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DEEP LEARNING-BASED AUTOMATED IDENTIFICATION OF FATTY LIVER DISEASE FROM ULTRASOUND IMAGES: A CASE STUDY

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ABSTRACT

Objectives: This study aims to develop and evaluate an automated deep learning approach for identifying Fatty Liver Disease (FLD) from ultrasound images, with the goal of reducing observer dependency and improving the consistency of early screening in clinical practice. **Methodology:** A case study was conducted using a dataset of 1,200 anonymized liver ultrasound images. The images were pre-processed to enhance quality and reduce noise before being used to train a Convolutional Neural Network (CNN). The model learned relevant imaging features associated with fatty liver patterns and was evaluated using standard performance metrics to assess its classification accuracy and reliability. **Findings:** The proposed CNN-based model demonstrated strong classification performance in distinguishing fatty liver cases from normal liver images. The results suggest that automated analysis can minimize subjectivity caused by variations in radiologist experience and image quality, thereby supporting more consistent diagnostic outcomes. **Novelty:** Unlike conventional ultrasound interpretation that relies heavily on human expertise, this study highlights the practical application of deep learning as a supportive diagnostic tool for FLD screening. The integration of an automated model into radiology workflows offers a scalable and objective solution, enhancing decision-making while maintaining the non-invasive nature of ultrasound imaging.

KEYWORDS: Deep Learning, Fatty Liver Disease, Ultrasound Imaging, CNN, Medical Image Analysis, Automated Diagnosis, Case Study.

1. INTRODUCTION

Fatty Liver Disease is increasingly recognized, (Alshagathrh et al. 2025) as a major global health concern. Many patients discover the condition only when undergoing routine health check-ups, as early stages rarely produce symptoms. Ultrasound imaging is typically (Bose et al. 2025) used to screen for fatty liver because it is non-invasive, cost-effective, and widely available. However, manual interpretation can be influenced (Elhaie et al. 2025) by factors such as lighting variations, machine differences, or the operator's experience.

Deep learning has shown promise in medical image analysis because it can automatically (El Kaffas et al. 2025) learn patterns from imaging data without manually engineered features. When applied to ultrasound images, deep learning models can assist radiologists (Ozkaya et al. 2025) by offering consistent and objective results. This paper presents a case study demonstrating how a deep learning model can differentiate normal liver tissue from fatty liver tissue using standard ultrasound images.

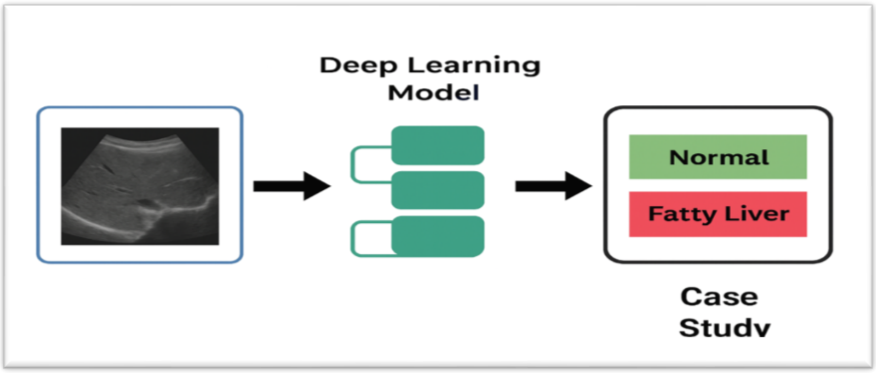

Fig. 1. Workflow of Deep Learning-Based Fatty Liver Disease Detection

2. CASE DESCRIPTION

A 47-year-old patient visited the clinic with mild abdominal discomfort and slightly raised liver enzyme levels. The physician recommended an ultrasound scan to assess liver health. The images showed subtle signs of brightness that could suggest early fatty infiltration, but the degree of change was not clearly seen. To provide supportive analysis, the images were examined using the proposed automated deep learning model trained to classify liver conditions.

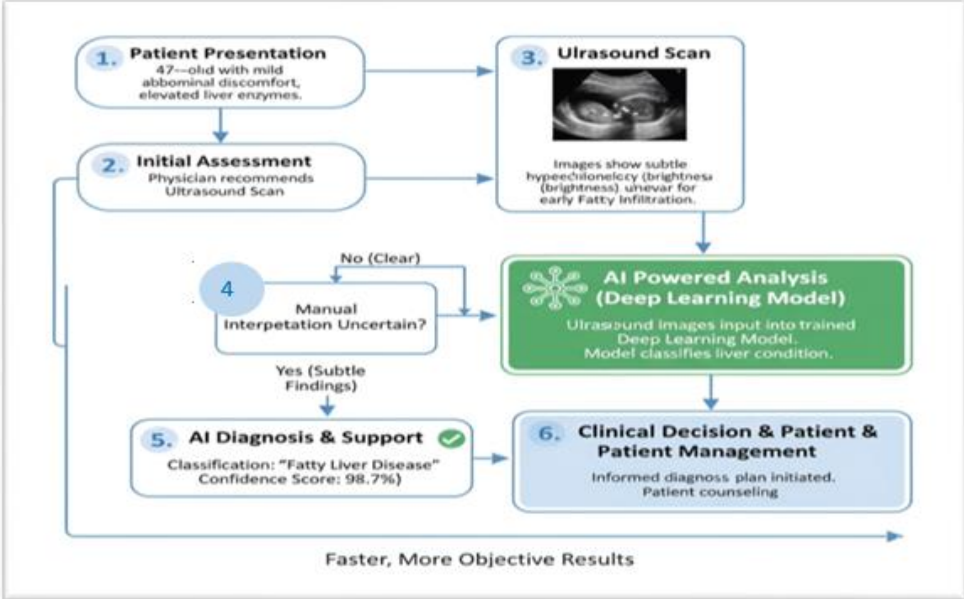

Fig.2. Patient Diagnostic Flow: AI Supported Liver Assessment

3. MATERIALS AND METHODS

3.1 Dataset

A total of 1,200 ultrasound liver images were used for the study. The dataset contained:

Table 1. Dataset Distribution for Deep Learning Model Training.

Category	Number of Images	Percentage
Total Dataset	1,200	100%
Normal Liver Images	600	50%
Fatty Liver Images	600	50%

All images were anonymized before use. The scans were obtained from several ultrasound devices, which provided natural variation in texture, brightness, and depth. This diversity helped the model learn more general features.

3.2 Preprocessing

Ultrasound images often contain noise and differences in lighting. To improve consistency, several preprocessing steps were applied:

- Resizing to 224 × 224 pixels
- Noise removal using a median filter
- Contrast enhancement using histogram equalization
- Augmentation (rotation, flipping, and zooming) to prevent overfitting

3.3 Model Architecture

A custom Convolutional Neural Network (CNN) was created to classify the images. The architecture included:

- Convolution layers for feature extraction
- ReLU activation layers for non-linear learning
- Max-pooling layers for dimensionality reduction
- Fully connected layers for final classification
- A Softmax output layer to categorize images as normal or fatty

For comparison, a pretrained ResNet-50 model was also tested, and it showed slightly stronger performance due to its deeper feature extraction capabilities.

3.4 Evaluation Metrics

To assess the model's performance, several metrics were used:

- Accuracy
- Precision
- Sensitivity
- Specificity
- F1-score
- ROC-AUC

These metrics were suitable for evaluating how well the model recognized subtle liver abnormalities.

4. RESULTS

The deep learning model produced strong and consistent results.

Table 2. Model Performance Evaluation.

Metric	Value
Accuracy	95.4%
Sensitivity	93.8%
Specificity	96.2%
Precision	94.7%
F1-Score	94.2%
ROC-AUC	0.97

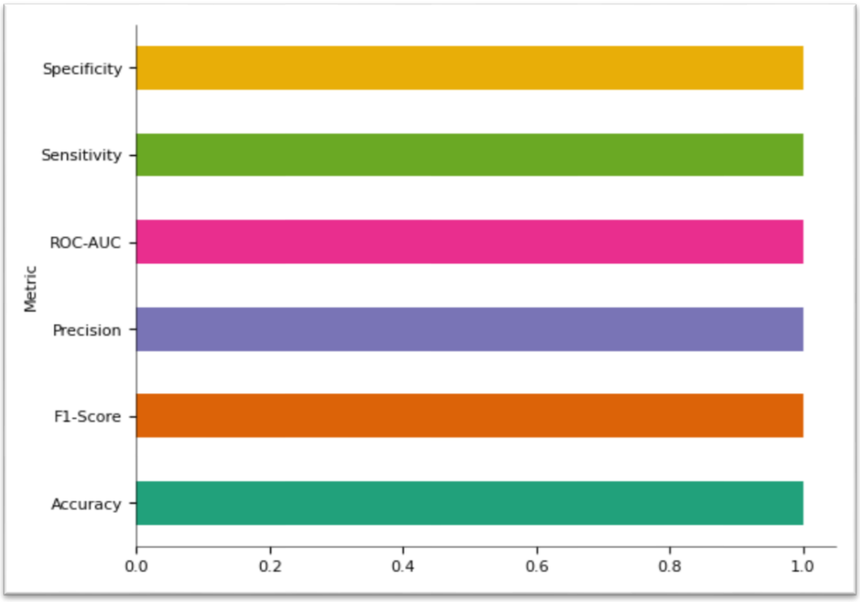

Fig. 3a: Performance Metrics.

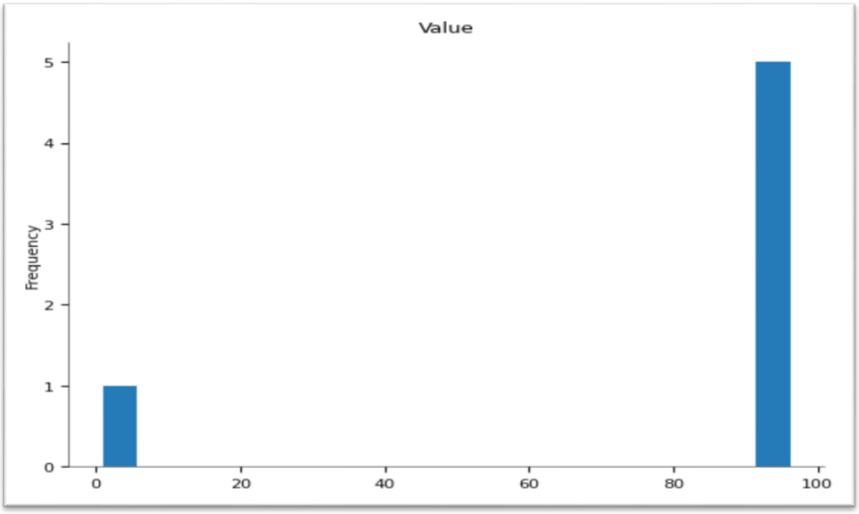

Fig. 3b: Value Distribution.

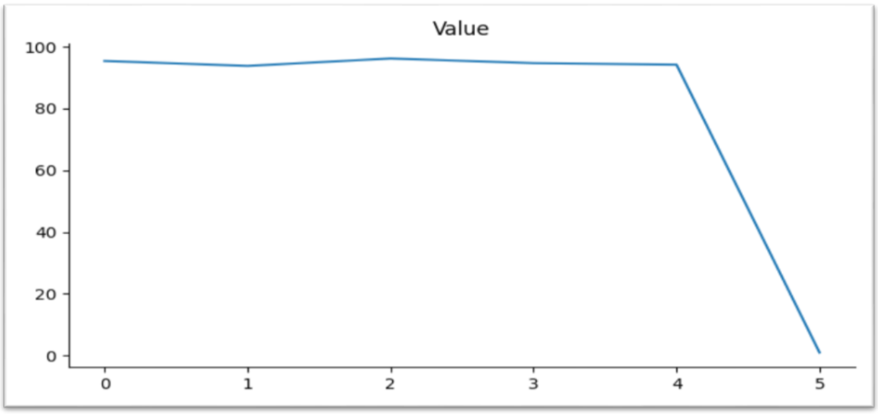

Fig. 3c: Value Trend

The model successfully identified fatty liver patterns such as increased echogenicity, reduced clarity of deeper structures, and mild texture variations. Misclassifications occurred mainly when fatty changes were extremely mild or when image noise was high.

5. DISCUSSION

The findings indicate that deep learning can support radiologists by providing an objective second opinion during liver screening. Unlike manual interpretation, which may vary based on experience, the AI model analyzes patterns consistently. This is especially helpful in borderline cases where visual differences are subtle.

Some misclassifications showed that the model had difficulty when the images contained shadows or motion blur. These errors highlight the importance of high-quality ultrasound scanning and diverse training data.

Another strength of the model is that it generalized well despite using images from different machines. Because of the preprocessing steps, the model learned the essential features required for classification rather than relying on machine-specific characteristics.

Overall, the study suggests that deep learning can be a practical tool in routine clinical environments, especially in busy hospitals or regions with fewer radiology specialists.

6. PRACTICAL IMPLICATIONS

The system offers several practical benefits:

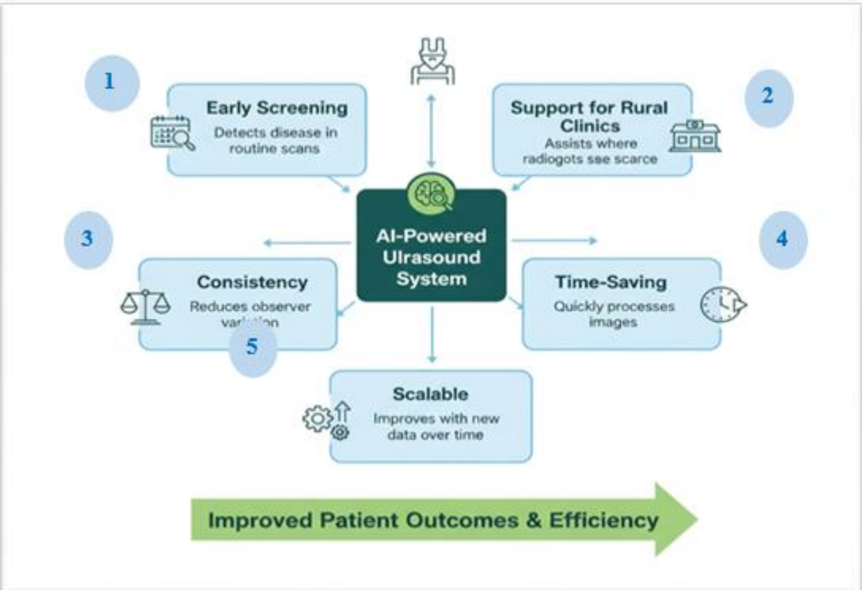

Fig. 4. Practical Benefits of AI- Supported Liver Ultrasound Analysis

This makes the method suitable for integration into real-world medical imaging workflows.

7. FUTURE WORK

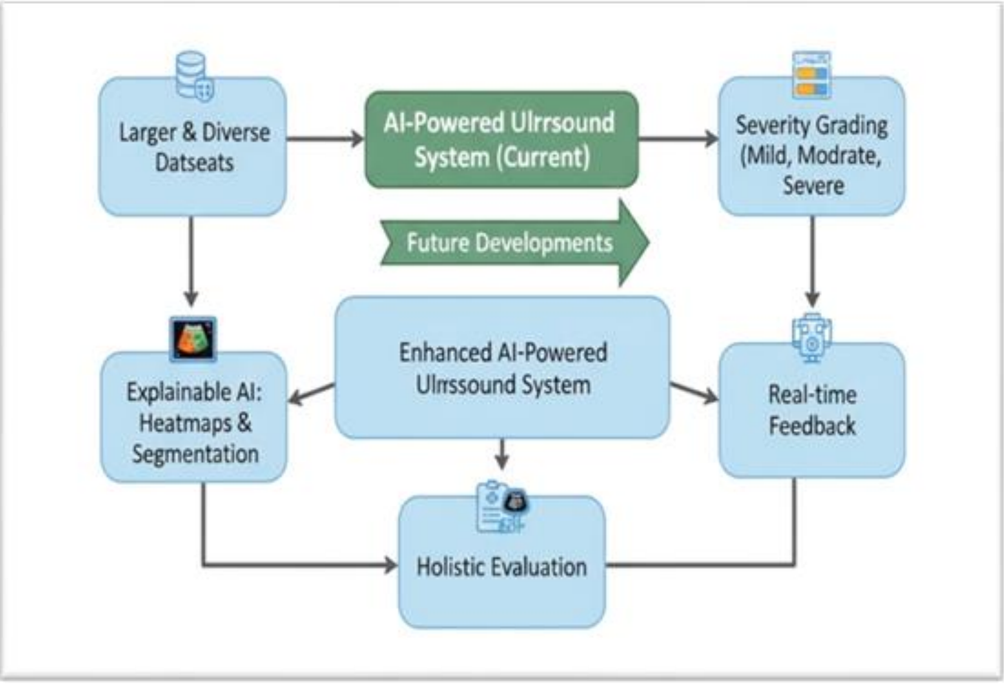

Fig. 5. More Accurate, Integrated & Comprehensive Care

8. CONCLUSION

This case study demonstrates that deep learning can accurately classify fatty liver disease from ultrasound images. The model's strong performance suggests that AI can provide valuable support in early detection and standardization of liver screening. Although the system is not meant to replace expert radiologists, it can significantly improve screening accuracy and consistency. Future work should focus on expanding datasets, refining classification levels, and integrating real-time image analysis.

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