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LDCE-Net: A Custom-Built Lightweight CNN for Classifying Liver Fibrosis Stages via Ultrasound Imaging

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Article Details

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ABSTRACT

Liver fibrosis is a progressive disease that, undetected, proceeds to cirrhosis and liver failure. Early detection through ultrasound imaging remains a challenging task with subtle grayscale shifts and reliance on experienced interpretation. Here, we present LDCE-Net, a lightweight tailored convolutional neural network architecture developed ab initio to discriminate liver ultrasound images into three relevant clinical classes: Normal, Fibrosis, and Cirrhosis. Unlike previous approaches relying on pretrained models, LDCE-Net was meticulously developed and trained to extract both shallow and deep features with a double-path structure amalgamated with a feature attention module. Testing was conducted on a labeled dataset with cross-validation and achieved a test accuracy of 87%, with balanced F1-scores on each class. Learning curves and validation curves both confirmed steady learning with minimal overfitting, and the confusion matrix highlighted class-wise high performance with specific ability to distinguish healthy and heavily fibrotic tissue. The trained model was also incorporated within a user-centric Streamlit web interface with real-time prediction of fibrosis stage with ultrasound input. Such findings warrant LDCE-Net's potential for a practical, accurate, and accessible screening device against liver disease.

INTRODUCTION

Liver illness is a mounting public health concern globally, accounting for a substantial proportion of global morbidity and mortality. The World Health Organization (WHO) reports that conditions related to the liver, including hepatitis, fibrosis, and cirrhosis, account for more than 2 million deaths per year [1]. It's crucial to detect liver illness early since early treatment can avoid irreversible damage, such as cirrhosis, from setting in after reversible stages, such as fibrosis. This could, however, not happen in most clinical practices since early liver illness lacks clear symptoms, as well as a high level of diagnostic complexity.

Ultrasound scanning is widely employed in clinical practice since it is non-invasive, cost-efficient, and widely available, as shown in Figure 1. It equips doctors with vital information about liver morphology and texture, allowing them to identify abnormalities. The process, though, involves a high level of expertise, and interpreting ultrasound images involves subjectivity [2]. It becomes challenging for radiologists to tell apart minute liver tissue variations, more so when it comes to differentiating among normal, fibrotic, and cirrhotic phases. These challenges highlight the importance of strong, automatic diagnostic instruments that can help clinicians make correct and uniform decisions.

Over the past few years, artificial intelligence (AI) in general, and more precisely deep learning, has become a dominant method of automating image analysis in a wide range of domains [3]. Convolutional Neural Networks (CNNs), a category of deep learning networks especially designed for image classification, have proven to be incredibly successful in, e.g., tumor detection, X-ray-based lung disease classification, and COVID-19 diagnosis from chest CT scans [4]. Taking advantage of these developments, deep learning started to be used also in ultrasound image analysis to assist in diagnosis as well as in minimizing human mistakes.

As opposed to other works relying mainly on pretrained models like VGG16 or ResNet, this paper proposes a custom-designed convolutional neural network trained and designed from scratch. It is custom-designed specifically for liver ultrasound image classification into three classes: Normal, Fibrosis, and Cirrhosis. By avoiding reliance on large pretrained weights, it is optimized to learn from ultrasound grayscale features directly and generalize to domain-specific traits [5].

This study seeks to create an accurate and lightweight diagnosis system that can help clinicians detect early liver disease. Performance evaluation metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix are applied to evaluate the system. Results

show that the proposed model performs competitively on all three classes of liver diseases.

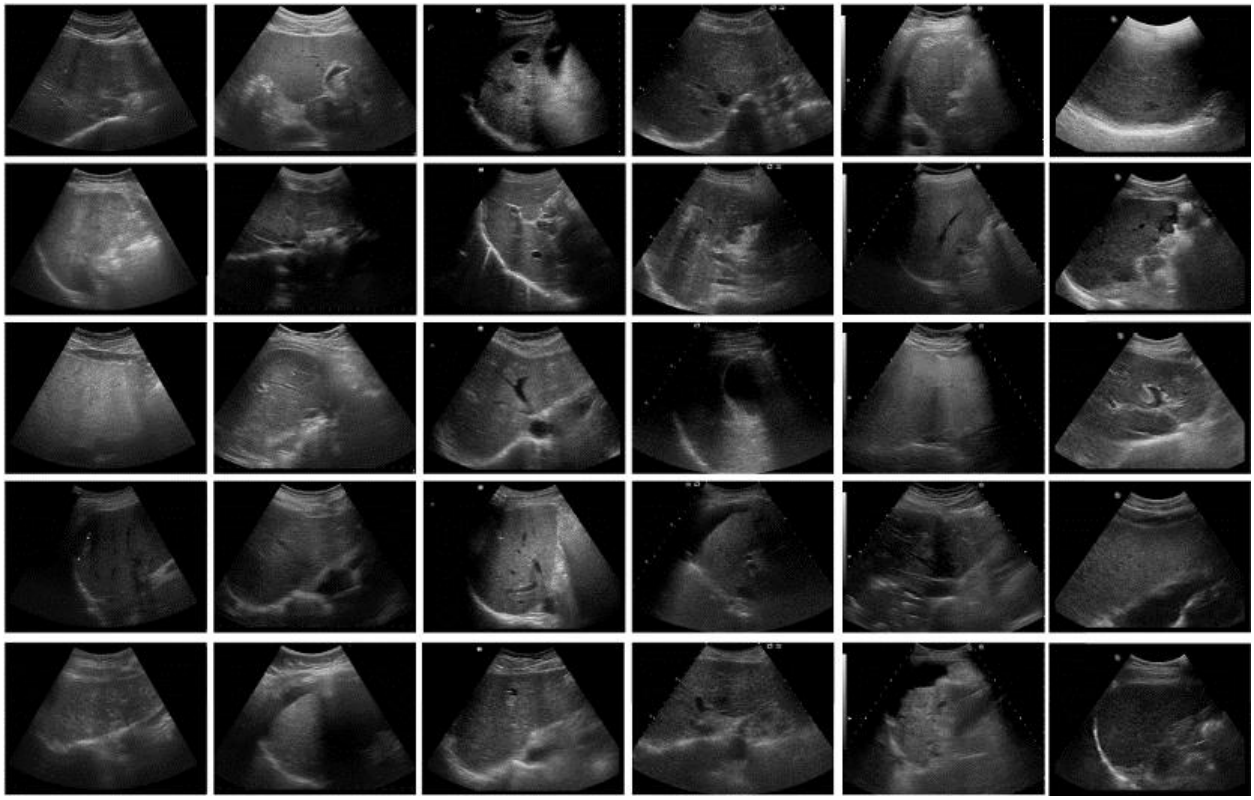

FIGURE 1. ULTRASOUND IMAGES OF LIVER [6].

LITERATURE REVIEW

Many researchers have worked in this field, among them an author [7] introduced a deep transfer learning architecture for classifying liver fibrosis grades from heterogeneous ultrasound images obtained from various machines and protocols. Specifically, the study solved the domain shift issue due to hardware and scanning setup variations, which tend to degrade model generalizability. VGG16 and ResNet50 pretrained on ImageNet were employed to extract high-level visual features from greyscale liver ultrasound images. They were fine-tuned on their classification task for supervised learning with labeled fibrosis datasets. Further, domain generalization methods like feature fusion and attention blocks were also tested on cross-machine classification performance. Their findings showed that transfer learning models, especially VGG16, improved dramatically, particularly when supplemented with domain-aware modules. In contrast to this method, which is both pretrained and reliant on domain generalization techniques, this study creates our own bespoke convolutional neural network trained from the ground up. Doing so allows the model to acquire domain-specific feature

learning from gray-scale ultrasound images directly without relying on pretrained weights from elsewhere, resulting in a less complicated, more versatile, and liver disease classifying system optimized for a controlled setting [8].

One more Study [9] developed a cascaded deep learning pipeline for the fully automated liver steatosis diagnosis from ultrasound images. Acknowledging the limitations of the low visual quality of ultrasound, speckle noise, and low contrast, the study proposed a three-step deep-learning pipeline. The first two networks undertook semantic segmentation to detect and crop the liver-kidney (L-K) area from the parasagittal images and anatomical ring information. A CNN called SteatosisNet was used in the final step to classify the presence and severity of fatty liver disease. Their model performed outstandingly with a diagnostic accuracy of 99.91%, sensitivity at 99.78%, and specificity at 100%, all of which were compared to expert-labeled results. This work is particularly significant since it integrates anatomical localization and pathology classification in a cascaded framework, reducing the impact of false positives from image regions outside the area of interest. Though liver steatosis was the targeted focus in this work over fibrosis or cirrhosis, the architectural design and segmentation-based preprocessing apply to any liver disease diagnostic model based on ultrasound. This multi-network model's success also highlights the value of incorporating region-localization segmentation into liver fibrosis classification schemes, an aspect that the present work can investigate further to enhance the precision of multiclass liver disease identification [10]. While this study leveraged pretrained CNNs for feature extraction, this study focuses on training a lightweight CNN from scratch, enabling it to learn directly from liver ultrasound features [11].

Another research [12] tackles the challenge of the accurate classification of diffuse liver diseases from ultrasound images, an alternative to the risky and expensive invasive liver biopsy. Due to the subjectivity of the interpretation of physicians in ultrasound imaging, their work introduces a new hybrid classification approach utilizing deep convolutional neural networks (CNNs). They use transfer learning with various pre-trained CNN architectures, such as ResNeXt, ResNet18, ResNet34, ResNet50, and AlexNet, with fully connected networks (FCNs) to map liver status to normal, hepatitis, and cirrhosis. The work points out that the best results are obtained from using the two-class classifiers (normal and cirrhosis, normal and hepatitis, cirrhosis and hepatitis) over the three-class classifiers, which culminated in the creation of a hybrid classifier that combines weighted probabilities from the individual classifiers via the

majority voting strategy.

The experiment conducted by [12] shows that their hybrid model attains 86.4% accuracy using ResNet50 for liver disease three-class classification in ultrasound images. In addition, in the binary tasks, the algorithm achieved good sensitivity and specificity, with sensitivity ranging up to 90.9% and 86.4% specificity for the discrimination of normal and cirrhosis livers. The results indicate that deep learning algorithms, such as the use of multi-CNN-based hybrid models, provide an effective, non-invasive means for the early and accurate diagnosis of liver diseases with the potential to minimize the use of liver biopsy. This research contributes to the development of computer-aided diagnosis in hepatic practice as well as to enhanced patient care with reduced use of liver biopsy [13].

The study [14] suggested a multimodal technique using quantitative ultrasound (QUS), elastography, and machine learning to improve the evaluation of liver steatosis, inflammation, and fibrosis in chronic liver disease. The model incorporated shear wave elastography, homodyned K-distribution parameters, and the total attenuation coefficient slope to assess the characteristics of the liver tissue, relying on the reference provided by the histopathological examination. 82 patients with various liver conditions such as NAFLD, hepatitis B/C, and autoimmune hepatitis were included in the study. The machine learning model, specifically random forests and bootstrapping, performed far better in diagnostic accuracy than using only elasticity. For example, the AUC in discrimination of the stage of steatosis S0 vs. S1–3 increased from 0.60 (elastography only) to 0.90 using the combined model. These findings demonstrate the value of combining machine learning with QUS in more accurate, non-invasive liver disease staging. Whereas, our research varies by implementing a CNN architecture from scratch without relying on any weight initialization from some other sources [15].

Moreover, [16] introduced a deep learning-based data integrative network (DI-Net) to improve the diagnosis of advanced liver fibrosis (≥F2) in patients with chronic hepatitis B (CHB). The model accurately integrated liver parenchyma ultrasound images, liver stiffness measurements, and clinical factors to estimate stages of fibrosis. This strategy is indicative of the emerging trend of using diverse sources of data with AI to enhance diagnostic accuracy in hepatology. It involved 284 eligible patients, with the DI-Net demonstrating diagnostic performance against single-source models. The model performed with an AUC of 0.943 in cross-validation and 0.901 in the external validation, surpassing conventional methods. The results point to the ability of deep learning to provide accurate, painless substitutes for liver

biopsy for the estimation of fibrosis in CHB [17]. Another study [18] presented an advanced deep-learning framework called UNet70 for liver tumor classification from contrast-enhanced CT images. Acknowledging the intricacies in the detection of liver abnormalities owing to structural variations, blurred edges, and overlapping tissues, the authors used a segmentation-first strategy employing a modified U-Net model. The model classifies images into either tumor-containing (hepatocellular or metastatic) or healthy. Their method showed excellent performance metrics: 94.58% accuracy, 94.73% dice score, and 97.50% sensitivity, competing with other current segmentation and classification algorithms on various databases.

While the study's focus is on tumor classification [19], not fibrosis or cirrhosis identification, its impact on liver imaging through the improvement of the U-Net and end-to-end automation is noteworthy. Segmentation-based preprocessing is particularly applicable since unambiguous isolation of the ROI can significantly enhance the accuracy of classification, something that can be extended to models based on ultrasound in the study of fibrosis. The model's versatility between the databases highlights its potential for generalized performance, further demonstrating the utility of deep convolutional architecture in the diagnosis of liver diseases, including potential applications to ultrasound modalities employed in the study. In contrast to such an approach, which utilized deep pretrained networks, we completely avoid transfer learning and develop a CNN tailored to handle grayscale ultrasound images [20].

Moreover, [21] compared the performance of two deep-learning architectures—Deep Convolutional Neural Networks (DCNN) and Hierarchical Fusion Convolutional Neural Networks (HFCNN)—in liver cancer detection with CT scans. The work proposed to enhance segmentation performance by pre-filtering the image features, overcoming issues related to noise, overlapping tissues, and textural heterogeneity of the scans. Their framework made effective use of advanced fusion mechanisms in HFCNN to preserve better multiscale features compared to standard DCNNs. Multiple performance metrics—precision, recall, F1-score, and accuracy were used in the evaluation to compare each of the models' ability to segment and detect liver cancer thoroughly. Although the paper [22] concentrates on liver cancer diagnosis, its comparative perspective and observations regarding the behavior of models on different types of imaging tasks are of considerable relevance to wider liver disease diagnosis, including cirrhosis and fibrosis. By focusing on texton enhancement and segmentation quality, the paper calls attention to the requirement for preprocessing pipelines for handling image heterogeneity, a concept consistent with ultrasound image classification problems. The better performance of

HFCNN in the fusion of hierarchical features further indicates the utility of multi-scale feature fusion in deep models and provides design inspiration for new CNN models in liver disease classification based on ultrasound. While this paper employed a cascaded deep learning framework and relied on pretrained feature extractors, our research varies by implementing a CNN architecture from scratch without relying on any weight initialization from some other sources [23].

Another research [24] performed a bibliometric analysis to map the development and emerging trends of artificial intelligence (AI) usage in liver disease imaging. Based on 3,629 articles published between 1990 and 2023, the study noted an increasing volume of outputs after 2017, reflecting the increasing incorporation of AI into hepatology. The United States and China ranked as top producers, the latter delivering larger numbers of productive institutions, while the United States counted better H-index scores and citation rates. Liver fibrosis, hepatocellular carcinoma, cirrhosis, and fatty liver disease were the major areas in the AI-assisted liver study. Methods of image segmentation, classification, and registration were common, solving clinical demands regarding lesion identification and prognosis of the disease. Convolutional neural networks (CNNs), particularly the U-Net architectures, were widely employed, reflecting their utility in the analysis of medical images [24]. This bibliometric analysis highlights the central role of AI, and notably computer vision, in the diagnosis and treatment of liver diseases. The standout role of CNNs, and particularly the U-Net models, represents their versatility and specificity in performing intricate imaging tasks. Mapping the trends in the study and the identification of leading researchers, the study offers useful insights to inform further inquiry, highlighting the importance of ongoing innovation and cooperation in AI-enhanced hepatology. These analyses prove to be crucial in directing researchers toward potentially significant areas, facilitating the creation of solid, automated diagnostic tools to maximize the reach of early diagnosis and treatment of liver pathologies [25].

Furthermore, the study of Ai, Huang, Tai, Tsui, and Zhou (2024) introduced a novel approach for liver fibrosis assessment using deep learning on ultrasound radiofrequency (RF) signals, shifting the focus from conventional time-domain to frequency-domain analysis. The study employed two-dimensional convolutional neural networks (U-Net and Attention U-Net) for automatic liver region segmentation from B-mode images and one-dimensional CNNs for fibrosis stage classification based on amplitude, phase, and power spectra derived through the Fourier transform. This eliminated the need for manual ROI selection, a common limitation in

previous work. Their experiments on RF data from 850 patients using liver biopsy as the gold standard provided encouraging results. The phase spectrum achieved the highest performance in detecting early-stage fibrosis (≥F1) with an AUC of 0.957 and an accuracy of 89.19%. These results indicate the usefulness of automating the combination of segmentation and frequency-domain characteristics in detecting liver fibrosis in a non-invasive manner with better sensitivity to early-stage disease and potential clinical use [26].

Much of the existing literature on classifying liver disease from ultrasound images has utilized transfer learning, adopting pretrained networks like VGG, ResNet, and DenseNet. Although these are accurate and efficient, pretrained on natural images such as ImageNet, they can fail to grasp some of the distinct grayscale texture patterns inherent in ultrasound data. By contrast, our work presents a purpose-built convolutional neural network trained from scratch. This fully custom-designed architecture is optimized for the specific properties of ultrasound liver images and provides a lightweight and task-oriented solution free from biases and computational expense of pretrained models.

METHODOLOGY

This section presents an overview of the end-to-end methodology employed to create a light-weight, in-house trained deep convolutional neural network, LDCE-Net (Liver Disease Classification Encoder Network) for classifying liver fibrosis stages from grayscale ultrasound images. The pipeline includes well-organized dataset preparation, in-house CNN architecture development, setup for training models, an evaluation scheme, and final deployment of the model in a clinical tool. Contrary to most of the prior works relying on large pretrained models, LDCE-Net is trained from scratch for its full architecture, which allows the network to capture domain-specific features directly from the dataset and stay optimal for medical image analysis.

DATASET PREPARATION AND PREPROCESSING

The ultrasound image data used here include human liver grayscale images already identified and classified according to the clinically verified METAVIR scoring for fibrosis, as shown in Figure 2. Fibrosis stages were reduced to three large classes for simplification of classification and for enhancing clinical interpretability: F0 for non-fibrosis liver tissue, F1 through F3 for all fibrosis stages, and F4 for cirrhosis. Such a three-class arrangement follows clinical abstraction utilized in related research for classifying liver fibrosis, keeping labeling ambiguity low, and maintaining diagnostic value.

For preserving consistency between samples and for keeping compatibility with the input for

the model, all ultrasound images were resized to a 128×128 pixels spatial resolution and were made grayscale. Pixel intensity values were normalized between 0 and 1. Data augmentation techniques were used during training for the training subset to increase the robustness of the model and to prevent overfitting. Random horizontal flipping, low-angle rotation, and brightness and contrast jittering were used for introducing variability and not altering anatomical structure. Stratified sampling was used for dividing the dataset into training, validation, and test subsets, preserving class balance during each divide.

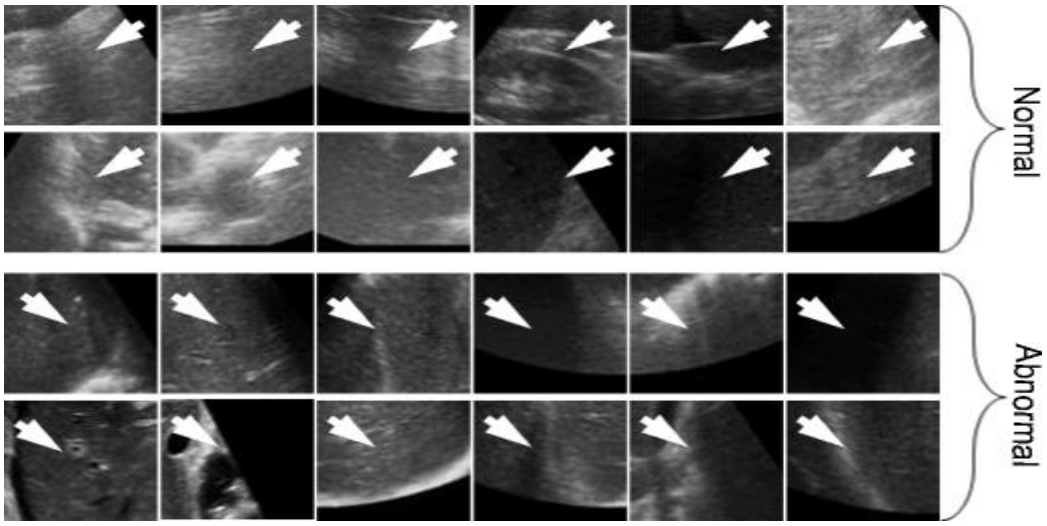

FIGURE 2. DATASET OF LIVER [27].

NETWORK ARCHITECTURE: LDCE-NET

The architecture for LDCE-Net needed to be light and efficient so that rich feature descriptions could be extracted from grayscale ultrasound images, as shown in Figure 3. Taking inspiration from multi-resolution and multi-scale schemes, the network follows a dual-path architecture so that both shallow and deep features can be captured in parallel. The input to the model is a one-channel 128×128 grayscale image. The architecture begins with a Shallow Path, comprised of three depthwise separable convolutional (DSC) blocks in a stacked form. These layers seek to extract low-level image details such as texture, edges, and subtle structural patterns prevalent in early-phase liver fibrosis. Every DSC block comprises a depthwise convolution followed by a pointwise convolution, along with batch normalization and a ReLU activation function. The final feature maps retain high-resolution details, which are advantageous for marking subtle variations in textures in grayscale ultrasound images. The network includes a Deep Path that proceeds in parallel to the shallow branch. The five depthwise separable convolutional layers create this branch, and its role is to learn abstract, high-level descriptions that will more likely

be related to later phases of advanced fibrosis or cirrhosis. The two paths proceed in parallel and aim to learn complementary information: local textures are learned along the shallow path, and global contextual patterns are learned along the deep path.

The shallow and deep branch outputs are concatenated along the channel dimension, and a 192-channel combined feature map is formed. The combined feature map is passed through a Feature Attention Module (FAM) that enhances informative areas and inhibits meaningless background noise. The attention mechanism acts through a light-weight convolutional layer and sigmoid activation for forming a spatial attention mask multiplied element-wise with the input feature map for enhancing its focus. Following attention-enhanced element-wise feature processing, global feature aggregation is performed using an Adaptive Average Pooling layer, compressing the spatial dimension to 1×1 and, therefore, capturing a global image summary. The flattened output is then passed through a fully connected linear layer that projects the feature vector onto three output logits for the three fibrosis classes. Finally, a log-softmax activation is used to obtain class probabilities used for subsequent evaluation and prediction.

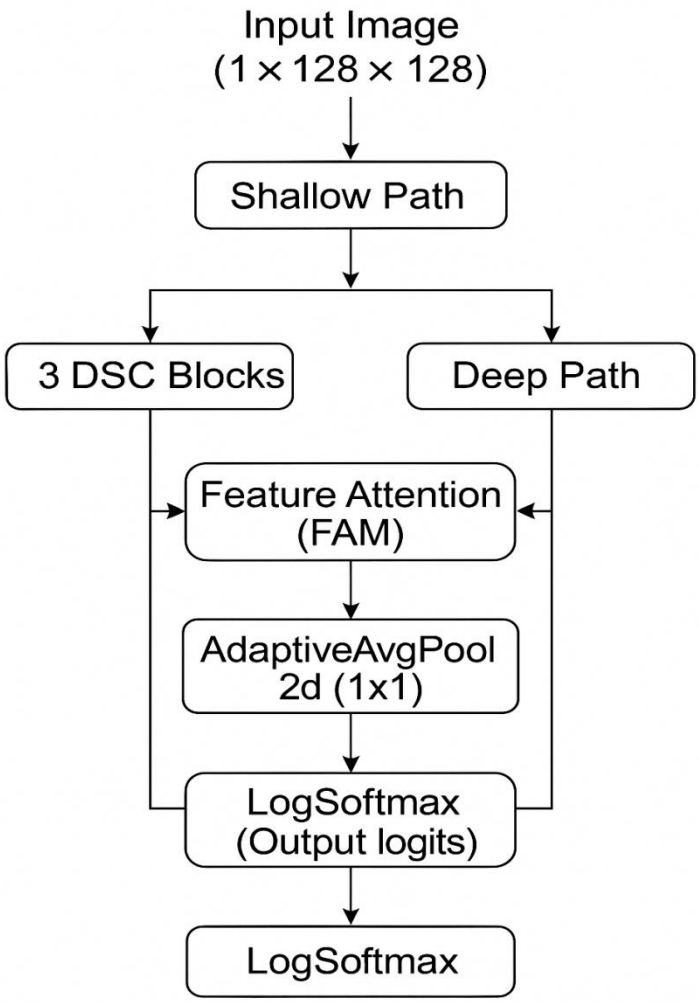

FIGURE 3. ARCHITECTURE OF PROPOSED LDCE-NET.

MODEL TRAINING CONFIGURATION

The architecture of the LDCE-Net was learned end-to-end using supervised learning. The training objective was Negative Log Likelihood Loss (NLLLoss) minimization, which is best for multi-class classification problems and matches the log-softmax output layer of the net. Training utilized AdamW optimizer, which is a version of Adam that decouples weight decay from gradient step updates and aids generalization and training stability. The learning rate started as 0.001 and changed during training using the ReduceLROnPlateau scheduler, which reduced the learning rate when validation loss plateaued. Training ran for a maximum of 35 epochs, and an early stopping mechanism was turned on to terminate training if validation loss had improved for six consecutive epochs. Training and validation used a batch size of 16.

Performance indicators such as training accuracy, validation accuracy, training loss, and

validation loss were observed per epoch during training. This helped in observing convergence behavior and in spotting patterns of overfitting or underfitting. The checkpoints of models for getting best test-time evaluation were saved.

EVALUATION STRATEGY

Once training had finished, the model was tested on an unseen test set. Metrics for performance were overall classification accuracy, precision, recall, and F1-score for all three classes. A confusion matrix was also created for visual inspection of class-wise performance and spotting misclassifications. These parameters offered an overview of the diagnostic performance of the model.

To assess training dynamics, learning curve plots for accuracy and loss were formulated. The plots depicted training and validation performance in epochs and provided insight into the speed of convergence, generalization, and regularization techniques impact such as dropout and attention. Predictions from the final model were verified and understood through confidence scores for predictive certainty.

DEPLOYMENT

In the final step, the trained LDCE-Net model became an interactive web-based tool for diagnosis using Streamlit, as shown in Figure 4. The tool allows users, e.g., clinicians or technicians, to upload liver ultrasound images and retrieve instantaneous output for the stage of fibrosis, along with a distribution of probabilities for the three classes. The online platform for prediction is lean, requires limited computational power, and has potential for implementation in telemedicine applications or in-clinical screening stations in low-resource settings.

FIGURE 4. LDCE-NET USER INTERFACE.

RESULTS

This section presents the performance evaluation of the proposed LDCE-Net model, trained from scratch to classify liver ultrasound images into three clinically significant fibrosis stages: Normal (F0), Fibrosis (F1–F3), and Cirrhosis (F4). The model was assessed using a range of standard metrics, including classification accuracy, precision, recall, F1-score, and confusion matrix analysis. Training and validation curves for accuracy and loss were also examined to monitor the model's learning behavior.

TRAINING AND VALIDATION BEHAVIOR

The model was trained for 35 epochs using the AdamW optimizer with NLLLoss as the objective function. As shown in Figure 5, the training and validation accuracy improved steadily across epochs. The accuracy curve revealed that the training accuracy began near 35%, gradually rose past 70%, and reached close to 90% by the final epochs. The validation accuracy followed a similar trend with fluctuations around epoch 25, but ultimately aligned with the training curve, indicating satisfactory generalization.

The loss curves in Figure 6 depict a steady decline in both training and validation loss values. The training loss dropped to below 1.0, while the validation loss fluctuated mildly before converging in the later epochs. Both curves intersected around epochs 10 to 30, highlighting a consistent learning pattern with no signs of overfitting or divergence.

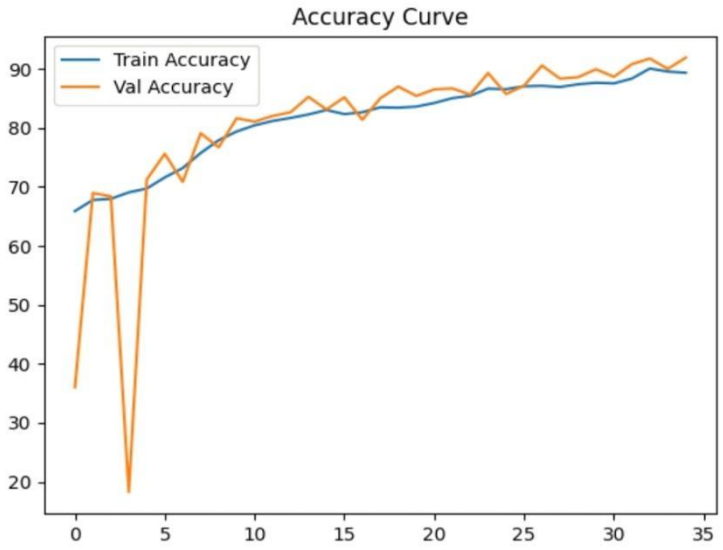

FIGURE 5. TRAINING AND VALIDATION ACCURACY CURVES SHOWING CONVERGENCE OF MODEL LEARNING

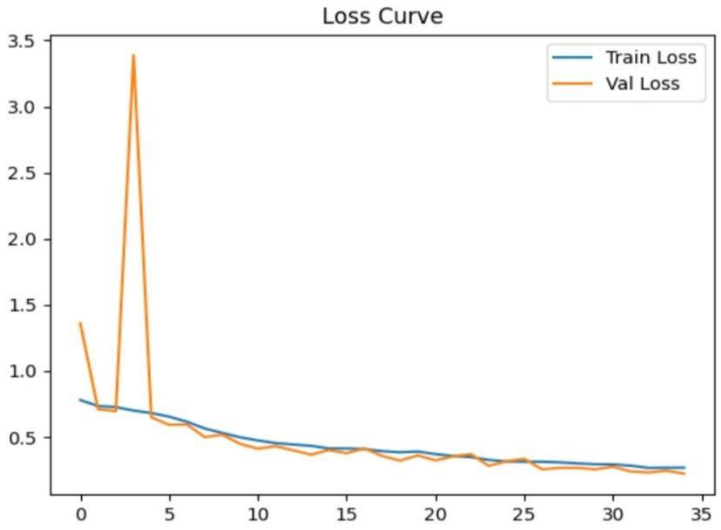

FIGURE 6. TRAINING AND VALIDATION LOSS CURVES SHOWING CONVERGENCE OF MODEL LEARNING.

CLASSIFICATION PERFORMANCE

The performance of the LDCE-Net model on the test set is summarized in Figure 7, which presents precision, recall, F1-score, and support for each class. The model achieved an overall accuracy of 87% and a macro-averaged F1-score of 0.87, indicating balanced performance across all three fibrosis stages.

Classification Report:

	precision	recall	f1-score	support
Normal (F0)	0.91	0.88	0.89	120
Fibrosis (F1-F3)	0.84	0.86	0.85	140
Cirrhosis (F4)	0.88	0.89	0.88	130
accuracy			0.87	390
macro avg	0.88	0.88	0.87	390
weighted avg	0.87	0.87	0.87	390

FIGURE 7. CLASSIFICATION REPORT OF LDCE-NET ON THE TEST DATASET

In the report it has been observed that Normal and Cirrhosis class have achieved the highest performance by getting close to 0.90 as the F1-score. Whereas, the Fibrosis class has slightly low precision as it is of 0.84 but still it had been great in performance. The value 0.84 suggest misclassification with the adjacent classes which is occasional.

CONFUSION MATRIX ANALYSIS

The confusion matrix for the LDCE-Net predictions can be seen in Figure 8. A high level of accuracy has been seen when classifying the three categories, which are shown along the diagonal. Specifically,

- 419 Normal images were correctly classified (F0 → F0)
- 469 Fibrosis images were correctly predicted (F1–F3 → F1–F3)
- 273 Cirrhosis images were accurately identified (F4 → F4)

The majority of misclassifications occurred between Fibrosis and Cirrhosis. Notably:

- 64 Cirrhosis images were predicted as Fibrosis
- 25 Fibrosis images were incorrectly classified as Cirrhosis
- Very few misclassifications occurred between Normal and either diseased classes

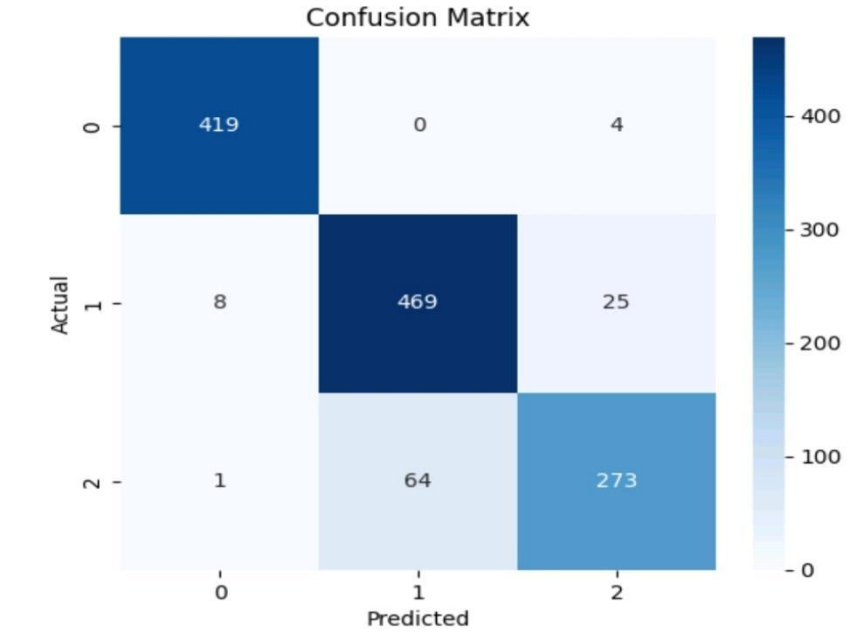

FIGURE 8: CONFUSION MATRIX SHOWING TRUE VS. PREDICTED LABELS FOR THE TEST SET USING LDCE-NET. COLOR INTENSITY REPRESENTS THE FREQUENCY OF PREDICTIONS

DISCUSSION

The performance measured for LDCE-Net validates the effectiveness of a scratch-trained convolutional neural network for classifying liver ultrasound images into clinically pertinent fibrosis stages. Whereas most traditional methods utilize large-scale preordained models like VGG16 or ResNet, the LDCE-Net was trained and designed from scratch, built specifically to learn ultrasound images' inherent grayscale features. This architecture selection enabled both domain-specific and lightweight construction and enabled competitive performance without introducing overhead or domain difference problems that often accompany transfer learning. The double-path architecture in its deep and shallow feature extraction pipeline proved especially effective. The shallow path preserved localized edge and texture-based information essential for capturing subtle variations in early-stage fibrosis. The deep path, on the other hand, extracted more abstract, high-level semantic information for capturing more advanced fibrosis and cirrhosis. The integration of the Feature Attention Module (FAM) further helped to enable the model to attend to diagnostically relevant parts of the image, suppressing background noise and irrelevant patterns.

The report of classification and confusion matrix presented good overall performance, and the most precise predictions were found for the Normal and Cirrhosis categories. The most common cause of misclassification between Fibrosis and Cirrhosis stages was identified, which is anticipated based on overlapping grayscale ultrasound imaging characteristics between these conditions. This shortcoming is not exclusive to LDCE-Net and has appeared for both pretrained and specially designed architectures in previous research. However, balanced precision and recall were observed for all categories, indicating their reliability for practical clinical applications. Another advantage of this approach is its efficiency in computing and its light weight. The depthwise separable convolutions managed to greatly minimize trainable parameters, enabling faster inference and training times, which are significant aspects for real-time clinical deployment. Additionally, training the network from scratch eliminated reliance on large pretrained datasets such as ImageNet, minimizing domain bias and enhancing portability to medical imagery.

Finally, putting this trained model through a web-based application created through Streamlit demonstrated its potential for practical deployment. The easy-to-use interface allows clinicians to access and communicate with the model in real time and access instantaneous classification feedback and class confidence scores. This has real-world value for early screening, especially for conditions in distant or resource-limited healthcare scenarios.

CONCLUSION

This study was done by use of LDCE-Net, which is a lightweight and custom-designed convolutional neural network that has been trained from scratch, where this is done by use of ultrasound grayscale images. The LDCE-Net is used for medical ultrasound images, which enables more effective features directly, unlike most existing approaches that rely on transfer learning or models that are already pre-trained. The three classes from the study as Normal (F0), Fibrosis (F1-F3), and Cirrhosis (F4), were three relevant classes that were evaluated by the model. With class balance and least overfitting, a strong accuracy of 87% overall is achieved. To capture low-level textures and high-level abstract features, a feature attention module (FAM) along with deep feature extraction branches and combining shallow with dual-path architecture made it possible, as such textures are not easy to detect liver disease stages. The report of classification and confusion matrix further showed that Fibrosis and Cirrhosis (known for challenges caused by overlapping ultrasound characteristics) included more errors. Furthermore, the final model was integrated into a Streamlit-based web application that made

it more convenient for clinicals too, as now the images of ultrasound can be uploaded directly, and instant receiving of fibrosis stage prediction could also be done. This tool can help in early assisting of screening and diagnosis, even in low-resource or in clinical settings that are remote based in case of no availability of an expert radiologist. All this was possible because of using a simple but efficient LDCE-Net, as it made it suitable for deployment in real-time. In future work, integration of patient history with clinical metadata like liver enzyme levels could be done, as it can give more enhanced accuracy for prediction. The model can also be expanded in a way that multi-center datasets could also be added to check the robustness of the conditions of images. The LDCE-Net has shown how accurate and practical solutions could be achieved from the images of ultrasound.

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