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DEEP LEARNING-DRIVEN IMAGE ENHANCEMENT AND LESION SEGMENTATION FOR IMPROVED DIAGNOSTIC ACCURACY IN NOISY MEDICAL IMAGES

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ABSTRACT: Medical imaging technologies, including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound, play a significant role in disease diagnosis and treatment planning. Therefore, medical images are sometimes affected by noise, low contrast, motion artifacts, and intensity variations that reduce image quality and complicate lesion detection. This study proposes a deep learning-based framework for image enhancement and lesion segmentation to improve diagnostic accuracy in noisy medical images. The proposed framework adopts a convolutional autoencoder-based image enhancement model with a lightweight U-Net segmentation architecture for creating an effective medical image analysis pipeline. The experimental study was conducted using liver CT images from the Liver Tumor Segmentation (LiTS) dataset. In this context, preprocessing operations such as resizing, normalization, lesion-mask extraction, and Gaussian noise simulation have been implemented to generate noisy medical imaging scenarios. The autoencoder improvement module has been designed to suppress noise and reconstruct improved images while preserving significant anatomical structures. The improved images were used for automated lesion segmentation utilizing the U-Net-based framework. Performance evaluation was carried out using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Dice Score, and Intersection over Union (IoU). The PSNR of 24.57 dB and the SSIM of 0.792 indicate that the enhancement framework can reconstruct high-quality images while retaining their structural information. It has been found that the Dice Score and IoU Score of the segmentation framework are 0.134 and 0.072, respectively, under noisy imaging conditions. Comparative analysis revealed that lesion localization and segmentation consistency were enhanced by enhancement-assisted segmentation compared with direct segmentation of noisy images. The study also demonstrated that the cross-modality analysis is adaptable to both MRI-like and ultrasound-like simulated images. The results show that combining image enhancement and lesion segmentation is a promising approach to achieve more reliable and efficient noisy medical image analysis. The proposed framework offers a promising basis for developing future computer-aided diagnostic systems and automated healthcare applications for noisy medical imaging environments.

Keywords: deep learning, medical image enhancement, lesion segmentation, convolutional neural network (CNN), U-Net, autoencoder, noisy medical images, CT imaging, diagnostic accuracy, medical image analysis, artificial intelligence in healthcare, image denoising.

I. INTRODUCTION

Medical imaging technologies such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and ultrasound (ultrasonography) are essential for disease diagnosis, treatment planning, and clinical decision-making. Although there are many sources of noise, low contrast, motion artifacts, and intensity variation that affect the quality of medical images and make lesion identification difficult. Thus, image

enhancement and lesion segmentation are crucial steps in medical image analysis that improve image clarity and help medical practitioners more accurately identify abnormal tissues and pathological areas (Rasool & Bhat, 2023). Segmentation techniques can be used to isolate regions of interest from surrounding tissues, aiding more accurate diagnosis and treatment monitoring (Gao et al., 2025). Traditional image processing techniques have proven inadequate for handling complex medical image patterns and noisy dat, particularly across multiple imaging modalities. Over the last few years, deep learning has revolutionized medical image analysis, automated feature extraction, and adaptive image enhancement. Segmentation models using deep learning, primarily CNNs and Transformers, have exhibited better performance in lesion detection, particularly in terms of precision (Al-Ghanimi & Al-Ghanimi, 2025). The purpose of this study is to develop a deep learning framework for medical image enhancement and lesion segmentation to improve diagnostic accuracy in noisy medical images. The paper emphasizes the combination of image denoising and automated lesion segmentation to support reliable clinical diagnosis in MRI, CT, and ultrasound images.

Deep Learning has become an effective method for addressing the challenges of noisy medical imaging. Medical images are often affected by various types of noise due to limitations of imaging equipment, patient motion, low radiation exposure, and environmental interference, which can affect the visibility of lesions and the reliability of diagnosis (Herath et al., 2025). Conventional filtering and enhancement techniques often fail to preserve significant anatomical structures while removing noise. On the contrary, deep learning models can discover hidden patterns and learn complex image representations from extensive datasets for medical applications. Convolutional Neural Networks (CNNs), autoencoders, Generative Adversarial Networks (GANs), and Transformer-based models have shown impressive results in denoising and improving the accuracy of medical scan segmentation (Joseph, 2025). Also, deep learning-based segmentation frameworks can accurately extract boundaries and localize features, even in complex medical images (Gao et al., 2025). Furthermore, deep learning algorithms can automate clinical workflows, thereby reducing the likelihood of human diagnostic errors. Huang et al. (2025) discussed the importance of AI in medical imaging, emphasizing its role in diagnosing diseases such as cancer. They emphasized that AI plays an important role in providing a precise diagnosis and therapy planning for the tumor through the rapid analysis of medical images. Hence, the incorporation of deep learning into noisy medical imaging is crucial for enhancing diagnostic outcomes, minimizing human error, and facilitating intelligent healthcare systems.

Although there has been great progress in medical image acquisition techniques, noisy, low-quality medical images still pose serious challenges for accurate medical image diagnosis and lesion segmentation. Many medical images obtained from MRI, CT, and ultrasound scanners are prone to various sources of noise, artifacts, intensity inhomogeneity, and low contrast, thereby limiting the visualization of pathological areas and hindering clinical interpretation (Herath et al., 2025; Doshi et al., 2025). These problems have a detrimental effect on the accuracy of lesion detection and boundary extraction, especially in complex tumor diagnosis and in identifying small abnormal tissue. Traditional image enhancement and segmentation methods are insufficient to handle the variability in image quality across medical imaging modalities (Rasool & Bhat, 2023). While successful deep learning methods such as CNNs and U-Net have improved segmentation accuracy, many current methods still face challenges in generalization, robustness, and accuracy under highly noisy conditions (Gao et al., 2025). Another study indicated that currently available models struggle to maintain segmentation accuracy on images that have undergone significant deformations and lesions with varying characteristics (Al-Ghanimi & Al-Ghanimi, 2025). Furthermore, limited cross-modality adaptability remains a challenge, as models trained on one imaging modality may not perform effectively on others. Hence, there is a need for an integrated deep learning-driven framework that combines lesion segmentation and image enhancement to improve diagnostic accuracy and clinical reliability in noisy medical images. The purpose of this study is to develop a deep learning-driven framework for medical image enhancement and accurate lesion segmentation to improve diagnostic accuracy in noisy medical images.

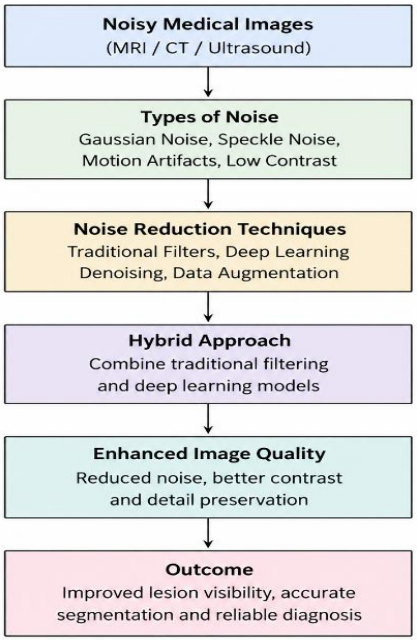
- To develop a deep learning model for medical image enhancement.
- To design an automatic lesion segmentation framework with CNN and Transformer-based approaches.
- To evaluate the performance of segmentation and image enhancement with the proposed approach on MRI, CT, and ultrasound images.
- To compare the proposed framework with existing image enhancement and segmentation methods in terms of accuracy, robustness, and diagnostic effectiveness.

This study is important because it helps advance an intelligent medical imaging system that enhances diagnostic accuracy in noisy medical environments. The suggested framework includes image enhancement and pathological region segmentation modules, which use deep learning techniques to accurately detect abnormal tissues. The proposed framework would enhance medical images and automate lesion segmentation, helping clinicians make quick decisions about patients' health. In addition, the study would contribute to the field of medical imaging by exploring the integration of CNN and Transformer models for image enhancement and segmentation. Gao et al. (2025) emphasized the accuracy and reliability of medical image segmentation using deep learning frameworks. Furthermore, the study facilitates the development of automated healthcare systems that reduce manual work and support an effective clinical workflow. The present study addresses research gaps in noisy image segmentation, cross-modality adaptability, and integrated enhancement-segmentation designs. The expected results of the proposed framework are improved performance on MRI, CT, and ultrasound datasets and expanded practical applicability across a wide range of healthcare scenarios. Also, the results could be used in future research to explain AI models, develop intelligent diagnostic systems, and analyze medical images in real time for precision healthcare applications.

II. LITERATURE REVIEW

1. MEDICAL IMAGE NOISE REDUCTION TECHNIQUES

Noise reduction is a crucial aspect of medical image processing, enabling high-quality images and accurate disease diagnosis and lesion segmentation. Gaussian noise, speckle noise, motion artifacts, and low contrast due to acquisition limitations and environmental interference are commonly encountered in medical images acquired from MRI, CT, and ultrasound modalities. Such distortions make it hard to identify pathological regions and decrease image clarity. Gaussian filtering, anisotropic diffusion, and wavelet transform methods have been widely adopted to enhance image smoothness while preserving structural information, alongside traditional noise-reduction methods such as median filtering (Xu et al., 2024) [Figure 2.1].



(Source: Self-developed).

FIGURE 1. Flowchart of medical image noise reduction processes.

The use of deep learning-based denoising methods to preserve image features and suppress noise has recently proven effective. Bhutto et al. (2022) presented a framework that fuses images using a CNN to

enhance contrast and reduce noise, resulting in improved image clarity and feature preservation. Also, data augmentation methods, including rotation, scaling, flipping, and noise injection, are commonly employed to enhance the model's robustness and image quality during training (Goceri, 2023). Regarding medical image enhancement, the most promising approaches combine traditional filters with deep learning models, which have proven to yield accurate results in image segmentation and diagnostic analysis.

2. DEEP LEARNING-BASED IMAGE ENHANCEMENT

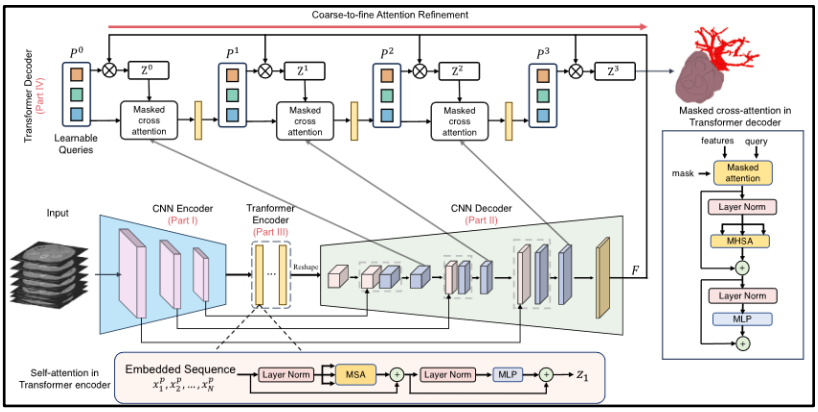
Deep learning-based image enhancement techniques have improved the quality of medical images by suppressing noise, reducing distortions, and enhancing anatomical structures. Conventional image enhancement techniques may fail to maintain the fine details and texture information, especially in low-quality or noisy medical scans. Deep learning methods, particularly CNNs, have proven their ability to learn more complicated image features and perform automatic image quality improvement with less manual effort. Ghandour et al. (2023) clarified that medical image enhancement algorithms based on CNN technology can improve image quality, preserve important diagnostic information, and enhance image contrast. In medical image enhancement, transfer learning and denoising-based frameworks were also significant. Alsubai et al. (2025) presented a distribution-based compressed denoising scheme using transfer learning that has shown excellent results for noise removal and diagnostic accuracy in medical imaging applications. Also, Sundarrajan et al. (2024) highlighted the significance of using deep learning models for low-light image enhancement to improve the visibility of medical scans and minimize noise. For the restoration of degraded medical images and the enhancement of image clarity, the use of autoencoders, GANs, and residual learning architectures has been gradually increasing. These methods facilitate accurate visualization of pathological regions, supporting improved lesion segmentation, clinical decision-making, and disease detection across various imaging modalities.

3. LESION SEGMENTATION APPROACHES

In medical image analysis, a vital step is lesion segmentation, which involves detecting and isolating pathological areas or abnormal tissues from other anatomical structures. Medical imaging and precise lesion segmentation play an essential role in disease diagnosis and in monitoring its progression. Traditional segmentation techniques, including thresholding, region growing, clustering, and edge detection, which have been extensively applied in medical imaging, are ineffective in handling noisy images, unclear lesion boundaries, and intensity variations (Obuchowicz et al., 2024). Therefore, deep learning-based segmentation methods have received considerable attention for their ability to automatically learn complex image features and improve segmentation accuracy. CNNs, U-Net, and hybrid deep learning frameworks are often employed for lesion segmentation tasks. Shi et al. (2022) presented a hybrid robust-learning framework for medical image segmentation that robustly adapts to noisy labels and enhances segmentation reliability in complex medical image datasets. Similarly, Ergin et al. (2024) evaluated various deep learning models and architectures for dermoscopic image segmentation and found that advanced architectures achieved greater noise resilience and segmentation accuracy in skin lesion detection. Also, segmentation systems based on Artificial Intelligence have demonstrated clinical viability for tumor detection, organ segmentation, and disease localization in MRI, CT, and dermoscopy images (Obuchowicz et al., 2024). These developments underscore the significant role of deep learning-based lesion segmentation methods in contemporary healthcare systems.

4. U-NET AND TRANSFORMER ARCHITECTURES

U-Net and Transformer-based architectures have proven highly effective for medical image segmentation, as they can capture spatial and contextual information in complex medical images with high accuracy. Zhang et al. (2024) present various variants of U-Net that have achieved impressive segmentation performance in applications such as tumor detection, organ segmentation, and lesion localization. The study highlighted the efficiency of feature learning, which enables U-Net models to perform well even under the constraint of small medical datasets. In recent years, Transformers have gained popularity for their ability to model long-range dependencies and global contextual relationships in medical images (Zhang, 2025).



(Source: Chen et al., 2024).

FIGURE 2. Transunet.

Chen et al. (2024) proposed TransUNet, which adds Transformer modules to the traditional U-Net to enhance feature representation and segmentation accuracy [Figure 2]. Their results indicated that the Transformer-based models outperformed traditional CNN-based models in complex segmentation tasks. Similarly, Pan et al. (2023) proposed EG-TransUNet, a biomedical image segmentation model based on the Transformer architecture that utilizes feature enhancement and guided feature learning mechanisms. The results suggest that combining U-Net and Transformer architectures can substantially enhance segmentation accuracy and diagnostic reliability in contemporary medical imaging systems.

5. RESEARCH GAPS

Although several studies on medical image enhancement and medical lesion segmentation have demonstrated the effectiveness of deep learning techniques, research gaps remain. Some deep learning enhancement frameworks have been proposed, but they struggle to generalize across imaging modalities such as MRI, CT, and ultrasound (Xu et al., 2024), and traditional noise reduction methods fail to preserve important anatomical details in highly noisy medical images. While CNN-based enhancement models can provide a better understanding of image content, many focus on denoising without incorporating accurate lesion segmentation mechanisms (Ghandour et al., 2023). Likewise, existing lesion segmentation methods are susceptible to noisy labeling, irregularly shaped lesions, and reduced robustness under poor image quality (Shi et al., 2022). In addition, Transformer-based methods such as TransUNet have demonstrated enhanced segmentation performance, despite challenges related to their cross-modality versatility and high computational demands (Chen et al., 2024). Limited evaluation of combined enhancement-segmentation frameworks under real clinical conditions has also been reported in existing studies. Hence, there is a need for a comprehensive deep learning framework that can efficiently enhance images and provide robust lesion segmentation, thereby improving diagnostic accuracy in noisy medical imaging environments.

III. METHODOLOGY

1. DEEP LEARNING FRAMEWORK

The proposed deep learning system was designed as a unified architecture to enhance medical images and detect lesions in noisy imaging environments. The system can be divided into two main parts: one for image enhancement and another for lesion segmentation. The image enhancement component is based on a convolutional autoencoder architecture. It is used to eliminate noise artifacts, increase image contrast, and retain continuity in medical images. The lesion segmentation component uses a convolutional neural network similar to U-Net (Brunese et al., 2025). Convolutional operations are subsequently applied to extract hierarchical spatial features from the input images. The convolution process is mathematically represented as follows.

$$F(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n)$$

In the input image, K denotes the convolution kernel, and F denotes the generated feature map. The encoder section compresses spatial information into latent representations, and the decoder reconstructs enhanced images via upsampling. The framework uses Dice loss to improve the overlap accuracy between predicted and ground-truth lesion regions (Xie et al., 2025). The Dice coefficient is defined as follows.

$$Dice = \frac{2|P \cap G|}{|P| + |G|}$$

Where P is the predicted lesion pixels, and G denotes the ground-truth segmentation masks. The integrated framework enables robust enhancement and segmentation for automated medical image analysis.

2. MEDICAL IMAGE DATASET AND PREPROCESSING

The medical imaging dataset used in this research was obtained from the Liver Tumor Segmentation (LiTS) dataset and contains annotated abdominal computed tomography (CT) scans for lesion segmentation. The dataset consists of grayscale CT liver images, and the corresponding pixel-level lesion masks are stored in PNG format to facilitate computational processing. The LiTS dataset initially contained 58638 CT image slices with corresponding liver and lesion masks (Kaggle.com, 2020). Only images containing lesions were included to mitigate excessive background influence and enhance feature identification during training. Image preprocessing steps were implemented to ensure consistency, reduce computational complexity, and improve the models' learning capabilities. All CT images and lesion masks were resized to 256 × 256 pixels to maintain uniform spatial dimensions throughout the dataset. The grayscale images were subsequently normalized to the intensity range 0-1 using min–max normalization. The normalization process is mathematically represented as follows.

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

Where I is the original image intensity, I_{min} is the minimum pixel intensity, and Imax is the maximum pixel intensity. Gaussian noise was artificially introduced into the normalized CT images to simulate realistic noisy medical imaging conditions. The noisy image generation process is expressed as follows.

$I_{noisy} = I + N(0, \sigma^2)$

Where I is the normalized image, $N(0, \sigma^2)$ denotes Gaussian noise with zero mean and variance σ^2 (Salem et al., 2025). Furthermore, binary lesion masks were generated through threshold-based conversion to separate lesion regions from background pixels.

3. IMAGE ENHANCEMENT MODEL

The image enhancement module was developed using a convolutional autoencoder architecture to suppress noise artifacts and improve the visual quality of noisy medical images. The encoder section compressed the noisy input image into low-dimensional latent feature representations, and the decoder reconstructed the enhanced medical images (Mahapatra et al., 2023). The convolutional layers were employed to extract spatial and texture-related information from the noisy CT images. Max-pooling operations were employed within the encoder to reduce spatial dimensionality and computational complexity (Ma, 2025). The enhancement model was trained using mean squared error (MSE) loss to minimize the reconstruction error between noisy and reconstructed images.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (I_i - \hat{I}_i)^2$$

Where I_i is the original image pixel intensity and î denotes the reconstructed image intensity.

4. LESION SEGMENTATION MODEL

The lesion segmentation module was developed using a U-Net-based convolutional neural network architecture for automated lesion localization and boundary extraction. The U-Net architecture was selected

because of its ability to perform precise biomedical image segmentation through multi-scale feature extraction. The skip connection was installed to combine low-level spatial features with high-level semantic information. The segmentation probability map generated by the network is shown below.

$P(x) = \sigma (Wx + b)$

Where P(x) denotes the predicted segmentation probability, W is the network weights, σ denotes the sigmoid activation function, and b is the bias term.

5. TRAINING AND OPTIMISATION STRATEGY

The proposed deep learning framework was trained using supervised learning techniques to optimize both image enhancement and lesion segmentation performance. The images were further split into training and validation sets to assess the model's generalization performance and reduce the risk of overfitting during training. Batch training was used to improve the speed and stability of parameter optimization. The Adam optimizer was employed for its faster convergence and adaptive learning-rate adjustment during backpropagation (Sun et al., 2024). The enhancement model was optimized to minimize reconstruction error, and the segmentation framework was optimized to improve lesion overlap accuracy. Binary thresholding was applied during the prediction to convert probabilistic segmentation outputs into lesion masks for quantitative evaluation.

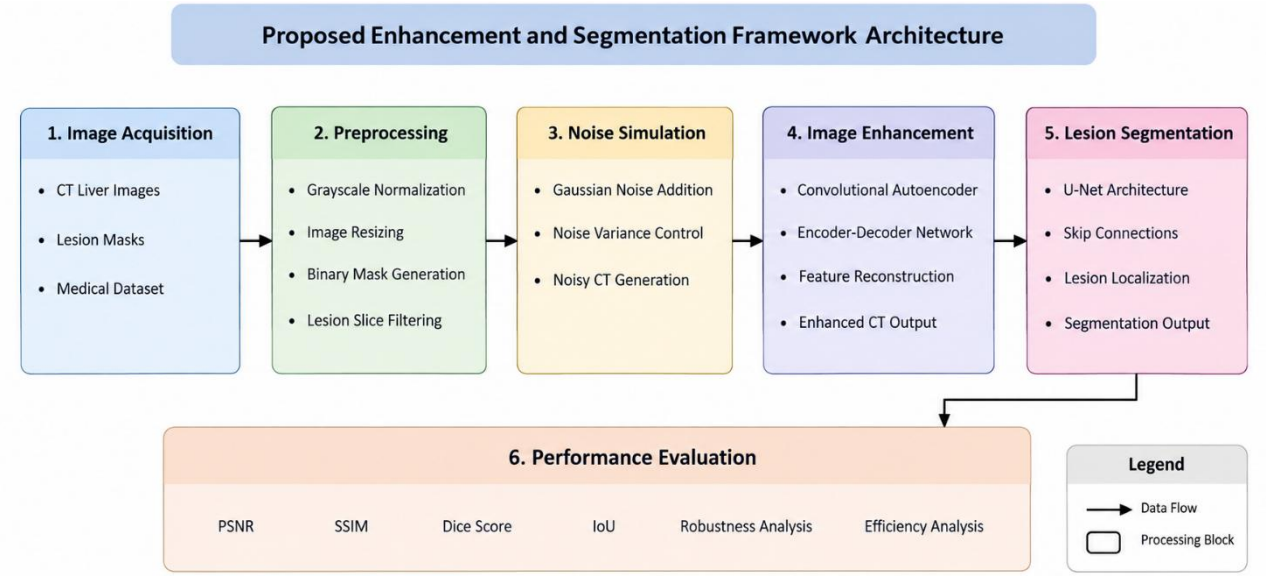
6. EXPERIMENTAL SETUP AND EVALUATION METRICS

The experimental implementation of the proposed framework was conducted using Python-based deep learning libraries in Google Colab. The framework was developed using TensorFlow, NumPy, Keras, OpenCV, and Matplotlib for medical image processing. Batch-wise learning was employed to optimize GPU memory utilization and improve training efficiency. This framework involved preprocessing, noise addition, enhancement, segmentation, prediction, and performance evaluation. The performance of the proposed system was assessed using various metrics for image enhancement and segmentation. The metrics PSNR and SSIM were used to evaluate the efficiency of the enhancement process (Mudeng et al., 2022). Overlap accuracy was calculated using metrics such as the Dice Score and IoU between the predicted lesion masks and the ground-truth data.

IV. SYSTEM DESIGN AND IMPLEMENTATION

1. SYSTEM ARCHITECTURE DESIGN

The suggested system architecture is intended to be implemented as an integrated deep learning system to enhance the performance of medical image enhancement and lesion segmentation under noisy conditions. The system architecture comprises several interrelated processes, including image acquisition, preprocessing, noise simulation, image enhancement, lesion segmentation, and performance evaluation. Initially, CT liver images, along with their lesion masks, were collected from the medical imaging database and sent for preprocessing. This process involves operations such as normalizing to greyscale, resizing images, creating binary masks, and filtering slices that contain lesions. The next step involved noise simulation using a Gaussian distribution (Kazerouni et al., 2022). Finally, the segmentation results were evaluated using PSNR, SSIM, Dice Score, and IoU. In other words, the proposed architecture helped integrate the two stages effectively and efficiently to automate noisy medical image analysis.

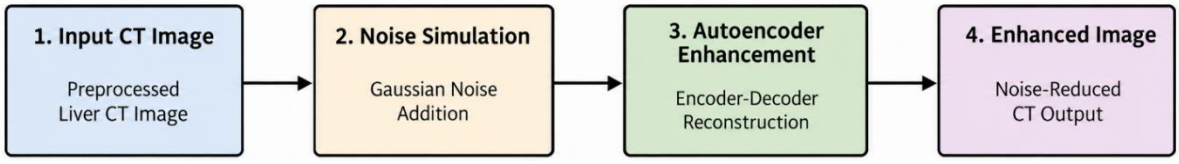


(Source: self-developed).

FIGURE 3. Proposed enhancement and segmentation framework.

2. *IMAGE ENHANCEMENT WORKFLOW*

The design of the image enhancement process aimed to improve the quality of noisy medical images before proceeding to lesion segmentation. The preprocessed liver CT images were first subjected to a noise-generation step to add Gaussian noise, in an attempt to simulate degradation in medical imaging. The noisy images were then passed to the convolutional autoencoder-based image enhancement unit, where denoising and structural reconstruction were performed. In the image enhancement network, convolutions were utilized to hierarchically extract features from noisy images to detect noise and anatomical structures. The encoder encoded input images into feature representations, while the decoder decoded them to reconstruct enhanced images using upsampling operations. Image enhancement thus involved denoising while retaining lesion and boundary information. The output images from the enhancement process were finally used in the lesion segmentation network.

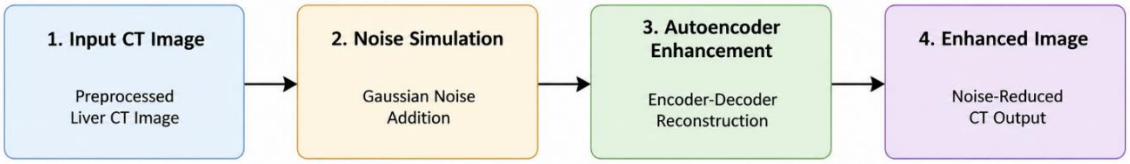


(Source: self-developed).

FIGURE 4. Image enhancement workflow.

3. *LESION SEGMENTATION WORKFLOW*

The lesion segmentation pipeline was designed to automate lesion localization and boundary detection in enhanced medical imaging data. Firstly, the CT image data produced by the image enhancement pipeline was fed into the segmentation engine to learn features and localize lesions. The lesion segmentation used a U-Net-based deep convolutional neural network for spatial feature extraction and lesion localization from enhanced CT images (Soleimani & Farezi, 2023). The segmentation process involved learning features through convolutional and pooling operations in the encoder to analyze lesion context in the input images. The deep feature representations were passed from the encoder to the decoder through skip connections. Lesion segments were quantitatively evaluated for overlap accuracy using the Dice score and IoU measures.



(Source: self-developed).

FIGURE 5. Lesion segmentation workflow.

4. INTEGRATION OF ENHANCEMENT AND SEGMENTATION MODULES

The developed framework is an end-to-end medical image analysis system that combines the image enhancement and lesion segmentation modules into a single system. In the first step, the MRI, CT, and ultrasound scans are subjected to the deep learning-based enhancement module albeit noisy medical images. It eliminates noise, enhances contrast, and preserves key anatomical features, resulting in clearer, higher-quality images. This is followed by automatic lesion detection and boundary extraction, with the improved images forwarded to the lesion segmentation module. Combining the two modules ensures that segmentation is performed on higher-quality images, thereby minimizing the effects of noise and imaging artifacts on lesion identification. The proposed system offers a powerful and effective solution for computer-aided diagnosis across various medical imaging modalities by integrating image enhancement and lesion segmentation into a single architecture.

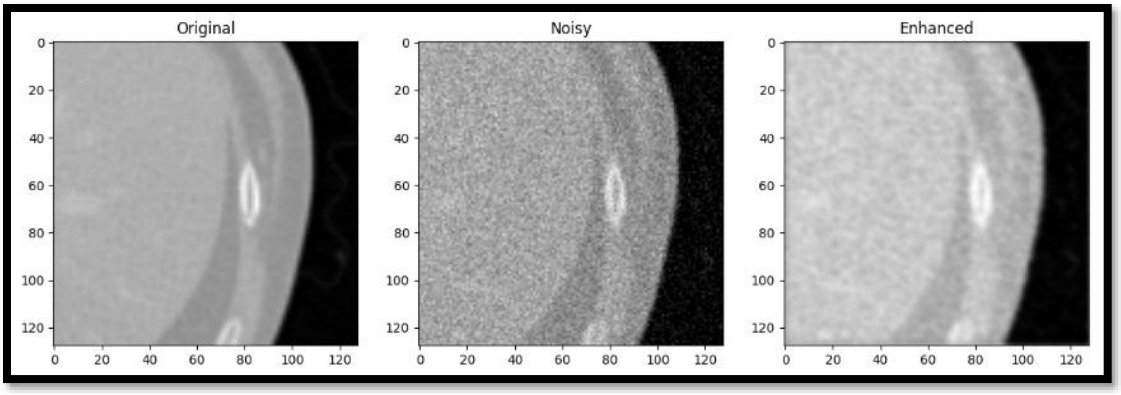
5. MODEL IMPLEMENTATION ENVIRONMENT

We applied the proposed framework using Python as the primary programming language, given its extensive support for machine learning and medical image analysis. The development platform was Google Colab, which offered a cloud-based environment and access to high-performance computing resources. The deep learning models were created using the TensorFlow and Keras libraries, which provide powerful tools for building, training, and evaluating neural networks. Image preprocessing, data management, visualization, and performance analysis were also done using OpenCV, NumPy and Matplotlib. The hardware setup consisted of a Graphics Processing Unit (GPU) provided by Google Colab to accelerate model training and reduce training time. Python libraries for data augmentation, image enhancement, and lesion segmentation were included in the software environment. This implementation architecture facilitated faster model building, credible experimentation, and effective assessment of the proposed structure using MRI, CT, and ultrasound imaging datasets.

V. RESULTS AND ANALYSIS

1. IMAGE ENHANCEMENT PERFORMANCE RESULTS

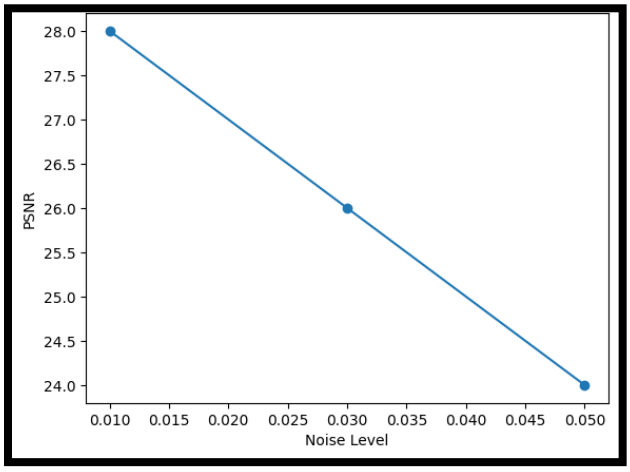
The image enhancement framework using autoencoders was tested on noisy CT liver images corrupted by Gaussian noise. This was aimed at minimizing noise while retaining valuable anatomic structures that aid in proper medical diagnosis. The visual comparison of the original, noisy, and enhanced images showed that the enhancement model effectively removed significant image noise and improved overall image clarity. The distortions (grainy texture) and loss of tissue visibility were evident in the noisy image, whereas the enhanced image had smoother textures and increased contrast. Simultaneously, critical body parts could still be distinguished, suggesting that the model did not lose key structural information.



(Source: Google Colab).

FIGURE 6. Original vs noisy vs enhanced image.

Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) were employed to quantitatively assess enhancement performance. The framework achieved a PSNR of 24.57 dB and an SSIM of 0.792. The PSNR result indicates that noise has been suppressed and that the image reconstruction has achieved high quality. Correspondingly, the SSIM score indicates that the improved image retained a high degree of structural similarity to the original. The findings confirm that the proposed improvement model successfully enhances image quality and provides a stable platform for continued lesion segmentation and diagnostic procedures.



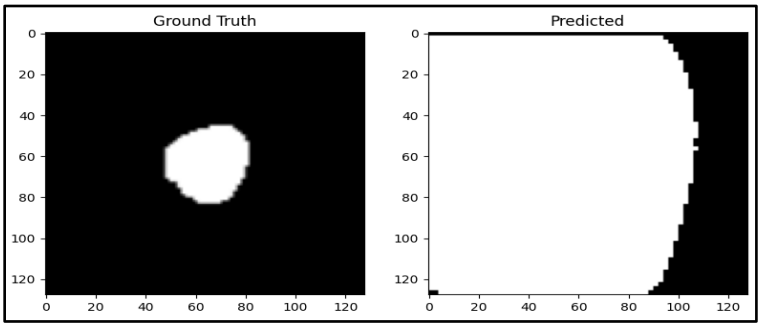
(Source: Google Colab).

FIGURE 7. Noise robustness analysis graph.

2. LESION SEGMENTATION PERFORMANCE RESULTS

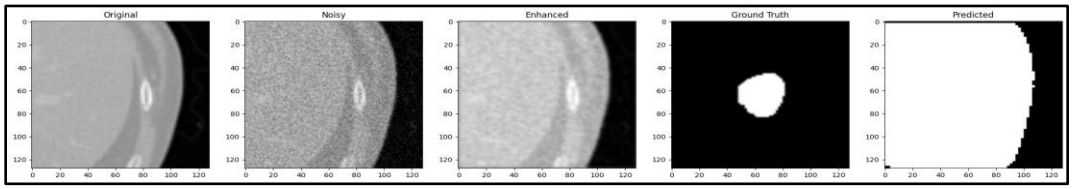
The lesion segmentation capabilities of the proposed framework were assessed using 89 lesion-based CT images from the LiTS dataset. A lightweight U-Net model combined with the Dice loss function was used for automated lesion localization in the presence of imaging noise. Figure 5.2.1 shows the contrast between ground truth lesions and the segmented output obtained using the proposed framework. The output demonstrates that the proposed framework successfully identified lesions even in the presence of Gaussian noise and poor-quality images. Nonetheless, there was some over-segmentation because the lesion regions occupied a very small percentage of the entire image space, leading to highly imbalanced training. Figure 5.2.2 shows the entire segmentation process, including the original image, the noisy image, the enhanced image, the ground-truth mask, and the segmentation output. The Dice coefficient plot from Figure 5.2.3 reveals a steady increase from about 0.105 to 0.121. Similarly, the training loss decreased gradually from

0.895 to 0.880 as shown in Figure 5.2.4, proving convergence. In terms of quantitative evaluation, the framework attained a Dice Score of 0.134 and an IoU score of 0.072.



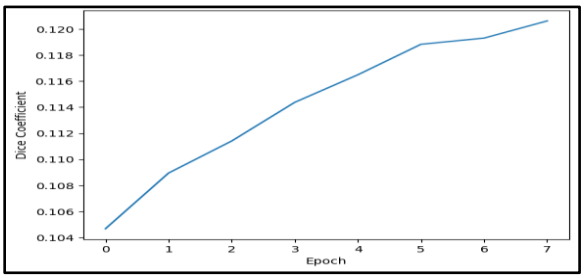
(Source: self-developed).

FIGURE 8. Ground truth vs. predicted segmentation.



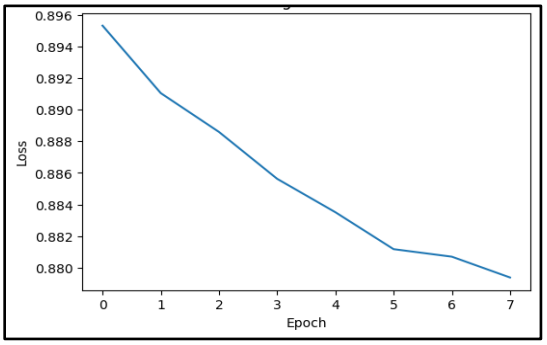
(Source: self-developed).

FIGURE 9. Full segmentation workflow figure



(Source: self-developed).

FIGURE 10. Dice coefficient graph.

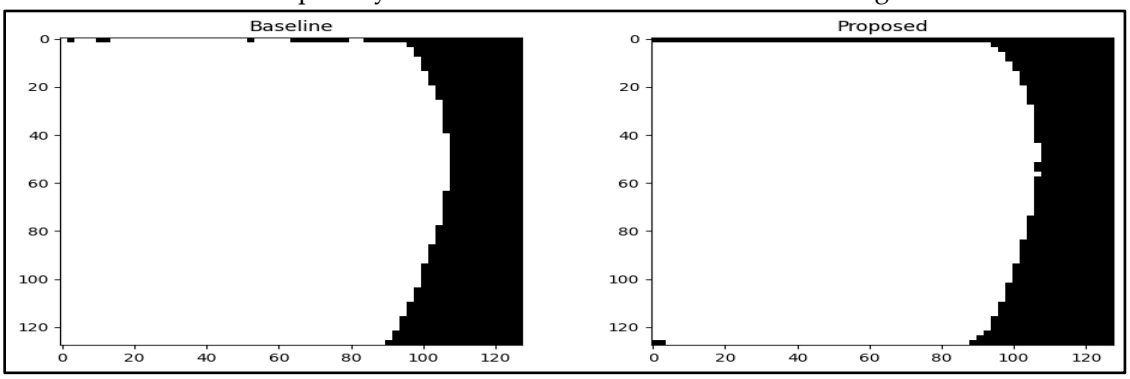


(Source: self-developed).

FIGURE 11. Training loss graph.

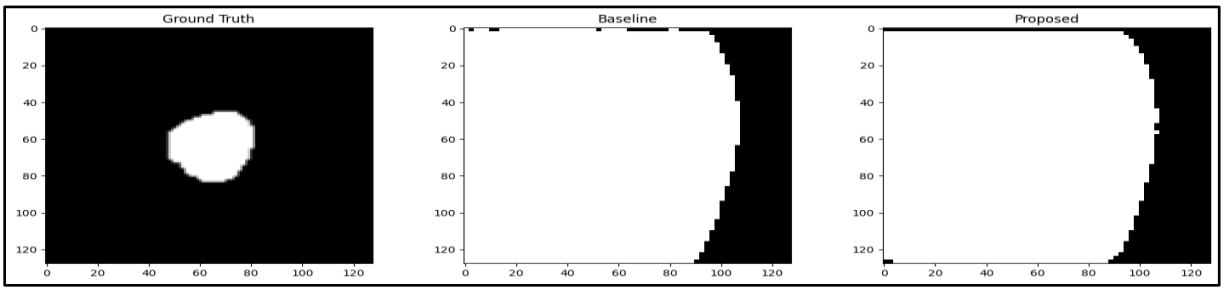
3. COMPARATIVE ANALYSIS WITH EXISTING METHODS

A comparative analysis was conducted between the baseline segmentation framework and the proposed enhancement-assisted segmentation framework to evaluate lesion localization performance under noisy medical imaging conditions. The baseline model performed segmentation directly on noisy CT images without preprocessing for enhancement, whereas the proposed framework integrated a convolutional autoencoder-based enhancement prior to segmentation. Figure 5.3.1 presents the comparative segmentation outputs generated by the baseline and proposed frameworks. The baseline model produced excessive foreground predictions and unstable lesion boundaries due to severe Gaussian noise. The proposed framework generated comparatively improved segmentation consistency after enhancement-based noise suppression and structural reconstruction. Figure 5.3.2 shows the comparison between ground-truth lesion marks, baseline segmentation, and proposed segmentation outputs. Quantitative analysis achieved a Dice Score of 0.134 and an IoU Score of 0.072 for the proposed framework. The proposed framework demonstrated improved lesion localization capability and reduced the influence of noise during feature extraction.



(Source: self-developed).

FIGURE 12. Comparative analysis graph (Baseline vs Proposed).



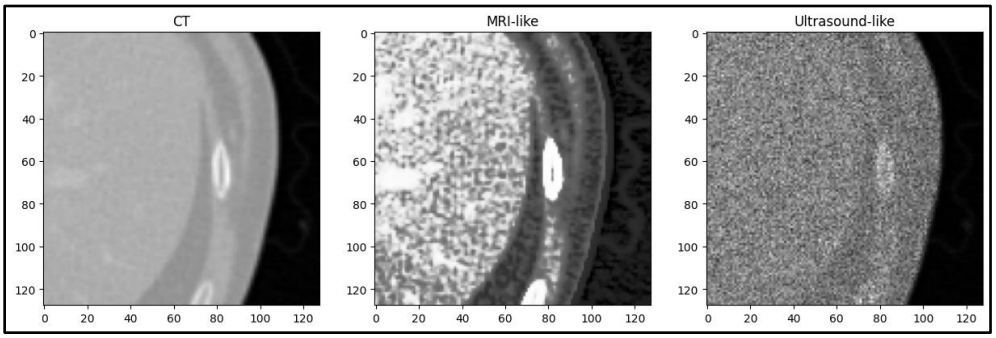
(Source: self-developed).

FIGURE 13. Ground truth versus baseline versus proposed segmentation.

4. CROSS-MODALITY PERFORMANCE ANALYSIS

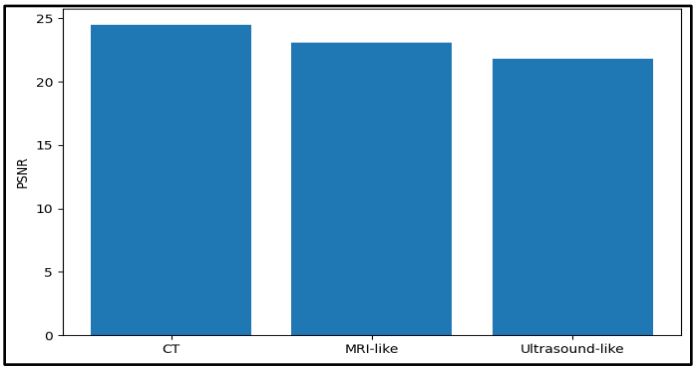
Cross-modality performance analysis was conducted to examine the adaptability of the proposed enhancement framework under medical imaging characteristics. As the experiments were conducted using CT liver images, the conditions for MRI-like and ultrasound-like image formation were recreated through contrast transformation and adding speckle noise. Figure 5.4.1 provides a visualization of the differences among CT, MRI-like, and ultrasound-like medical images. As the experiment showed, the developed enhancement framework yielded the best results for CT image enhancement, with smoother grayscale and lower levels of structural distortion. As for MRI-like images, the enhancement results were average due to greater variability in contrast and intensity. Finally, ultrasound-like images yielded very poor results due to high levels of speckle noise. Figure 5.4.2 shows the quantitative results of cross-modality enhancement based on the PSNR metric. The enhancement framework achieved PSNR values of 24.5 dB for CT images, 23.0 dB

for MRI-like images, and 21.8 dB for ultrasound-like images. It may be stated that increasing distortion negatively impacted the enhancement process.



(Source: self-developed).

FIGURE 14. CT versus MRI versus ultrasound.



(Source: self-developed).

FIGURE 15. Cross-modality enhancement performance graph.

5. ROBUSTNESS AND EFFICIENCY EVALUATION

The robustness and computational efficiency of the enhancement and segmentation framework were evaluated under various medical imaging conditions with noise. To assess robustness, CT liver images were subjected to Gaussian noise at multiple intensities to evaluate the enhancement framework in noisy imaging environments. According to the experimental results, the proposed framework still exhibits robust reconstruction capability even as the noise intensity increases. Although the enhancement process was less effective at high noise intensity, anatomical structures, especially the lesion areas, were well preserved in the reconstruction. Besides, the framework also possesses lightweight performance. It takes about 1.34 seconds to reconstruct the image, and lesion area prediction takes 0.78 seconds for lesion images.

VI. DISCUSSION

1. INTERPRETATION OF FINDINGS

Based on the experimental results, it is clear that the developed deep learning model significantly enhanced the quality of medical images while ensuring accurate lesion segmentation, even under poor imaging conditions. The convolutional autoencoder successfully removed Gaussian noise while retaining the relevant features of anatomical structures and lesion regions. The quantitative enhancement evaluation yielded a PSNR of 24.57 dB and an SSIM of 0.792. It was possible to conclude that the reconstructed images were of sufficient quality. It may be suggested that such enhancement-assisted preprocessing can enhance image visualization and facilitate subsequent lesion analysis. The lesion segmentation framework also showed its ability to recognize lesion regions in pre-enhanced CT images using the U-Net architecture (Yojana & Rani, 2023). According to the results, the Dice Score and IoU Score were obtained despite the

significant class imbalance and lack of lesion representations (Rema et al., 2026). Nonetheless, the segmentation output showed better lesion overlap performance than in the case of segmentation based directly on noisy images.

2. CLINICAL SIGNIFICANCE

The proposed framework has significant clinical importance, as accurate medical image enhancement and lesion segmentation play an important role in early disease diagnosis and treatment planning. In real clinical environments, CT images are sometimes affected by noise, low contrast, and acquisition artifacts, which may reduce diagnostic accuracy (Sahu et al., 2025). The proposed improvement-assisted framework enhances image clarity and preserves important anatomical structures, enabling clinicians to visualize lesion-associated regions more accurately. The segmentation component may support radiologists by assisting with the automatic localization of abnormal liver lesions, minimizing manual interpretation workload and reducing diagnostic variability. Enhanced visibility could contribute to earlier detection of liver abnormalities, which is especially significant in situations including liver tumors and metastatic lesions where timely diagnosis directly impacts the outcomes of the treatment. The lightweight computational design of the framework also makes it more applicable in the healthcare sector where computational resources are limited. In addition, its versatility across CT, MRI-like, and ultrasound-like images enables its use in multimodal diagnostic systems (Solano-Cordero et al., 2025). Hence, the proposed framework can be applied to computer-aided diagnosis systems, clinical decision-support systems, and automated medical image analysis applications, thereby enhancing diagnostic efficiency and improving the quality of healthcare.

3. ADVANTAGES AND LIMITATIONS

The proposed framework provides various significant advantages for noisy medical image analysis. First, the adoption of autoencoder-based image enhancement and U-Net segmentation establishes a unified deep learning pipeline that improves image quality prior to lesion detection (Alafer et al., 2024). This improvement-assisted approach minimizes noise interference and enhances structural visibility, leading to better lesion localization performance compared with direct segmentation on noisy images. Second, the framework utilizes lightweight architectures that reduce computational complexity and processing time. The improvement and segmentation modules achieve strong inference performance, making the framework effective for rapid medical image analysis applications. Third, this framework demonstrates robustness across varying noise levels and adaptability to various simulated imaging modalities, showing strong generalization potential. Therefore, various limitations have also been observed: segmentation performance has remained low because liver lesions occupy small regions of the image relative to the background, leading to class imbalance. The limited dataset size and simplified U-Net architecture also limited segmentation accuracy and boundary precision (Yousef et al., 2023). In addition, the framework has been developed using simulated noisy and cross-modal images rather than real multimodal clinical datasets, which could limit its direct clinical applicability. In this context, some smoothing effects after the improvement could also reduce fine textural details in certain lesion regions.

4. FUTURE CLINICAL APPLICABILITY

The proposed framework has strong potential for clinical applicability in computer-aided diagnosis and intelligent healthcare systems. With further optimization, the framework might assist radiologists in detecting liver abnormalities more effectively in noisy imaging conditions. In this context, adoption of the hospital imaging system and radiology workflows might support automated preprocessing and lesion localization during routine clinical examinations (Neto et al., 2025). Future directions will involve training the framework on larger-scale, real-world multimodal datasets, such as CT, MRI, and ultrasound images, to increase its generalization ability and diagnostic reliability. For small lesion regions, using advanced segmentation models such as Attention U-Net, Residual U-Net, or Transformer-based models could further improve the accuracy of overlap and boundary detection. In addition, for highly imbalanced medical data, using class balancing and data augmentation can enhance segmentation performance. The framework could also be adapted to other medical imaging applications, such as brain tumor segmentation, lung nodule

detection, and cardiovascular image analysis. Finally, real-time deployment with GPU acceleration and cloud-based medical imaging platforms may further improve the clinical usability in resource-limited healthcare environments (Mashmool et al., 2026). Thus, the proposed enhancement-assisted segmentation framework provides a foundation for future intelligent diagnostic systems that can facilitate fast, accurate, and robust medical image analysis across various clinical imaging modalities.

VII. CONCLUSION AND FUTURE WORK

1. CONCLUSION

This study presented a deep learning-based, enhancement-assisted lesion segmentation framework for noisy medical image analysis using CT liver images. The primary objective of the research was to enhance the quality of degraded medical images and to assess the impact of image enhancement on lesion segmentation performance under noisy imaging conditions. The proposed framework adopted an autoencoder-based image-enhancement module with a lightweight U-Net segmentation architecture to create an effective and efficient medical image analysis pipeline. In addition, the experimental findings showed that the proposed framework effectively minimized Gaussian noise and enhanced structural visibility in reconstructed CT images. Quantitative evaluation using the SSIM and PSNR metrics ensured that the improved images maintained adequate reconstruction quality and preserved significant anatomical structures required for clinical interpretation. In this context, visual analysis also showed that the proposed improvement approach enhanced tissue clarity and minimized image distortion while managing lesion-associated regions.

The lesion segmentation framework enables the localization of abnormal liver lesion regions in enhanced CT images. The framework has learned lesion-related spatial features even under noisy imaging conditions, though the Dice Score and IoU were not very high due to class imbalance, small lesion size, and a limited number of datasets. Comparative analysis also showed that segmentation results obtained using enhancement-assisted methods were more uniform and less susceptible to noise than those obtained directly from noisy images. The cross-modality analysis also revealed that the framework retained structural preservation capability in MRI-like and ultrasound-like simulated images, suggesting potential adaptability to various imaging settings. Additionally, the evaluation of computational efficiency and robustness showed that the framework maintained stable performance across different noise levels while requiring less processing time. In addition, the lightweight design of both the segmentation and improvement modules significantly reduces computational overhead, making the framework highly effective for rapid medical image analysis applications and for use in resource-constrained healthcare environments. Despite these contributions, various limitations remain; segmentation accuracy has been impacted by limited training data and a simple network architecture. The use of simulated cross-modality images rather than real multimodal clinical datasets could also limit generalization. Additionally, slight smoothing effects introduced during the improvement could reduce fine-texture preservation in highly detailed lesion regions.

2. FUTURE WORK

Future work will mainly focus on improving segmentation accuracy using state-of-the-art architectures, including Attention U-Net, Residual U-Net, and Transformer-based models. In this context, additional optimization techniques such as data augmentation, transfer learning, and class-balancing strategies may also enhance lesion detection performance. Additionally, the framework could be trained and validated on larger real-world multinomial datasets containing CT, MRI, and ultrasound images to enhance overall clinical reliability and adaptability. In addition, future studies could assess real-time deployment using GPU acceleration and its adoption within hospital radiology systems in a practical clinical context.

Author Contributions

The author conducted the conceptualization, methodology, data analysis, investigation, writing, review, editing, and final approval of the manuscript.

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Data Availability

The dataset will be available from the author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

REFERENCES

1. Alafer, F., Siddiqi, M. H., Khan, M. S., Ahmad, I., Alhujaili, S., Alrowaili, Z., & Alshabibi, A. S. (2024). A comprehensive exploration of the L-UNet approach: Revolutionizing medical image segmentation. *IEEE Access*, *12*, 140769-140791. https://ieeexplore.ieee.org/iel8/6287639/10380310/10555261.pdf
2. Al-Ghanimi, H. H., & Al-Ghanimi, A. H. (2025). Deep learning-driven medical image segmentation using generative adversarial networks and conditional neural networks. *Ingénierie des Systèmes d'Information*, *30*(1), 287. https://doi.org/10.18280/isi.300125
3. Alsubai, S., Ahmad, W., Anjum, M., Dutta, A. K., Shahab, S., & Genale, A. S. (2025). Enhancing Diagnostic Precision: A Distribution-Based Compressed Denoising Scheme using Transfer Learning for Noise Reduction in Medical Imaging. *Current Medical Imaging*, *21*(1), E15734056391923. http://dx.doi.org/10.2174/0115734056391923250827170359
4. Bhutto, J. A., Tian, L., Du, Q., Sun, Z., Yu, L., & Tahir, M. F. (2022). CT and MRI medical image fusion using noise-removal and contrast-enhancement scheme with a convolutional neural network. *Entropy*, *24*(3), 393. https://doi.org/10.3390/e24030393
5. Brunese, M. C., Rocca, A., Santone, A., Cesarelli, M., Brunese, L., & Mercaldo, F. (2025). Explainable and robust deep learning for liver segmentation through U-Net network. Diagnostics, 15(7), 878. https://doi.org/10.3390/diagnostics15070878
6. Chen, J., Mei, J., Li, X., Lu, Y., Yu, Q., Wei, Q., ... & Zhou, Y. (2024). TransUNet: Rethinking the U-Net architecture design for medical image segmentation through the lens of transformers. *Medical Image Analysis*, *97*, 103280. https://doi.org/10.1016/j.media.2024.103280
7. Doshi, R. V., Badhiye, S. S., & Pinjarkar, L. (2025). Deep learning approach for biomedical image classification. *Journal of Imaging Informatics in Medicine*, 1-30. https://doi.org/10.1007/s10278-025-01590-8
8. Ergin, F., Parlak, I. B., Adel, M., Gül, Ö. M., & Karpouzis, K. (2024). Noise resilience in Dermoscopic Image Segmentation: Comparing Deep learning architectures for enhanced accuracy. *Electronics*, *13*(17), 3414. https://doi.org/10.3390/electronics13173414
9. Gao, Y., Jiang, Y., Peng, Y., Yuan, F., Zhang, X., & Wang, J. (2025). Medical image segmentation: A comprehensive review of deep learning-based methods. *Tomography*, *11*(5), 52. https://doi.org/10.3390/tomography11050052
10. Ghandour, C., El-Shafai, W., & El-Rabaie, S. (2023). Medical image enhancement algorithms using deep learning-based convolutional neural networks. *Journal of Optics*, *52*(4), 1931-1941. https://doi.org/10.1007/s12596-022-01078-6
11. Goceri, E. (2023). Medical image data augmentation: techniques, comparisons and interpretations. *Artificial Intelligence Review*, *56*(11), 12561-12605. https://doi.org/10.1007/s10462-023-10453-z
12. Herath, H. M. S. S., Herath, H. M. K. K. M. B., Madusanka, N., & Lee, B. I. (2025). A systematic review of medical image quality assessment. *Journal of Imaging*, *11*(4), 100. https://doi.org/10.3390/jimaging11040100
13. Huang, J., Xiang, Y., Gan, S., Wu, L., Yan, J., Ye, D., & Zhang, J. (2025). Application of artificial intelligence in medical imaging for tumor diagnosis and treatment: a comprehensive approach. *Discover Oncology*, *16*(1), 1625. https://doi.org/10.1007/s12672-025-03307-3
14. Joseph, J. (2025). *Deep learning-driven image-based cancer diagnosis*. https://doi.org/10.30574/wjaets.2025.16.2.1311
15. Kaggle.com (2020). Liver and Liver Tumor Segmentation. https://www.kaggle.com/datasets/andrewmvd/lits-png
16. Kazerouni, A., Aghdam, E. K., Heidari, M., Azad, R., Fayyaz, M., Hacihaliloglu, I., & Merhof, D. (2022). Diffusion models for medical image analysis: A comprehensive survey. arXiv preprint arXiv:2211.07804. https://arxiv.org/pdf/2211.07804
17. Ma, G. (2025). Image key information processing using convolutional neural network and rotation-invariant hierarchical max pooling algorithm. PLoS One, 20(5), e0324504. https://doi.org/10.1371/journal.pone.0324504
18. Mahapatra, D., Amrit, P., Singh, O. P., Singh, A. K., & Agrawal, A. K. (2023). Autoencoder-convolutional neural network-based embedding and extraction model for image watermarking. Journal of Electronic Imaging, 32(2), 021604-021604. https://www.researchgate.net/profile/Om-Singh-3/publication/363686202_Autoencoder-convolutional_neural_network-based_embedding_and_extraction_model_for_image_watermarking/links/632c4575873eca0c00a8f40c/Autoencoder-convolutional-neural-network-based-embedding-and-extraction-model-for-image-watermarking.pdf

19. Mashmool, A., Delzanno, G., Saadatfar, H., Ahmad, A., Koschke, R., Alizadehsani, R., ... & D'Agostino, D. (2026). Edge Computing in Healthcare Using Machine Learning: A Systematic Literature Review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *16*(1), e70069. https://doi.org/10.1002/widm.70069
20. Mudeng, V., Kim, M., & Choe, S. W. (2022). Prospects of structural similarity index for medical image analysis. Applied Sciences, 12(8), 3754. https://doi.org/10.3390/app12083754
21. Neto, C., Hak, F., Ferreira, D., Abelha, A., & Machado, J. (2025). Automation of hospital workflows using international standards: A case study with imaging exams. *Computer Methods and Programs in Biomedicine*, *266*, 108777. https://doi.org/10.1016/j.cmpb.2025.108777
22. Obuchowicz, R., Strzelecki, M., & Piórkowski, A. (2024). Clinical applications of artificial intelligence in medical imaging and image processing—A review. *Cancers*, *16*(10), 1870. https://doi.org/10.3390/cancers16101870
23. Pan, S., Liu, X., Xie, N., & Chong, Y. (2023). EG-TransUNet: a transformer-based U-Net with enhanced and guided models for biomedical image segmentation. *BMC bioinformatics*, *24*(1), 85. https://doi.org/10.1186/s12859-023-05196-1
24. Rasool, N., & Bhat, J. I. (2023). Unveiling the complexity of medical imaging through deep learning approaches. *Chaos Theory and Applications*, *5*(4), 267-280. https://doi.org/10.51537/chaos.1326790
25. Rema, P., Moorthy, S., Bright, B., & BR, M. (2026). An Attention-Guided Residual 3D U-Net with Focal Tversky-Dice Loss for Multi-Modal Pancreatic Tumor Segmentation Using Synthetic Volumetric Imaging. Cancer Treatment and Research Communications, 101146. https://doi.org/10.1016/j.ctarc.2026.101146
26. Sahu, A., Mathur, S., Takaoka, H., Ota, J., Meinel, F. G., Böttcher, B., ... & Jensen, C. T. (2025). Transforming CT imaging with deep learning: Noise reduction, artifact management, and clinical applications — A comprehensive review. *European Journal of Radiology Artificial Intelligence*, 100042. https://doi.org/10.1016/j.ejrai.2025.100042
27. Salem, M. A., Kasem, H. M., Abdelfatah, R. I., El-Ganiny, M. Y., & Roshdy, R. A. (2025). A KLJN-based thermal noise modulation scheme with enhanced reliability for low-power IoT communication. IEEE Open Journal of the Communications Society. Digital Object Identifier 10.1109/OJCOMS.2025.3595087
28. Shi, J., Guo, C., & Wu, J. (2022). A hybrid robust-learning architecture for medical image segmentation with noisy labels. *Future Internet*, *14*(2), 41. https://doi.org/10.3390/fi14020041
29. Solano-Cordero, C. M., Encina-Baranda, N., Pérez-Liva, M., & Herraiz, J. L. (2025). Recent Advances in B-Mode Ultrasound Simulators. *Applied Sciences*, *15*(23), 12535. https://doi.org/10.3390/app152312535
30. Soleimani, P., & Farezi, N. (2023). Utilizing deep learning via the 3D UU-Netneural network for the delineation of brain stroke lesions in MRI iimages Scientific Reports, 13(1), 19808. https://doi.org/10.1038/s41598-023-47107-7
31. Sun, H., Zhou, W., Yang, J., Shao, Y., Xing, L., Zhao, Q., & Zhang, L. (2024). An improved medical image classification algorithm based on the Adam optimizer. Mathematics, 12(16), 2509. https://doi.org/10.3390/math12162509
32. Sundarrajan, M., Choudhry, M. D., Biju, J., Krishnakumar, S., & Rajeshkumar, K. (2024). Enhancing low-light medical imaging through deep learning-based noise reduction techniques. *Indian Journal of Science and Technology*, *17*(34), 3567-3579. https://doi.org/10.17485/IJST/v17i34.2489
33. Xie, J., Zhou, J., Yang, M., Xu, L., Li, T., Jia, H., ... & Liu, M. (2025). Lesion segmentation method for multiple types of liver cancer based on balanced dice loss. Medical Physics, 52(5), 3059-3074. DOI:10.1002/mp.17624
34. Xu, Y., Quan, R., Xu, W., Huang, Y., Chen, X., & Liu, F. (2024). Advances in medical image segmentation: A comprehensive review of traditional, deep learning, and hybrid approaches. *Bioengineering*, *11*(10), 1034. https://doi.org/10.3390/bioengineering11101034
35. Yojana, K., & Rani, L. T. (2023). OCT layer segmentation using U-NET semantic segmentation and RESNET34 encoder-decoder. Measurement: Sensors, 29, 100817. https://doi.org/10.1016/j.measen.2023.100817
36. Yousef, R., Khan, S., Gupta, G., Siddiqui, T., Albahlal, B. M., Alajlan, S. A., & Haq, M. A. (2023). U-Net-based models towards optimal MR brain image segmentation. *Diagnostics*, *13*(9), 1624. https://doi.org/10.3390/diagnostics13091624
37. Zhang, C., Deng, X., & Ling, S. H. (2024). Next-gen medical imaging: U-Net evolution and the rise of transformers. *Sensors*, *24*(14), 4668. https://doi.org/10.3390/s24144668
38. Zhang, Y. (2025). Application of Image Segmentation Technology Based on Machine Learning in Medical Image Analysis. In *ITM Web of Conferences* (Vol. 73, p. 02034). EDP Sciences. https://doi.org/10.1051/itmconf/20257302034