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LIVER STEATOSIS SEGMENTATION USING DEEP LEARNING

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ABSTRACT
Liver steatosis, or fatty liver disease, is a rapidly growing global health issue caused by excessive fat accumulation within liver tissues, which can progress to severe conditions such as fibrosis, cirrhosis, or liver cancer if not detected early. Although medical imaging modalities such as ultrasound, MRI, and CT scans are widely used for diagnosis, manual interpretation is time-consuming, subjective, and prone to inter-observer variability. To overcome these challenges, this study proposes an automated and objective diagnostic system that accurately identifies and segments fatty liver regions at the pixel level.
The system utilizes advanced deep learning models—primarily U-Net for segmentation and Region-Based Convolutional Neural Networks (R-CNN) for enhanced feature extraction and localization—to detect fatty tissue boundaries with high precision. Additionally, a classification module is integrated to distinguish between healthy liver scans and those affected by steatosis, offering a consistent and reliable diagnostic pathway. The methodology involves training the model on two distinct datasets: baseline scans from healthy human livers and medical images from diagnosed patients. The healthy liver dataset helps the model learn standard structural and textural patterns, forming a reference for normal anatomy. When patient scans are uploaded, the system compares them against these learned healthy patterns, allowing accurate differentiation and grading of fatty infiltration.
This integrated approach ensures faster processing, improved diagnostic accuracy, and objective measurement by eliminating manual guesswork. By combining U-Net-based segmentation, R-CNN-driven feature analysis, and a classification algorithm, the proposed system provides an efficient, automated, and highly reliable tool for early detection and assessment of liver steatosis, ultimately supporting clinicians and improving patient outcomes.

INTRODUCTION
Fatty liver disease has emerged as a major global health concern, primarily driven by lifestyle changes, obesity, and metabolic disorders. The condition develops when excess fat accumulates in liver tissues, and if not detected early, it can progress to severe stages such as fibrosis, cirrhosis, or even liver cancer. Early identification is critical, yet current diagnostic practices rely heavily on visual inspection of medical images such as ultrasound, MRI, and CT scans. This manual interpretation is time-consuming and often subjective, leaving room for inconsistencies between clinicians. As a result, two experts reviewing the same scan may draw different conclusions, which can delay appropriate treatment and reduce diagnostic reliability . These challenges highlight the urgent need for automated, accurate, and objective tools that can assist in the early detection and evaluation of liver steatosis.
To address these limitations, the proposed system introduces an advanced deep learning–based framework capable of automatically detecting and segmenting fatty liver regions with high precision. The system integrates U-Net for pixel-level segmentation and Region-Based Convolutional Neural Networks (R-CNN) for robust feature extraction and localization of affected regions. Additionally, a classification algorithm is incorporated to differentiate healthy liver scans from those exhibiting steatosis. This method is trained using two complementary datasets: baseline scans of healthy human livers and medical images from diagnosed patients. By learning the structural characteristics of normal liver tissues, the model establishes a strong reference for comparison, enabling more accurate grading of fatty infiltration when patient scans are analyzed.

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By combining segmentation, feature extraction, and classification into a unified pipeline, the system significantly enhances diagnostic speed, reduces human error, and provides consistent results. This automated approach ultimately supports clinicians in making faster and more reliable decisions, contributing to improved disease management and better patient outcomes.

The main contributions of this research can be summarized as follows:

1) **Unified Deep Learning Framework** an end-to-end automated system integrating segmentation, feature extraction, and classification for liver steatosis detection on manual diagnosis.
2) **Accurate Segmentation and Feature Learning** Combination of U-Net for precise pixel-level segmentation and R-CNN for robust feature extraction and localization of fatty regions.
3) **Fast, Consistent, and Clinically Relevant Diagnosis** Provides objective, reproducible, and rapid predictions, supporting early detection and effective clinical decision-making.

RELATED WORK

Early automated methods focused on classical image processing techniques such as thresholding, edge detection, and region-based segmentation. However, these approaches were highly sensitive to noise, intensity variations, and complex anatomical structures, limiting their reliability in clinical applications. Subsequently, machine learning methods such as Support Vector Machines (SVM) and Random Forests were introduced, which utilized handcrafted features for classification. Despite moderate success, these methods lacked robustness and generalization capability across diverse datasets.

With the advancement of deep learning, convolutional neural networks (CNNs) have significantly improved performance in medical image analysis. Architectures such as U-Net and its variants have become widely adopted for liver segmentation tasks due to their encoder–decoder structure and skip connections, which preserve spatial information and enable precise localization of liver regions [1]. Several studies have demonstrated that U-Net–based models achieve high accuracy in segmenting liver tissues from CT and MRI images, even in the presence of low contrast and structural variability.

Region-based deep learning models have also been explored for steatosis detection. For instance, Mask R-CNN, an extension of Faster R-CNN, has been successfully applied for segmenting steatosis regions in histopathological images, achieving promising performance in terms of precision and recall [2]. These models enhance localization by combining region proposal mechanisms with deep feature extraction, making them suitable for detecting complex and clustered fatty regions.

Recent studies have further emphasized the role of deep learning in quantitative assessment and staging of liver steatosis. A number of works have reported that CNN-based models significantly improve the accuracy and reproducibility of steatosis quantification, particularly in MRI and ultrasound imaging [3]. These approaches have demonstrated superior performance compared to traditional non-invasive diagnostic techniques.

Despite these advancements, most existing research focuses either on segmentation or classification as independent tasks. Limited work has been done on integrating segmentation, feature extraction, and classification into a unified framework [4]. Furthermore, many models rely on single-type datasets, which restricts their ability to generalize across different patient populations and imaging modalities.

PROBLEM STATEMENT

Liver steatosis diagnosis using medical imaging remains highly dependent on manual interpretation, resulting in subjectivity, inter-observer variability, and increased diagnostic time. Existing approaches based on traditional image processing and classical machine learning techniques lack robustness and fail to generalize across diverse imaging conditions and patient variations. Moreover, current systems do not provide accurate pixel-level segmentation and quantitative assessment required for reliable disease grading.

Therefore, there is a need to develop an automated and scalable system capable of accurately detecting, segmenting, and classifying liver steatosis from medical images. The proposed solution aims to address these challenges by leveraging deep learning techniques to achieve improved accuracy, consistency, and efficiency in clinical diagnosis.

PROPOSED SYSTEM

The primary problem in liver steatosis diagnosis is the heavy dependence on manual examination of ultrasound, MRI, and CT images, which leads to inconsistent, slow, and subjective results. To overcome these limitations, the proposed system introduces a fully automated deep learning–based framework designed to accurately detect,

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segment, and classify fatty liver conditions. The system is built using two advanced models: U-Net for precise pixellevel segmentation of fatty regions and R-CNN for extracting deeper structural features and localizing abnormal tissue patterns. In addition, a classification algorithm is applied to distinguish healthy liver scans from those affected by steatosis. The model is trained on two datasets—baseline scans of average healthy human livers and medical images of diagnosed patients. The healthy dataset helps the system learn normal liver structure, while the patient dataset teaches it to identify abnormalities. When new patient scan reports are uploaded, the system compares them against the learned healthy patterns to determine the presence and severity of fatty infiltration. By integrating segmentation, feature extraction, and classification into a unified architecture, the proposed system addresses the core issues of manual diagnosis, offering faster, more accurate, and objective results for clinical decision-making.

SYSTEM ARCHITECTURE

The architecture of the proposed system consists of several modules:

1) **Data Upload Module (Flask) -** Collects patient data from healthcare datasets and IoT devices.
2) **Processing Status Module** - Provides transparency, improves usability, and ensures the system feels responsive and trustworthy.
3) **Results and Comparison Module -** Once model completes segmentation and classification, the results are presented clearly comparison provides an objective, data-driven evaluation for decision-making.
4) **Database Module -** manages the storage of trained model weights, Uploaded patient scans, Classification outputs and reports.
5) **Visualizer and Download Module -** makes the system more clinically interpretable
6) **Deployment Module -** ensures real-world usability by deploying the system in an accessible and reliable environment.

A. Workflow of the Proposed System

The workflow of the Liver steatosis segmentation using deep learning consists of several sequential steps that operates as an end-to-end pipeline for automated liver steatosis detection, integrating data acquisition, processing, analysis, and result delivery. The workflow begins with the data upload module, where medical images (e.g., ultrasound, CT, MRI) are securely submitted through a Flask-based interface. The system performs validation checks on format, resolution, and metadata before forwarding the data to the preprocessing stage.

During processing, the system provides real-time status updates to inform users about stages such as preprocessing, segmentation, and classification. The core analysis is performed using a U-Net model for precise liver and fatty region segmentation, followed by an R-CNN for feature extraction and localization. A classification module then categorizes the liver condition into different severity levels. Additionally, the system computes quantitative metrics and compares patient results with baseline healthy data to ensure objective assessment.

All inputs and outputs are managed by a database module, enabling structured storage, retrieval, and longitudinal tracking of patient data. The visualization module presents segmentation results, heatmaps, and comparison outputs, while also allowing report downloads for clinical use. Finally, the system is deployed in a secure environment with cloud or GPU support, ensuring accessibility, scalability, and reliable performance in real-world healthcare settings.

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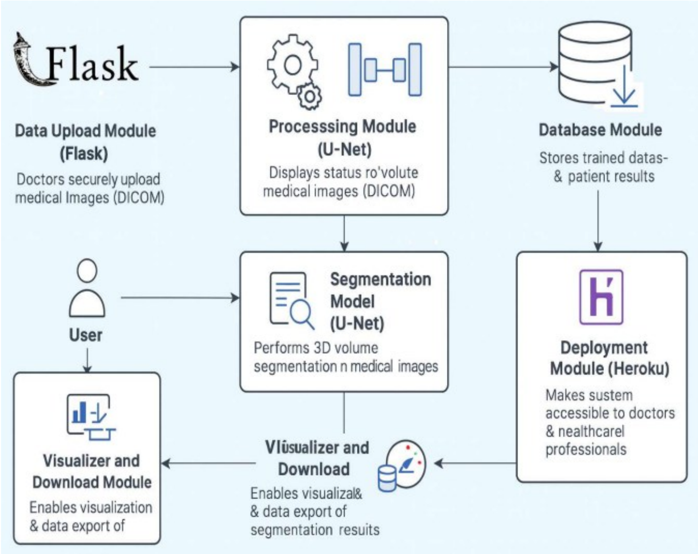

Figure: This figure illustrates the overall architecture of proposed Liver Steatosis Segmentation using Deep learning, showing data flow from data upload to Deployment

OBJECTIVES

The primary objective of this research is to develop an automated and reliable system for liver steatosis detection using medical imaging and deep learning techniques. The specific objectives are as follows:

1) **To design an end-to-end deep learning framework** that integrates segmentation, feature extraction, and classification for liver steatosis analysis.
2) **To achieve accurate pixel-level segmentation** of liver and fatty regions using advanced architectures such as U-Net.
3) **To classify liver conditions into severity levels** (normal, mild, moderate, severe) with high accuracy and consistency.
4) **To enable quantitative assessment and comparison** of patient scans with baseline healthy data for objective diagnosis.

METHODOLOGY

The proposed methodology follows a structured deep learning pipeline for automated liver steatosis detection from medical images. Initially, liver scan images (ultrasound, CT, or MRI) are collected and pre-processed through resizing, normalization, and noise reduction to ensure uniform input quality. Data augmentation techniques are also applied to improve model generalization.

The pre-processed images are then passed through a U-Net–based segmentation model, which performs pixel-level identification of liver regions and fatty tissues. This enables precise localization and quantification of steatosis-affected areas. Following segmentation, a Region-Based Convolutional Neural Network (R-CNN) is employed to extract high-level features and accurately localize abnormal regions within the liver.

The extracted features are subsequently fed into a classification module that categorizes the liver condition into different severity levels, such as normal, mild, moderate, or severe steatosis. Additionally, quantitative metrics such as fatty infiltration percentage are computed and compared with baseline healthy data to provide an objective assessment.

All results are stored and visualized through an integrated system, enabling clear interpretation via segmentation overlays, heatmaps, and reports. This end-to-end methodology ensures accurate, consistent, and efficient diagnosis, reducing reliance on manual interpretation and supporting clinical decision-making.

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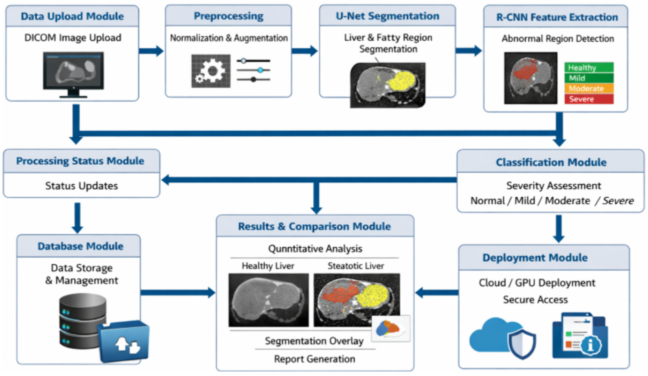

Figure 8 Workflow of Liver Steatosis Segmentation, detailing steps from data collecting to deployment

ALGORITHM

Algorithm: Liver Steatosis Segmentation using Deep Learning
Input: Patient health data (vitals, lab results, historical medical records)
Output: produces outputs (Segmented Liver Image, Fatty Region Mask, Classification Result)
Step 1: Acquires liver scan image from user and validate image format, resolution, and metadata.
Step 2: Resize the image to fixed dimensions and normalize pixel intensities to range apply noise reduction and perform data augmentation during training.
Step 3: Input preprocessed image into U-Net model and extract features using encoder layers
Step 4: Apply region proposal on segmented output, extract deep features from candidate regions. And identify and localize abnormal fatty regions.
Step 5: Feeds the extracted features into classification model and compute class probabilities.
Step 6: Calculates the fatty area and compare results with baseline healthy dataset.
Step 7: Overlay segmentation mask on original image, display classification result and metrics and store results in database.
Step 8: Present results via user interface and allow download of segmented images and reports.
End Algorithm

EXPERIMENTAL SETUP

The proposed liver steatosis detection framework was evaluated using a combination of publicly available and clinically sourced liver imaging datasets, including ultrasound, CT, and MRI scans. The dataset consists of two categories: (i) baseline healthy liver images and
(ii) images from patients diagnosed with varying degrees of steatosis.
All images were pre-processed through resizing, intensity normalization, and noise reduction to ensure uniformity. Data augmentation techniques such as rotation, flipping, and scaling were applied to improve model robustness and prevent overfitting. The segmentation task was performed using a U-Net architecture trained with a combination of Binary Cross-Entropy and Dice Loss to enhance pixel-level accuracy. For feature extraction and region localization, an R-CNN model was integrated, followed by a classification layer to categorize liver conditions into normal, mild, moderate, and severe steatosis.The models were implemented using deep learning frameworks such as TensorFlow/PyTorch and trained on a GPU-enabled system to accelerate computation.
Classification performance was evaluated using accuracy, precision, recall, and F1-score. Additionally, the system's ability to quantify fatty infiltration was validated by comparing predicted fat percentages with ground truth annotations. The experimental results demonstrate that the proposed integrated framework achieves high segmentation precision and reliable classification performance, outperforming traditional image processing and classical machine learning approaches. The system also shows strong generalization across different imaging modalities, confirming its effectiveness for real-world clinical applications.

PERFORMANCE METRICS

To evaluate the effectiveness of the proposed system, several performance metrics are used.

1) **Segmentation**– Assess the accuracy of fatty region extraction

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2) **Classification** – Indicates the proportion of correct positive predictions.
3) **Recall** – Measures the ability of the model to detect fatty lipids.
4) **F1 Score** – Harmonic mean of precision and recall.
5) **Prediction Latency** – Time taken by the model to generate predictions.
6) **Estimation**– Assess the severity of liver steatosis.

RESULTS AND ANALYSIS

The proposed deep learning–based liver steatosis detection system demonstrates effective segmentation, classification, and quantitative assessment of fatty liver regions from medical images. The U-Net model successfully identifies and segments steatotic regions with high precision, while the integrated classification module accurately categorizes liver conditions into different severity levels. The system also provides quantitative analysis, such as percentage of fatty infiltration, enabling objective evaluation. Visualization tools, including segmentation overlays and heatmaps, enhance interpretability and allow clinicians to validate model predictions effectively.
The performance of the proposed system was evaluated using multiple medical imaging datasets, including ultrasound, CT, and MRI scans. Various evaluation metrics were used to assess segmentation and classification performance, including Dice Similarity Coefficient (DSC), Intersection over Union (IoU), accuracy, precision, recall, and F1-score. Table 1 presents the performance comparison of different approaches used in the system.

Model	Accuracy	Precision	Recall	F1 Score
SVM	84%	82%	80%	81%
Random Forest	88%	86%	85%	85.5%
U-Net + R-CNN	94%	93%	92%	92.5%

Table 1: Comparative performance of machine learning models

FUTURE ENHANCEMENT

The proposed system can be enhanced by adopting advanced architectures such as attention-based U-Net and transformer models to improve segmentation accuracy. Expanding the dataset with diverse, multi-center clinical data will further strengthen model robustness and generalization.
Future improvements include incorporating 3D volumetric analysis for better evaluation of liver fat distribution and integrating longitudinal data for disease progression tracking. Additionally, cloud-based deployment, EHR integration, and improved explainability techniques can increase clinical usability and trust.

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CONCLUSION

This research presented a **Liver Steatosis Segmentation for personalized Segmenting fatty lipids accumulated around liver and predictive analytics.** The proposed system is simple but effective system for automatic segmentation of liver steatosis using deep learning. The system takes liver images, preprocesses them, runs a trained U-Net-like segmentation model, and outputs a clear mask showing fatty regions along with simple numerical measurements.
This approach reduces manual effort, gives more consistent results, and can assist doctors in early diagnosis of fatty liver disease. Although our project is on a small scale with limited data and hardware, it shows how deep learning can be applied in medical imaging to support clinical decisions and open the door to more advanced healthcare tools in the future.

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