

Attention-Enhanced Residual Networks for Advanced Liver Fibrosis Classification in Deep Learning Models

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ABSTRACT: Liver fibrosis, a precursor to cirrhosis and liver cancer, requires early and accurate classification to improve patient outcomes. Traditional image analysis techniques and conventional deep learning models like U-Net face challenges in capturing fine-grained features essential for fibrosis staging. To address these limitations, this study introduces an advanced deep learning architecture Attention-Enhanced Residual Network (Attention ResNet) designed specifically for liver fibrosis classification. The proposed model integrates improved residual modules within both encoder and decoder paths to boost feature extraction and ensure stable gradient flow. A Kernel based Fuzzy C-Means (KFCM) is incorporated before skip connections to enrich segmentation through simultaneous channel and spatial attention. Additionally, a Boundary Descriptors layer at the bottleneck extracts contextual information across scales, enhancing the model's representation power of feature extraction. Evaluation on medical imaging datasets done by Python shows that AER-Net delivers superior classification specificity and accuracy of 93% and accuracy of 93% respectively.

Keywords: Liver fibrosis, Cirrhosis, Attention-ResNet, KFCM, Boundary Descriptors.

1. Introduction

Liver cancer is a highly prevalent malignant tumor that continues to rank among the world's leading causes of cancer-related mortality, especially in China [1]. In the upcoming years, the mortality rate from liver cancer is expected to continue to increase, posing a major risk to public health and safety. In order to drastically lower patient mortality rates, early detection and precise diagnosis are therefore essential. Computed Tomography (CT) has become an essential diagnostic technique in contemporary healthcare in this regard. Advanced X-ray equipment is used in CT scans to rotate around the patient and take pictures from various angles [2]. These images are then processed to create comprehensive cross-

sectional views of internal structures. In order to produce high-resolution images and enable more precise diagnosis and focused treatment planning, CT imaging depends on high-precision sensors [3]. Despite these advancements, the manual delineation of liver tumors in CT images remains a labor-intensive and time-consuming task, often subject to variability based on the physician's interpretation. Moreover, the low contrast and complex morphology of liver tumors relative to surrounding tissues further complicate the process.

In the pre-processing stage, a mean filter is applied to the image to reduce steady and round-off noise, thereby enhancing overall accuracy [4]. This technique effectively improves image contrast

while maintaining good image quality. However, it suffers from reduced accuracy due to over-amplification of noise in uniform regions [5]. To further improve accuracy, Artificial Neural Networks (ANNs) are utilized. To simplify the model and prevent overfitting, a Support Vector Machine (SVM) is trained alongside the ANN. This approach also effectively handles the long training times associated with large datasets [6]. However, it is sensitivity to data scaling and poor performance when dealing with non-linear data or outliers [7]. To address these issues, Kuwahara filter is used for the better quality of the image and to avoid the noises.

High-quality images with clear, well-defined edges significantly enhance the performance of segmentation algorithms, enabling more precise detection of conditions such as cirrhosis and liver cancer [8]. While edge detection techniques are simple and easy to implement, they often produce low-intensity pixel values, limiting accuracy. Watershed segmentation effectively identifies object boundaries by preventing unsegmented areas, but it is sensitive to noise and small intensity variations, leading to over-segmentation [9]. To overcome these issues, KFCM segmentation is applied, improving image quality and ensuring more consistent segmentation results.

Following segmentation, classification techniques play a crucial role in categorizing liver diagnosis, which is vital for effective diagnosis and treatment planning. Naïve Bayes classifiers are computationally efficient for large datasets but struggle with complex feature relationships [10]. Artificial Neural Networks (ANNs) offer high flexibility and are widely used, though often lack interpretability due to complex tuning [11]. Convolutional Neural Networks (CNNs) reduce model parameters and perform well, however risk overfitting and performance degradation. To address these issues, AI based Morpho Class Net Classifier is employed in significant areas and thus enhancing classification accuracy for various liver diagnosis detection. The main contributions are:

- To enhance data quality in liver fibrosis classification, the pre-processing step using the Kuwahara filter is employed to reduce noise and smooth medical imaging data related to liver fibrosis are preserved while minimizing distortions caused by noise.
- To improve segmentation accuracy, KFCM is applied to perform soft partitioning of image pixels, effectively delineating the regions of interest in liver scans.
- To optimize classification performance, Attention-ResNet are utilized, which incorporate attention mechanisms and residual learning.

2. Recent Works

Wei et al [12] 2023 proposed BSS-TFNet with an attention-enhanced architecture designed to suppress background signals in time-frequency liver imaging data. By focusing on relevant spectral features and minimizing noise, the model significantly improves diagnostic precision. However, the processing of time-frequency representations and attention mechanisms lead to increased computational demands.

Al-Rasheed et al [13] 2023 demonstrated liver lesion prediction, ensemble methods combining transfer learning models with Conditional Generative Adversarial Networks (CGANs) have shown improved performance by leveraging diverse feature representations. These ensembles enhance prediction accuracy, especially when trained on synthesized data generated by CGANs. However, handling multiple pre-trained models and generated data significantly increases memory requirements, posing challenges for real-time clinical application.

Ahmed et al [14] 2025 presented a MSA-UNet3+ leverages multi-scale attention mechanisms to enhance feature extraction in diagnosis of liver images. The integration of a supervised prototypical contrastive loss further improves

segmentation accuracy by promoting better class separation. However, processing high-resolution medical images and managing large datasets result in increased computational load and memory usage.

Talaat et al. [15] (2023) proposed a attention-augmented algorithm for detecting diseases in human liver. Similarly, in pediatric liver cancer

detection, models like A2M-LEUK benefit from high input resolution, as larger datasets often improve accuracy in machine learning. However, this also leads to substantial computation time and memory consumption, posing challenges in processing and scalability for real-time clinical applications.

3. Proposed Work Explanation

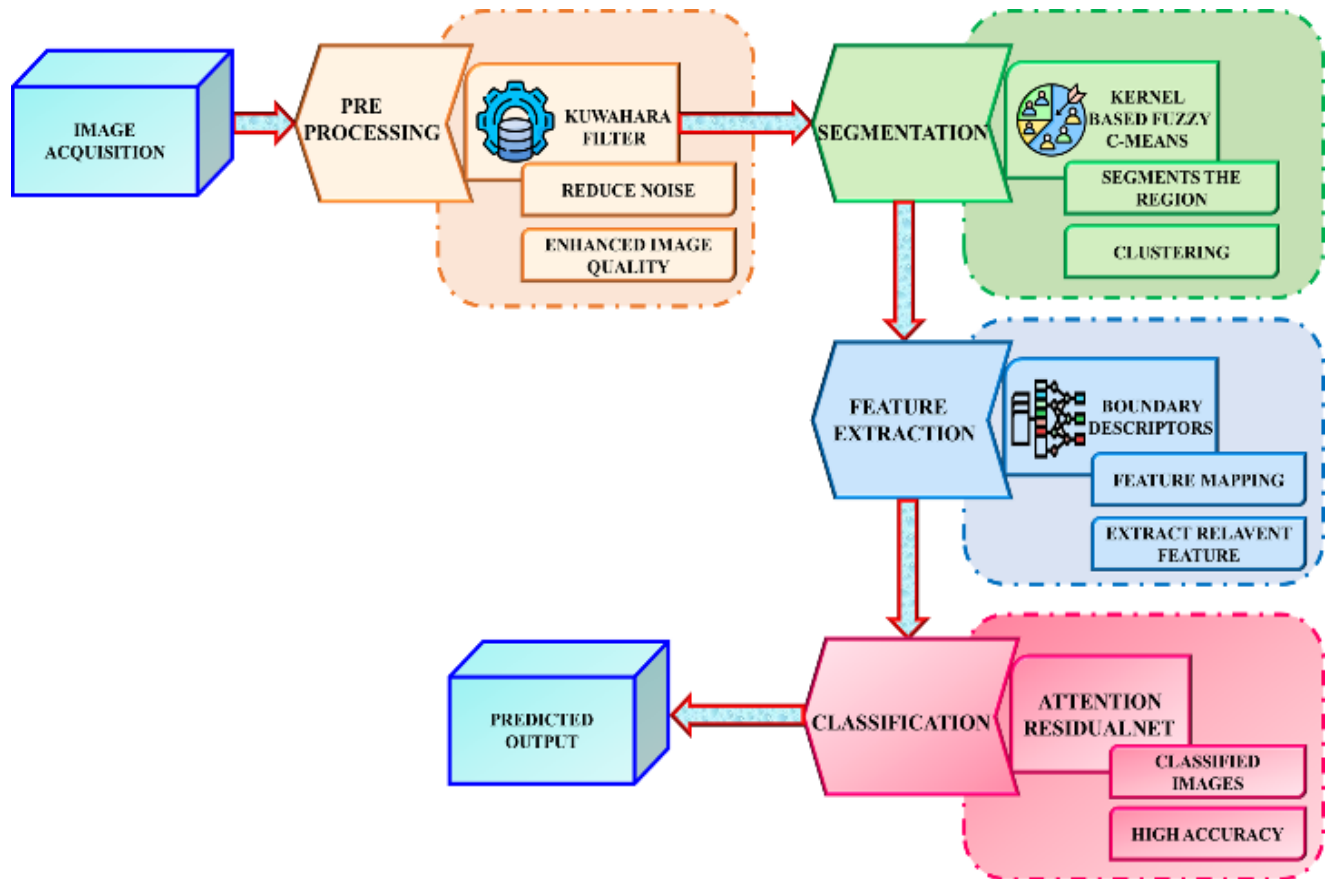


Figure 1: Proposed Block Diagram

Figure 1 illustrates a image-based classification, particularly useful in liver disease diagnosis systems. The process initially begins with image acquisition, where raw data is collected. The next step is pre-processing, where a Kuwahara filter is applied to reduce noise and enhance image quality. The refined image is then passed to the segmentation phase, which uses KFCM clustering to segment relevant regions. These segmented areas are then analyzed in the feature extraction stage using boundary descriptors to map and extract significant features. The extracted features are subsequently used in the classification stage, which employs an Attention Residual Network (ResidualNet) to classify the images with high

accuracy. Finally, the system outputs the predicted result.

3.1 Mathematical Expressions and Symbols

3.1.1 Pre-processing by Kuwahara Filter

The Kuwahara filter is used in the pre-processing stage to reduce noise while preserving edges. This non-linear smoothing technique improves the clarity of medical images, ensuring important structural details of the liver are retained.

Algorithm 1: Kuwahara Filter

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1: Input: Image I, filter radius R
2: Output: filtered image output
3: procedure KUWAHARA
4: for i in 1..H, j in 1..W do
5:  $p = i(i, j)$ ;
6: if  $i(i, j)$  is fit then
7:  $R_{fit} = R$ 
8: else
9:  $R_{fit} = \min(i, j, H - i + 1, W - j + 1) - 1$ 
10: end if
11:  $Q_{t=0..3}^p = \text{findquadrants}(p, R_{fit}, I)$ ;
12:  $\text{means}[] = \text{mean}([Q_0^p, Q_1^p, Q_2^p, Q_3^p])$ ;
13:  $\text{vars}[] = \text{variance}([Q_0^p, Q_1^p, Q_2^p, Q_3^p])$ ;
14:  $\text{out}(i, j) = \text{KuwaharaPixel}(\text{means}, \text{vars})$ ;
15: end for
16: end procedure

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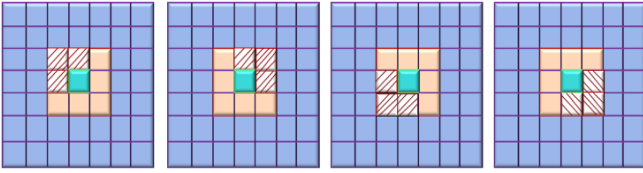


Figure 2: Filtering each area of image

Figure 2 illustrates each area filtering in the pre-processing phase of liver diagnosis. The different shading and patterns, such as striped areas, predicts various filtering techniques applied to enhance features or suppress noise, which is crucial for accurate diagnosis. The sequence likely demonstrates the iterative nature of the filtering process, with each subsequent image showing a refined version of the previous one.

3.1.2 Segmentation by KFCM

To effectively identify and isolate regions of interest in liver images, the KFCM method is employed for segmentation. Unlike conventional clustering techniques, KFCM uses fuzzy logic, enabling each pixel to associate with multiple clusters to varying degrees an approach well-suited for medical images with indistinct tissue boundaries.

To define a nonlinear map as $\Phi: x \rightarrow \Phi(x) = F$, where $x \in X$. X denotes the data space,

and F the transformed feature space with higher or even infinite dimension. KFCM minimizes

the following objective function

$$J_m(U, V) = \sum_{i=1}^C \sum_{k=1}^n u_{ik}^m \|\Phi(x_k) - \Phi(v_i)\|^2 \quad (1)$$

Where,

$$\|\Phi(x_k) - \Phi(v_i)\|^2 = K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i) \quad (2)$$

$$J_m(U, V) = \sum_{i=1}^C \sum_{k=1}^n u_{ik}^m (1 - k(x_k, v_i)) \quad (3)$$

Minimizing Eq. (3) under the constraint of U , it have

$$u_{ik} = \frac{(1/(1-K(x_k, v_i)))^{1/(m-1)}}{\sum_{j=1}^C (1/(1-K(x_k, v_j)))^{1/(m-1)}}, \forall i = 1, 2, \dots, c, k = 1, 2, \dots, n \quad (4)$$

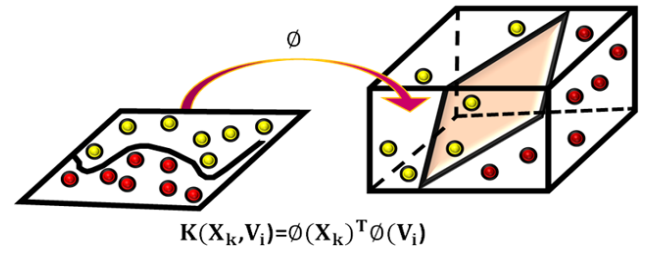


Figure 3: Architecture of KFCM

Figure 3 illustrates a transformation from a 2D input space to a 3D output space. It shows how data points are mapped through a function

$$K(X_k, V_i) = \Phi(X_k)^T \Phi(V_i) \quad K(X(k), V_i) = \Phi(X(k))^T \Phi(V_i) \quad (5)$$

This process highlights the relationship between the original data distribution and its representation in a higher-dimensional space, enhancing analysis capabilities.

3.1.3 Classification by Attention Resnet

To accurately classify the stages of liver fibrosis, an Attention Resnet is utilized. This architecture combines the strengths of residual learning with attention mechanisms to improve feature representation and model focus.

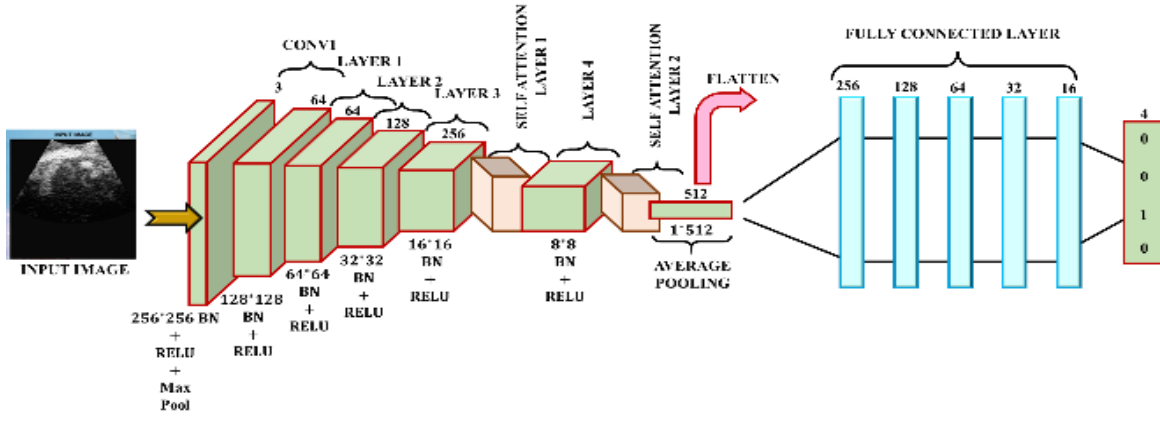


Figure 4: Architecture of Attention based Resnet

To preserve this information, learnable parameters γ and β are introduced for transformation and reconstruction:

$$y(k) = \gamma(k)x^{\wedge}(k) + \beta(k) \quad (6)$$

Here,

$$E[x^{\wedge}k]\gamma(k) = Var[xk] \quad (7)$$

$$\beta(k) = E[x(k)] \quad (8)$$

These reconstruction parameters retain the original layer's features even after normalization. Figure 4 illustrates the architecture of the classifier process, where μ represents the mean of x in a mini-batch and σ represents its standard deviation.

4. Results and Discussion

The proposed methodology focuses on the classification of advanced liver fibrosis using Attention Resnet within deep learning frameworks. Implementation is carried out using Python, which facilitates the development and evaluation of the deep learning architecture in this study.

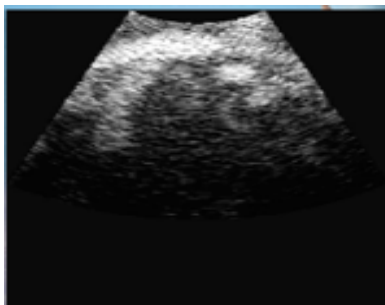


Figure 5: Input Image

Figure 5 represents an ultrasound scan of the liver, commonly used as an input image for liver disease diagnosis, including conditions like liver fibrosis, cirrhosis, or tumors.

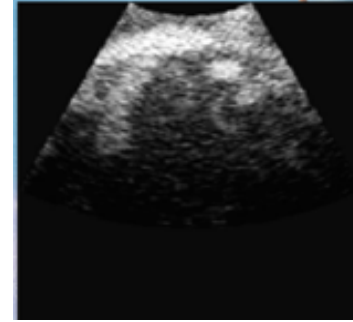


Figure 6: Resized Image

Figure 6 resized image of the liver is used as input for diagnostic analysis. Despite being reduced in size, the image preserves sufficient contrast and texture details critical for deep learning-based classification and medical evaluation.



Figure 7: Greyscale Image

Figure 7 represents grayscale ultrasound image of the liver, resized for computational analysis. It highlights the varying tissue densities within the liver, essential for identifying conditions such as fibrosis or cirrhosis.

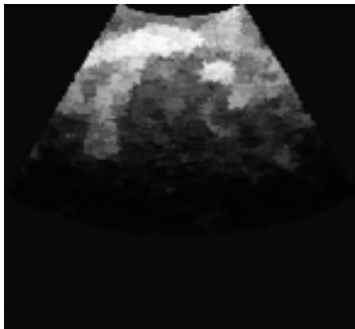


Figure 8: Kuwahara Filter

Figure 8 represents a liver ultrasound that has been processed using the Kuwahara filter, a non-linear smoothing technique. The filter effectively reduces noise while preserving edges and important structural details, enhancing the overall image quality.

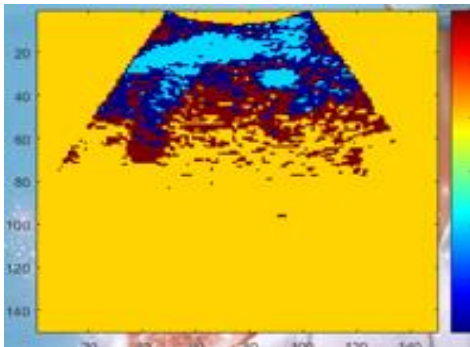


Figure 9: Image by KFCM process

Figure 9 showcases the segmentation output using KFCM clustering applied to a liver ultrasound scan. The technique segments the image into distinct regions based on pixel intensity and spatial similarity. KFCM enhances segmentation accuracy by considering non-linear relationships in the data.

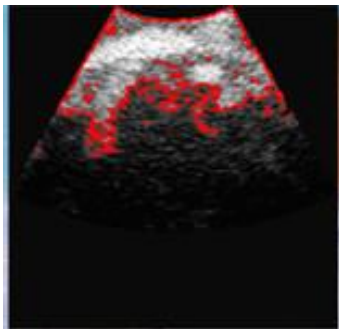


Figure 10: Image by Boundary Descriptors

Figure 10 illustrates the application of boundary descriptors for feature extraction from a liver

ultrasound scan. The red outlines highlight the detected boundaries of regions of interest, such as potential lesions or fibrosis-affected areas.

Cirrhosis	55		4	2	2
Fibrosis		108			
Fibrosis			104		4
Fibrosis	2		6	70	6
Fibrosis			4	5	75

Figure 11: Confusion Matrix

Figure 11 displays a confusion matrix used to evaluate the performance of a liver fibrosis classification model. Each row represents the actual class, while each column represents the predicted class.

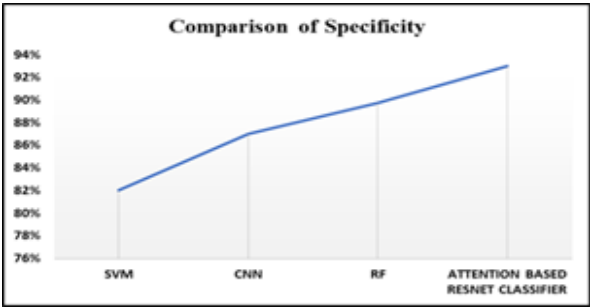


Figure 12: Specificity Comparison

Figure 12 compares the specificity of four classification models: SVM [16], CNN [17], RF [18] and an attention-based ResNet classifier. The specificity increases from 82% for SVM to 92% for the attention-based ResNet classifier.

Table 1: Comparison of Accuracy

METHOD	ACCURACY
KNN [19]	90%
SVM [16]	86%
Attention-based ResNet	92.7%

Table 1 represents the comparison of the accuracy of different techniques such as KNN, SVM and Attention based ResNet with the accuracies of 90%, 86% and 92.7%.

5. Conclusion

This work shows liver fibrosis, a critical precursor to cirrhosis and liver cancer, demands early and

precise classification to support effective clinical intervention. This study proposes the AER-Net, an advanced deep learning framework tailored for liver fibrosis classification. By incorporating improved residual modules, the model enhances feature extraction while maintaining stable gradient flow throughout training. The integration of KFCM segmentation before skip connections enriches spatial and channel attention, allowing for more refined tissue segmentation. Furthermore, the inclusion of a Boundary Descriptors layer at the bottleneck improves multi-scale contextual feature representation. Experimental results using medical imaging datasets in Python demonstrate that AER-Net outperforms conventional methods in terms of classification specificity and accuracy of 93% respectively.

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