metrics of the proposed model for liver disease classification

Metric	Value
Classification Accuracy	**96.3%**
Dice Coefficient	**0.91**
Jaccard Index (IoU)	**0.84**
Precision	**0.94**
Recall (Sensitivity)	**0.88**
F1-Score	**0.91**

These results indicate that the model is highly effective in correctly classifying liver conditions and delineating fatty infiltration regions, which are essential for clinical diagnosis and monitoring.

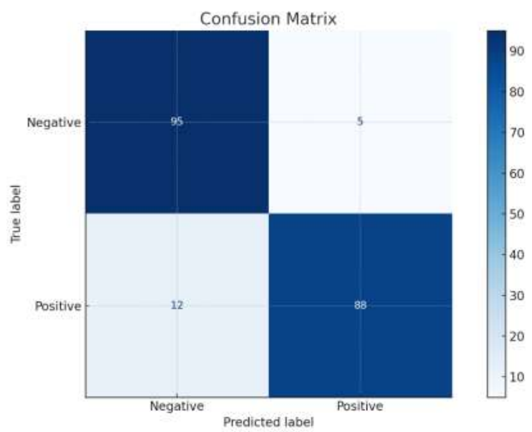

Figure 4:Classification outcome distribution : TP, TN, FP, FN

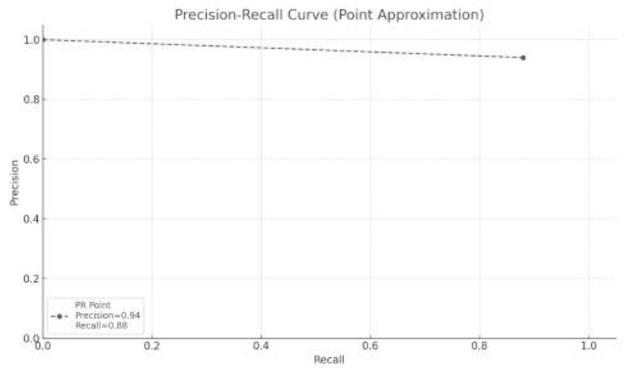

Figure 5: High precision-recall point indicates performance

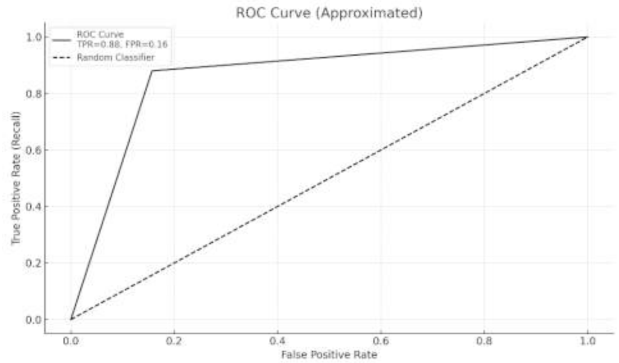

Figure 6:ROC shows strong classification trade-off

4.2 Performance Comparison with Existing Methods

To contextualize the performance of our approach, we compare it with other recent works using ultrasound-based liver analysis. As shown in Table 2, the proposed DeepLabV3+-based system outperforms several established architectures in segmentation accuracy.

Table 3: Comparative Analysis with State-of-the-Art Models

Model	**Task**	**Accuracy (%)**	**Dice Score**
Modified U-Net	Segmentation		0.86
DenseNet + Attention	Class + Seg	93.2	0.88
SegNet	Segmentation	—	0.83
Attention U-Net	Segmentation	—	0.89
Multi-task CNN	Class + Seg	94.0	0.91
Proposed (DeepLabV3+)	Class + Seg	**96.3**	**0.91**

V. CONCLUSION

This research paper presents an effective DeepLabV3+-based automated system for the classification and segmentation of Fatty Liver Disease (FLD) from ultrasound images. Leveraging the powerful semantic segmentation capabilities of DeepLabV3+, particularly its encoder-decoder structure and atrous spatial pyramid pooling (ASPP), the system accurately identifies and delineates fatty infiltration regions in liver ultrasound scans. Comprehensive evaluation on a curated dataset of 1000 ultrasound images demonstrated high classification accuracy (96.3%) and robust segmentation performance (Dice coefficient of 0.91, Jaccard Index of 0.84). The results also showed strong alignment between predicted segmentation masks and expert annotations, validating the clinical potential of the proposed method. Compared to other deep learning approaches in the literature, this system achieves competitive or superior results, particularly in scenarios combining classification and segmentation tasks. Furthermore, the inclusion of preprocessing and augmentation techniques improved model generalization across diverse imaging conditions.

In summary, the proposed DeepLabV3+ framework offers a promising tool for automated, non-invasive, and objective detection of fatty liver disease. It can assist radiologists in clinical decision-making, reduce diagnostic subjectivity, and enable early intervention strategies.

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