

Advances in U-Net and Image Processing: A Path to Early Cancer Diagnosis

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Abstract—Early and accurate diagnosis is the most critical step in the successful treatment of cancer. In contemporary medical image analysis, combining image processing methods with the U-Net deep learning model offers robust assistance to clinicians. Pre-processing methods such as contrast enhancement, noise reduction, and colour normalisation significantly increase the quality of medical images, such as histopathology scans, providing a more reliable foundation for analysis. The U-Net model, a robust deep learning algorithm for medical image segmentation, can more effectively delineate tumor boundaries when trained on this enhanced data. This synergistic approach, where improved data quality boosts U-Net's segmentation accuracy, enables the clearer detection of cancerous tissues. This review examines how combining these methodologies provides more accurate and reliable results, ultimately contributing to improved early diagnosis, effective treatment planning, and extended life expectancy for cancer patients. Therefore, this approach could be used to revolutionize early cancer detection and manage cancer treatment more effectively.

Index Terms—Cancer, Ovarian Cancer, Image Processing, U-Net, Deep Learning, Artificial Intelligence, Early Diagnosis.

I. INTRODUCTION

Cancer ranks as the second most prevalent and fatal disease worldwide, following cardiovascular conditions. According to World Health Organization statistics, 20 million new cancer cases were reported in 2022, and 9.7 million people died from the disease that year. By 2050, the global cancer burden is projected to rise to 35 million cases [1]. Cancer treatment usually begins with surgery, where part or all of the tissue where the cancer develops is removed. Then, depending on the type and stage of cancer, chemotherapy, radiation therapy, hormone therapy, smart drug therapy and immunotherapy are the methods applied. Most cancer types have 4 stages. In stage 1, cancer is small, confined to the organ, and generally easier to treat. Stage 2 indicates that the tumor has increased in

size but has not yet spread. By stage 3, cancer may begin to extend into surrounding tissues [2]. In the advanced stage 4, the patient faces serious risk as the cancer has metastasized to other organs. Since metastatic cancer cells tend to be more resilient, standard chemotherapy may be insufficient to eliminate them [3]. Therefore, early diagnosis of cancer is extremely important in order to ensure successful treatment and maximize disease-free survival [4].

Medical imaging is crucial for the early detection, diagnosis, and treatment planning of cancer, utilizing a range of modalities which includes mammography, X-ray, ultrasound, computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI), as illustrated in Figure 1 [5]–[10]. Although these imaging technologies are widely used, histopathology, the microscopic analysis of stained tissue sections, continues to be the gold standard for definitive cancer diagnosis. As a specialized branch of histology, which explores the structural and functional organization of tissues from the cellular to organ level, histopathology focuses specifically on identifying pathological changes in diseased tissues [11]. In clinical oncology, histopathological analysis is essential not only for confirming malignancy but also for determining the specific histological subtype of the cancer, which often guides therapeutic decision-making [12]. Tissue samples are stained, imaged microscopically, and archived for evaluation. The accurate classification of these samples is critical, as treatment efficacy can vary significantly based on histological subtype. In this context, artificial intelligence has emerged as a transformative tool to support and enhance the diagnostic process in histopathological imaging [13].

This study investigates the individual contributions of image preprocessing techniques, alongside the segmentation capabilities of the U-Net deep learning architecture in medical

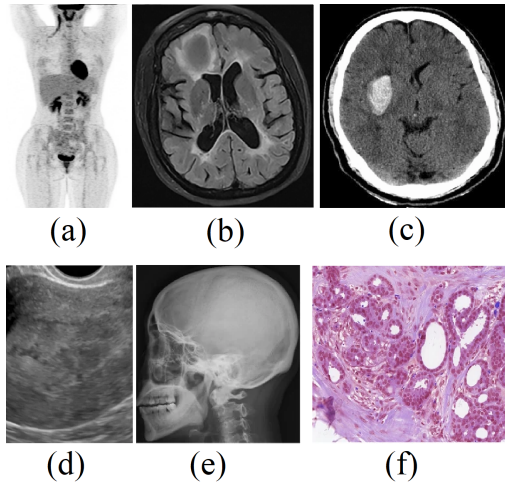


Fig. 1. Examples from Different Medical Imaging Techniques (a) PET (b) MRI (c) CT (d) Ultrasound (e) X-Ray (f) Histology

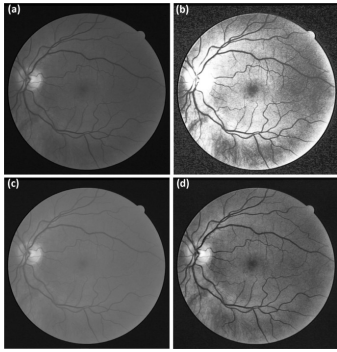


Fig. 2. Application of Various Contrast Enhancement Techniques to the Green Channel of a Random Fundus Image (a) original green channel, (b) Histogram Equalization, (c) Contrast Stretching, and (d) CLAHE

image analysis for cancer diagnosis. The combined impact of these methods is assessed with respect to their potential to improve diagnostic accuracy and facilitate more effective treatment planning.

II. IMAGE PROCESSING AND U-NET

Image enhancement is a critical application of image processing that improves the quality of digital images by sharpening features and appearance, making subsequent analysis more accurate [14]. In the medical field, the quality of biomedical images is a significant factor in diagnostic reliability. Images produced by lower-quality devices can be unclear or lack sufficient contrast, increasing the risk of misdiagnosis [15]. By applying image processing techniques, such as the contrast enhancements shown in Figure 2, an image's diagnostic utility can be improved. This enhancement is crucial for supporting early and accurate clinical diagnosis [16].

U-Net is a commonly employed Convolutional Neural Network (CNN) designed for precise biomedical image segmentation. Its architecture features a contracting path (encoder) that extracts features to capture contextual information, and

a symmetric expanding path (decoder) that provides accurate localization for the final segmentation. A key innovation of U-Net is the use of 'skip connections' between the encoder and decoder, allowing the network to combine deep semantic features with shallow, high-resolution details [17]. This design makes U-Net highly efficient and enables it to achieve accurate segmentation of cancer, even with the limited datasets often available in the medical field [18].

III. APPLICATIONS OF IMAGE PROCESSING AND DEEP LEARNING IN CANCER DIAGNOSIS

A. The Role of Image Processing Techniques in Cancer Diagnosis

Image processing techniques are pivotal in cancer diagnosis, offering clinicians tools for faster and more accurate assessments. Operations such as denoising, edge detection, and contrast enhancement improve the visibility of tumors in MRI and CT scans, while color normalization and texture analysis enhance the interpretability of histopathology images by standardizing data across different patients [19]. Ultimately, these methods facilitate the rapid detection of cancerous cells, enabling earlier treatment initiation and improving patient life expectancy and quality of life [20]. Chaudhary and Singh developed a system that uses image processing techniques to detect lung cancer at an early stage, based on CT images. They applied three enhancement methods—Fast Fourier Transform, Auto Enhancement, and Gabor Filter—to identify lung nodules, followed by segmentation using thresholding and watershed methods. The study found that the Gabor filter yielded the best enhancement results, and watershed segmentation outperformed thresholding in accuracy [21]. In different research performed by Avinash et al., three distinct enhancement techniques were applied to 44 lung X-ray images, where the peak signal-to-noise ratio (PSNR) was used to evaluate the results from the different methods. The findings indicated that the performance of Alpha Trimmed Filter (AEA) was better than the others with a mean PSNR of 43.2803 [22]. Kamala and Shivaram enhanced ovarian ultrasound images using four filter techniques—Median, Fourier, Butterworth, and Daubechies Wavelet—to reduce noise and improve cyst detection. Performance was evaluated with MSE, SNR, and PSNR metrics. Results showed that the Daubechies Wavelet filter achieved the best performance, with PSNR of 74.60, SNR of 32.96, and MSE of 0.0022 [23]. In a different study, Nishio et al. used 15,000 histopathological lung tissue images for the purpose of developing a CAD system capable of classifying the images into five distinct groups. The application of a homology-based technique combined with texture analysis supported the machine learning algorithm in the image pre-processing stage. The results showed that the homology-based technique achieved an accuracy of 99.43% [24]. In their 2025 study, Farshchitabrizi et al. used generative adversarial networks (GANs) to perform attenuation correction on PET images. They assessed three GAN architectures, Conditional GAN, Wasserstein GAN, and CycleGAN—using a dataset of 16,402 CT images and 12,366 PET images. The study reported

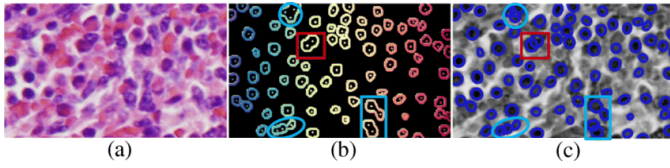


Fig. 3. Histopathology Image Segmentation: (a) Original Image, (b) Nuclei Centers with Corresponding Boundaries, (c) Appropriate Ellipse Fitting for Touching and Overlapping Nuclei

mean absolute error (MAE) and mean squared error (MSE) values of 2.15 ± 0.34 and 3.14 ± 0.56 , respectively, indicating effective correction performance [25]. Table 1 summarizes the image processing studies for the early detection of cancer discussed in this article.

B. The Role of U-Net Techniques in Cancer Diagnosis

The U-Net model is highly effective for cancer diagnosis due to its capacity for high-accuracy image segmentation. By precisely delineating the boundaries of tumors and other abnormal tissues, it provides critical support to radiologists and pathologists. U-Net's use of skip connections helps accurately define small and complex structures in medical images, enabling consistent and automated results that support cancer staging, treatment planning, and patient follow-up by reducing human error [26]. Used especially in MRI, CT, histopathology and ultrasound images, U-Net can be trained with minimal data and accelerates early diagnosis processes [27]. Figure 3 illustrates the nuclei segmentation process with U-Net [28].

The application of U-Net in oncology is extensive, with numerous studies adapting the architecture for various diagnostic challenges. Early work by Hu et al. employed a 2.5D segmentation technique on MRI images to predict nasopharyngeal cancer, testing it on 19 patients and achieving a Dice score of 0.6067. They noted that 2D U-Net offers superior computational efficiency compared to 3D U-Net due to lower processing and storage demands, while 3D images incur higher computational costs [29]. In the study of Robin et al., U-Net was applied to 115 stained histopathology images for segmenting breast tumours. Subsequent to resizing the images, extracting features and segmenting the images, sample images were used for testing the U-Net model. The results showed that the accuracy achieved was 94.2% [30]. Wang and co-workers applied contrastive learning-based PPC-UNet, achieving a Dice Score of 0.833. Segmentation of 165 histopathology images was performed for colorectal adenocarcinoma [31]. Zou et al. proposed an ultrasound-enhanced U-Net model to detect ovarian lesions using 600 ultrasound images from 35 patients. The model, incorporating an 18-layer ResNet and trained over 200 epochs, achieved 89% accuracy [32]. In the study of Kiran et al., DenseRes-UNet was employed for segmenting nuclei that were clustered or overlapped from histopathology images. A total of 310 H&E stained multi-organ histopathology images were contained within the dataset used in the study. According to the study results, the accuracy, F1 score, and Aggregated Jaccard Index for the system were 89.77%, 90.36%, and

78.61%, respectively [33]. The study of Saha et al. focused on segmenting ultrasound images for the purpose of detecting ovarian follicles, with the outcome being a new system named MU-Net in which MobileNetV2 and U-Net are combined. The study dataset was formed by extracting 3,419 2D slides from 3D ultrasound images. According to the authors, the accuracy obtained from the developed system reached 98.4% [34]. In a different study performed by Nagarajan and Nawabjan, ovarian cancer was classified using 497 CT images. U-Net was used to segment the augmented image dataset, and then the output was fed into DCNN such that types of ovarian carcinoma could be classified. The study findings revealed that classification accuracy achieved by DCNN with segmented feature maps was 91.63% [35]. The study of Li et al. employed the OCELOT dataset for the purpose of enhancing the ability to detect cancer cells in histopathology images. They developed a vision transformer UNet model that enhanced the ability to extract features from 667 tissue images. According to the results, the F1 score achieved for the validation set was 0.755 [36]. Chen et al. improved ovarian cancer segmentation accuracy using U-Net by applying image inpainting to 1,496 2D ultrasound images. Two image sizes (256×256 and 512×512) were tested, achieving SSIM values of 0.9246 and 0.9208, respectively. Overall segmentation accuracy increased from 71.51% to 76.06% [37]. Ho et al. proposed a deep learning model to predict BRCA mutations from H&E-stained ovarian cancer tissue images. The model was developed using a human-in-the-loop approach, combining manual input with pre-trained segmentation. It achieved an IoU of 0.74, recall of 0.86, and precision of 0.84 [38]. Further research was performed by Rahmani et al. in which a deep learning technique for segmenting breast cancer based on 2D ultrasound images was presented. Contained within the dataset were 487 images of benign tumours and 210 images of malignant tumours, where the average size was 500×500. Subsequent to 55 iterations, the overall Dice score achieved by the developed model was 84.72% [39]. Ortega-Ruiz et al. proposed the DRD U-Net, an enhanced U-Net architecture incorporating Dilation, Residual, and Dense blocks for multi-class semantic segmentation of H&E-stained breast tissue. Using 12,930 image patches from The Cancer Genome Atlas, the model achieved a Dice score of 0.85 and a specificity of 0.93 in segmenting breast tumours [40]. Zhou et al. developed DFA-UNET, a dual-stream feature-fusion attention U-Net for lung cancer lymph node segmentation. Featuring a residual decoder, hybrid attention module, and dual-stream encoder, the model was tested on ultrasound images and achieved a top Dice Score of 0.86, outperforming nine other U-Net variants [41]. In another study published in 2025, Kashyap et. al developed an automated deep learning model on CT scans for lung tumor detection and segmentation. 1654 images were used to train a three-dimensional U-Net multi-resolution ensemble model to detect and segment lung tumors. The proposed model achieved 92% sensitivity and 82% specificity on the test set [42]. Ejjiyi et al. introduced ATEDU-NET, a model designed to overcome the limitations of traditional skip connections for precise segmen-

TABLE I
IMAGE PROCESSING STUDIES FOR CANCER DETECTION

Author	Year	Cancer Type	Dataset Size	Imaging	Approach	Result
Chaudhary and Singh	2012	Lung	NA	CT	Gabor Filter, Auto Enhancement and Fast Fourier Transform	Average Intensity with Gabor Filter 247.56
Avinash et.al	2017	Lung	44	X-Ray	Gabor Filters, DWT and AEA	AEA= 43.28
Kamala and Shivaram	2021	Ovarian	20	Ultrasound	Median Filter, Fourier Filter, Butterworth Filter and Daubechies Wavelet Filter	PSNR mean Daubechies Wavelet Filter MSE=0.0022 SNR=62.96 PSNR=74.60
Nisho et.al	2021	Lung	15000	Histopathology	Homology Based	99.43% Accuracy
Farshchitabrizi et.al	2025	Ovarian	187680	PET + CT	GAN Architecture	MAE: 2.15 ± 0.34 MSE: 3.14 ± 0.56

tation of X-ray, breast ultrasound, and retinal fundus images. The architecture incorporates Progressive Context Refinement Modules and Global Context Modules. Evaluated on a breast ultrasound dataset of 780 images, the model demonstrated strong performance, achieving an IoU of 98.16%, a Dice score of 62.14%, and a sensitivity of 81.14%. [43]. Table 2 summarizes the U-Net studies for early detection of cancer discussed in this article.

C. Combination of U-NET and Image Processing Techniques for Cancer Diagnosis

The integration of image processing techniques with the U-Net model creates a powerful, synergistic approach to cancer diagnosis. By applying pre-processing operations such as denoising, contrast enhancement, and color balancing to MRI, CT, or histopathology scans, the input data is optimized for the neural network. This preparatory step increases the sensitivity of the U-Net model, enabling a clearer and more accurate segmentation of cancerous tissues [44]. The efficacy of this combined strategy is well-documented in the literature. Ullah et al. performed a study in which 285 3D brain images with dimensions of 240x240x155 were used to automatically segment brain tumours. After applying intensity normalization, bias field correction, histogram equalization, and Gibbs ringing artifact removal, U-Net was employed to segment the images. The Dice score recorded was 0.91 [45]. Ilhan et al. applied U-Net for brain tumour segmentation using BRATS datasets from 2012, 2019, and 2020. The study involved denoising with a 5x5 filter and enhancing tumour regions using histogram-based localization. After processing, the model achieved Dice scores of 0.94, 0.85, and 0.88 for BRATS 2012, 2019, and 2020, respectively [46]. In their study, Jeya Sundari and Britha proposed a deep learning-based ovarian tumour diagnosis model called UEDL-OVD. The model enhanced image quality using a black widow optimization algorithm, extracted features with VGG16, and detected tumours via a stacked autoencoder. Experiments conducted on datasets of varying sizes (100 to 500 images) showed the best precision (0.735) and recall (0.612) when using 100 images. The image enhancement step achieved a contrast of 0.97 and a contrast ratio of 92.74% [47]. Rudiansyah et al. conducted a recent study in which image enhancement was combined with U-Net to segment

cervical cancer. A total of 917 images with a size of 150x140 were included in the dataset. The initial step involved the application of gamma correction, CLAHE, and median filter to augmented pap-smear images. Subsequent to enhancement, the images were fed into U-Net, resulting in an accuracy of 89% being achieved [48]. Alafer et al. proposed L-UNet, a lightweight U-shaped CNN with fewer parameters that reduces complexity without sacrificing performance. Tested on multiple datasets—including lung, liver, skin cancer, chest X-rays, and COVID-19—the model achieved high segmentation accuracy of 99.15% for lung images and 93.4% for COVID-19 chest X-rays. [49]. In their study, Vijayakumar et al. proposed a novel lung cancer detection approach combining image enhancement with a Capsule Neural Network (CapsNet)-based segmentation. Using 1,097 CT images from the Iraq Oncology Teaching Hospital dataset, to enhance image quality, authors applied a Switched Mode Fuzzy Median Filter, followed by Rolling Guidance Filtering and image resizing. CapsNet was then used for segmentation, benefiting from its ability to retain spatial features, require less training data, and reduce feature loss. The method achieved a high accuracy of 98% in detecting lung cancer [50]. Mazhar et.al proposed a new method based on CNN and Gray Wolf Optimisation (GWO) to improve early diagnosis of skin cancer. The authors worked on the HAM-10000 dataset which contains 10,015 images. In the study published in 2025, the GWO-supported CNN model increased the diagnosis accuracy by at least 5%. The proposed model achieved 95.11% accuracy with GWO, while it achieved 92.66% accuracy without GWO [51]. Table 3 summarizes the Image Processing and U-Net combined studies for early detection of cancer discussed in this article.

IV. CONCLUSION

This review has examined the integration of image processing techniques and the U-Net deep learning model for cancer detection, revealing a powerful synergy between the two domains. Image pre-processing methods, including contrast enhancement and color normalization, establish a reliable foundation by improving medical image quality. When this enhanced data is fed into the U-Net architecture, the model's ability to identify critical pathological structures is significantly amplified, leading to improved segmentation accuracy

TABLE II
U-NET STUDIES FOR CANCER DETECTION

Author	Year	Cancer Type	Dataset Size	Image	Approach	Result
Hu et.al	2018	Nasopharyngeal	19	MRI	U-Net	Dice Score= 0.60
Robin et.al	2021	Breast	115	Histopathology	U-Net	Accuracy= 94.2%
Wang et.al	2021	Colorectal Adenocarcinoma	165	Histopathology	Contrastive Learning Based PPC-UNet	Dice Score= 0.83
Zou et.al	2022	Ovarian	600	Ultrasound	U-Net, ResNet18	89% Accuracy
Kiran et.al	2022	Multiorgan	310	Histopathology	DenseRes U-Net	78% Accuracy
Saha et.al	2022	Ovarian	3419	Ultrasound	MU-Net	98.4 Accuracy
Nagarajan and Nawabjan Li et.al	2022	Ovarian	497	CT	U-Net DCNN	91.63% accuracy
	2023	Cell Detection	667	Histopathology	Vision Transformer U-Net	0.755 F1 Score
Chen et.al	2023	Ovarian	1496	Ultrasound	U-Net	76.06% accuracy
Ho et.al	2023	Ovarian BRCA Mutation	609	Histopathology	U-Net	0.74 IoU
Rahmani et.al	2024	Breast	697	Ultrasound	U-Net	0.84 Dice Score
Ortega et.al	2024	Breast	12930	Histopathology	DRD U-Net	0.85 Dice Score
Zhou et.al	2024	Lung	263	Ultrasound	DFA U-Net	0.86 Dice Score
Kashyap et. al	2025	Lung	1654	CT	Multi-Resolution Ensemble U-Net	92% Sensitivity
Ejjiyi et.al	2025	Breast	780	Ultrasound	ATEDU-NET	98.16 % IoU

TABLE III
STUDIES COMBINATION OF IMAGE PROCESSING AND U-NET

Author	Year	Cancer Type	Dataset Size	Image	Approach	Result
Ullah	2021	Brain	285	CT	Intensity Normalization, Bras Field Correction, Histogram Equalization, Artifact Removal + U-Net	Dice Score=0.91
Ilhan et.al	2021	Brain	114753	MRI	Histogram Equalization, U-Net	Dice Score= 0.94
Jeya, Sundari and Britha	2023	Ovarian	500	Ultrasound	Black Window Optimization UEDL-OVD	92.74% Contrast Ratio
Rudiansyah et.al	2024	Cervical	917	Pap-smear	Median Filter, Gamma Correction, CLAHE + U-Net	89% Accuracy
Alafer et.al	2024	Multiorgan	Multi	Multi	CLAHE, L Shaped U-Net	99.15% Accuracy
Vijayakumar	2025	Lung	1097	CT	RGF, SMFMF, CapsNet	98% Accuracy
Mazhar	2025	Skin	10015	Photo	Gray Wolf Optimization CNN	95.11% Accuracy

and more robust boundary detection. This combined approach leverages optimized data to maximize the performance of a powerful segmentation model, thereby enhancing clinical decision-making and reducing diagnostic errors. Looking ahead, future research should continue to explore this synergy. Key areas of focus include the development of optimized pre-processing pipelines tailored to specific imaging modalities and the investigation of next-generation deep learning architectures that can further refine segmentation performance. The continued integration of these methodologies holds immense potential to advance early diagnosis and treatment planning, ultimately promising to deliver better patient outcomes in oncology and other data-driven medical fields.

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