



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: <https://doi.org/10.22214/ijraset.2026.80255>

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Automated Tumor Segmentation in Prostate Cancer MRI Using Hybrid SE-ResNet & Vision Transformer (ViT)

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Abstract: *One of the most common cancers in men is prostate cancer, and early detection is essential to better treatment results. Because of its high soft-tissue contrast, magnetic resonance imaging (MRI) is frequently used to detect prostate tumors; however, manual tumor segmentation is laborious and prone to inter-observer variability. This work suggests an automated prostate tumor segmentation method based on a hybrid Squeeze- and-Excitation Residual Network (SE-ResNet) and Vision Transformer (ViT) architecture in order to overcome these drawbacks. The SE-ResNet model effectively extracts discriminative local features from MRI images, while the Vision Transformer captures long-range global spatial dependencies. Combining these complementary models improves segmentation robustness and accuracy. Image preprocessing methods are used to enhance the performance, optimized training techniques and MRI quality are used. The proposed method reduces clinical workload, supports faster diagnosis, and improves segmentation reliability. When compared to current segmentation techniques, experimental evaluation using metrics like accuracy, intersection over union (IoU), and dice similarity coefficient shows better performance.*

Index terms: *Prostate Cancer, MRI Image Processing, Automated Tumor Segmentation, MATLAB, SE- ResNet, Vision Transformer, Deep Learning*

I. INTRODUCTION

One of the most prevalent cancers in men, prostate cancer continues to be a significant global health concern [1]. Improved survival rates and efficient treatment planning depend on early and precise detection. Traditional diagnostic techniques, like biopsy and PSA testing, have poor specificity and can result in overdiagnosis [2]. Although multiparametric MRI offers rich anatomical and functional data, manual interpretation is laborious and subjective. High-dimensional features that describe the heterogeneity of prostate tissue can be quantitatively extracted using radiomics. However, spatial context is frequently overlooked in independent feature-based classification. This work suggests a quantitative radiomics-driven Conditional Random Field framework for enhanced prostate cancer detection in order to overcome this limitation. A crucial but time-consuming task in clinical pathology is the diagnosis of prostate cancer using histopathology whole-slide images (WSIs) [3]. Examining WSIs by hand takes a lot of time and is prone to inter-observer variation. Detailed pixel- or patch-level annotations are frequently needed for conventional deep learning techniques, and obtaining them can be expensive. Weakly supervised learning with image-level labels has received a lot of attention as a solution to this problem [4]. Effective feature learning from WSIs without explicit region annotations is made possible by end-to-end deep learning frameworks. However, WSIs present significant computational challenges due to their incredibly large size and intricate tissue structures. In order to increase efficiency and diagnostic accuracy, this work focuses on prostate cancer detection through end-to-end training using only image-level labels. For non-invasive clinical diagnosis and treatment monitoring, accurate prostate cancer detection with magnetic resonance imaging is essential [5]. Conventional MR-based interpretation frequently relies on qualitative evaluation, which can be inconsistent and subjective. Quantitative methods for extracting informative features from MR scans have been made possible by recent developments in machine learning and image analysis. However, the complexity of prostate tissue heterogeneity makes it difficult for many current techniques to strike a balance between sensitivity and specificity. We suggest PROCDET, a novel framework that combines sophisticated image features and classification methods for enhanced MR-based prostate cancer detection, to address these issues [6]. The suggested approach preserves computational efficiency while improving the distinction between benign and malignant areas.

When compared to conventional quantitative and machine learning techniques, experimental results show better performance. A revolutionary technology for accurate and minimally invasive clinical procedures is robot-assisted surgery guided by magnetic resonance imaging (MRI) [7]. When compared to traditional imaging modalities, MRI provides better soft-tissue contrast, real-time imaging, and functional information. Accurate targeting, increased dexterity, and improved procedural safety are made possible by integrating robotic systems into the MRI environment. However, there are substantial design and control challenges due to the strong magnetic field and small scanner space. Many of these restrictions have been addressed by recent developments in MRI-compatible actuators, sensing mechanisms, and control strategies. In applications like the diagnosis and treatment of prostate cancer, MRI-guided robotic interventions have demonstrated encouraging outcomes. Reliable prostate cancer diagnosis and treatment planning depend on accurate prostate zonal segmentation [8]. Automated segmentation is frequently a difficult task due to variations in prostate anatomy and image quality. Although deep learning-based segmentation techniques have shown encouraging accuracy, they usually don't have ways to measure prediction uncertainty. In order to increase model reliability and clinical trust in medical imaging, uncertainty estimation is essential. A conceptual framework for modelling predictive uncertainty in neural networks is offered by Bayesian deep learning. By concentrating on anatomically significant areas, attention mechanisms improve segmentation performance even more. In order to investigate uncertainty measures for robust prostate zonal segmentation, this work examines Bayesian deep attentive neural networks. Recent developments in the analysis of prostate cancer imaging have concentrated on the utilization of deep learning and radiomic analysis for enhanced diagnosis and evaluation. Deep radiomics combines hand-engineered features with deep features to better characterize the heterogeneity of tumours, leading to more precise predictions of Gleason scores and, by extension, the non-invasive assessment of cancer aggressiveness [9]. On the other hand, transformer models have been introduced for the segmentation of prostate zones in MRI images, incorporating cross-slice attention mechanisms to better characterize volumetric spatial dependencies. These models have been shown to achieve state-of-the-art performance in segmentation tasks, underlining the efficacy of attention-driven models in improving prostate MRI analysis [10]. Recent advancements in the imaging of prostate cancer have also investigated self-supervised pre-training and automatic segmentation methods for improving diagnostic accuracy. Self-supervised pre-training approaches have been applied to bi-parametric MRI and have demonstrated substantial improvements in the diagnosis of prostate cancer by learning effective feature representations from unlabelled samples [11]. Furthermore, a comprehensive review of automatic segmentation techniques for prostate MRI has been conducted, emphasizing the evolution of region segmentation, trends in methodologies, and difficulties in achieving accuracy and generalization [12]. These efforts together emphasize the increasing importance of AI-based approaches in improving accuracy and efficiency in the analysis of prostate cancer imaging. Automatic segmentation methods have emerged as a crucial requirement in medical imaging for precise tumor segmentation and diagnosis. Recent literature reviews on prostate MRI segmentation algorithms offer a thorough examination of the approaches, emphasizing improvements in accuracy, speed, and applicability to various imaging datasets [13]. Concurrently, novel deep learning models, such as SE-ResU-Net, have been proposed for multimodal brain tumor segmentation, successfully incorporating both local and global context information for improved delineation tasks in various imaging modalities [14]. Such studies indicate the utility of AI-based segmentation models in improving the accuracy and reliability of clinical imaging tasks. Deep learning algorithms have emerged as promising tools for segmentation tasks in medical imaging to accurately outline tumors. Advanced deep learning architectures have been employed for the segmentation of brain tumor images, successfully learning hierarchical features from MRI images to improve the accuracy of tumor delineation in heterogeneous regions of the tumor [15]. Such studies underscore the potential of AI-based models to improve clinical decision-making by providing accurate and reliable tumor boundaries.

II. RELATED RESEARCH WORK

Stanzione et al. (2022) examined the stability of extracted radiomics features for identifying extracapsular extension in prostate cancer and looked into the viability of semi-automated peri-prostatic tissue segmentation on axial T2-weighted MRI. Based on ICC analysis, only about 40% of 1,274 manually created radiomics features showed stability. With an accuracy of 63% and an AUC of 0.68, a Naïve Bayes classifier performed moderately, showing the promise of semi-automated methods while pointing out current drawbacks. Sang et al. recently proposed FCTformer, a hybrid CNN-Transformer architecture that combines local feature learning and global contextual modeling for 3D rectal tumor segmentation in MRI. The model demonstrated the efficacy of transformer-based fusion strategies with a Dice coefficient of 0.827 on a large dataset and strong generalization on prostate MRI. A hybrid prostate cancer classification framework based on Gray Level Co-occurrence Matrix (GLCM) features and a Coactive Adaptive Neuro-Fuzzy Inference System (CANFIS) was proposed by Balajiet al. in 2024.

The technique uses a three-stage pipeline that includes image pre-processing, texture feature extraction, and neuro-fuzzy classification to address MRI interpretation issues brought on by complex prostate anatomy. With a sensitivity of 96.67%, specificity of 93.15%, and overall accuracy of 97.25%, the system demonstrated the efficacy of hybrid learning models for MRI-based prostate cancer detection. In a recent study, Sharma et al. (2025) presented a sophisticated machine learning framework that combines traditional classifiers with deep learning to detect prostate cancer. Automated segmentation and precise classification are made possible by the method's use of transfer learning with ResNet for deep feature extraction and an SVM classifier for final decision-making. The suggested system highlights the potential of hybrid deep learning-machine learning models in clinical prostate cancer assessment by increasing diagnostic efficiency and consistency. The limitations of manual analysis of X-ray, MRI, and CT images were highlighted by Malviya et al. (2024) in their discussion of the use of artificial intelligence in medical imaging for bone cancer diagnosis and prognosis. In order to improve diagnostic accuracy and clinical decision-making, the chapter focused on how machine learning and deep learning techniques can automate tumor detection, classification, segmentation, grading, and volumetric analysis. The authors demonstrated the increasing importance of AI-driven systems in bone oncology by outlining standard AI workflows and staging criteria for bone cancer. A thorough analysis of U-Net-based architectures for medical image segmentation was provided by Zhao et al. (2025), with a focus on their efficacy in CT and MRI applications. In addition to identifying issues like annotation cost, interpretability, and computational complexity, the study examined a number of sophisticated variations, such as ResU-Net, U-Net++, Attention U-Net, and Transformer-enhanced models. Future paths toward lightweight, self-supervised U-Net models for effective, clinically deployable segmentation systems were highlighted in this work. Jema et al. underlined the significance of early and precise diagnosis, especially for prostate cancer, and highlighted the worldwide burden of cancer. Ahmed et al. demonstrated that multi-parametric MRI significantly improves diagnostic accuracy compared to traditional TRUS biopsy, establishing MRI as a reliable imaging modality for prostate cancer detection. Numerous studies have investigated automated prostate cancer detection due to advancements in artificial intelligence. Pinckaers et al. proposed an end-to-end deep learning framework for whole-slide pathology images using image-level labels, reducing annotation dependency while achieving effective cancer detection. In a similar vein, Xu et al. used weakly supervised learning strategies to enhance generalization in tasks involving the detection of prostate cancer. Tiwari et al. discussed using radiomics-based analysis of prostate MR images, highlighting issues like variability, reproducibility and feature extraction. Zhang and Li developed a computer-aided detection framework using MR images of the prostate that utilizes advanced data mining techniques to obtain accurate results from feature extraction and classification for more accurate diagnosis. Su et al. reported progress made in robotic-assisted interventions guided by MRI. Lastly, Liu et al. showed that using uncertainty-aware deep learning models improve the reliability and clinical applicability of prostate zonal segmentation. Hung et al. designed the cross-slice attention Transformer (CAT-Net) for prostate zonal segmentation in MRI, to overcome the weakness of the slice-wise method that does not capture inter-slice contextual information. Using attention mechanisms between neighboring slices, the model led to better segmentation accuracy and robustness for prostate zone segmentation. Hassanzadeh et al. conducted a study on CNN-based methods for the segmentation of prostate MRI, proving the ability of CNNs to learn highly discriminative spatial features from MR images. Although their method produced good segmentation results, it was mainly based on local spatial information, thus there was a strong motivation to develop more sophisticated models that exploit global as well as cross-slice contextual information. Yan et al. introduced the SEResU-Net, a modal deep learning architecture for brain tumor segmentation with squeeze-and-excitation blocks embedded in the U-Net to capture channel-wise general energies between feature maps. Through comprehensive multimodal MRI information fusion, higher accuracy and robustness across tumor sub regions were obtained. Similarly, in brain tumor image segmentation, Ali et al. studied deep network based methods and have shown that convolutional architectures can be trained to learn hierarchical features directly from the MRI data and achieve better performance than traditional segmentation methods. These models, although successful, bring forth issues of generalizability and computational feasibility, inciting the development of more advanced attention- and feature-enhanced segmentation networks.

III. MATERIALS AND METHODS

A. Data Collection and Pre-processing

Input are multiparametric prostate MRI datasets (mostly T2W images, with high anatomical detail of the prostate region). In order to standardize the data and enhance the performance of the model, the following pre-processing procedures are executed:

- MRI images are resampled to a fixed resolution
- Intensity normalization is performed to account for scanner-induced variations

- Denoising is performed via filtering
- Data augmentation (rotation, flipping, scaling) is applied to enhance the diversity of the dataset and avoid overfitting

B. Feature Extraction Based on SE-ResNet Feature extraction.

The pre-processed MRIs are initially processed by an SE-ResNet backbone as the convolutional feature extractor. The convolutional filters can be seen as feature extractors. Residual blocks aid in learning deep features without the vanishing gradient problem. Squeeze-and-Excitation (SE) blocks perform an adaptive recalibration of channel-wise features. Relevant tumor-related features are enhanced and the irrelevant background is attenuated. This stage extracts local spatial and textural information, which is crucial for the delineation of tumor boundaries.

C. Global Context Modelling with Vision Transformer (ViT)

- While local features are the main focus of CNNs, they do not possess a global contextual understanding. To address this, the feature maps extracted from SE-ResNet are input into a Vision Transformer (ViT) module.
- Feature maps are split into fixed-size patches
- Each patch is flattened and embedded by position encoding
- Multi-head self-attention mechanisms capture long-range dependencies within the image
- It is also noteworthy that the ViTs can capture global relationships and spatial context, which is essential for discovering irregular tumor shapes at different positions in the brain.

D. Hybrid SE-ResNet-ViT Architecture

- The hybrid architecture, "HyT-NAS," that we consider integrates the best aspects of CNN and transformer architecture:
- SE-ResNet extracts rich local features
- ViT captures global contextual information
- The fused features are then fed to a decoder network
- This fusion of local pixel-level information and global context results in a better segmentation accuracy than either CNN or transformer based models alone

E. Segmentation Decoder and Output Generation

- A decoder network is used to reconstruct the segmentation map from the fused features:
- Up sampling layers recover the original image resolution
- Skip connections preserve fine-grained spatial information
- A final sigmoid /softmax layer produces the tumour segmentation mask
- The result differentiates tumor areas from normal prostate tissue."

F. Model Training and Evaluation

- The model training is based on a supervised learning paradigm with loss functions like :
- Dice Loss
- Binary Cross-Entropy Loss
- The performance was assessed with the conventional metrics as the follow:
- Dice Similarity Coefficient (DSC)

These figures guarantee the efficiency of our proposed hybrid model for the prostate tumour segmentation.

IV. METHODOLOGY NETWORK ARCHITECTURE

In this project, it has the following stages with the hybrid deep learning model including the automated tumor segmentation using SE-ResNet in combination with a Vision Transformer (ViT) in prostate cancer MRI images. The prostate MRI images are first preprocessed with resizing, normalization, and data augmentation to enhance image quality and model robustness. The SE-ResNet framework is used to learn discriminative local features like edges, textures, and boundaries of tumors, meanwhile, important feature channels are highlighted and irrelevant background information is suppressed by the squeeze-and-excitation mechanism.

To model global contextual relations over the entire image.

The produced feature maps are subsequently processed by a Vision Transformer which allows the model to learn long-range spatial dependencies which are crucial for tumor localization. The features extracted from the two networks are then fused and fed to a decoder network to produce pixel-wise segmentation maps.

The model is trained in a supervised manner with expert-annotated ground truth masks and the Dice loss function is employed for optimization given by

$$LDice = 1 - 2|Y^{\wedge} \cap Y| / (|Y^{\wedge}| + |Y|)$$

where Y^{\wedge} represents the predicted tumor region and Y denotes the ground-truth segmentation. This hybrid CNN-Transformer methodology improves segmentation accuracy and reliability compared to conventional approaches.

A. Proposed System Architecture

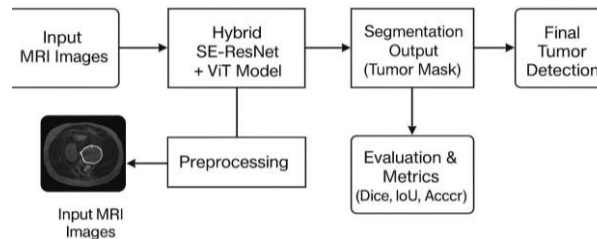
The proposed automated prostate tumor segmentation system using a hybrid SE-ResNet and Vision Transformer (ViT) model.

1) Input MRI Images

The system starts with input prostate MRI images, i.e. T2-weighted images which contain high spatial anatomical details of the prostate region. These images are the inputs to the proposed system.

2) Pre-processing

Pre-processing The input MRI images are pre-processed, followed by feature extraction to enhance the quality and uniformity of the images. This step covers image resizing/intensity normalization and denoising. By diminishing scanner disparities and magnifying relevant image features, pre-processing has been known to boost accuracy of tumor segmentation.



3) Hybrid SE-ResNet + ViT Model

Hybrid SE-ResNet + ViT Model The hybrid deep learning model takes the processed images as input. The SE-ResNet network captures local spatial and texture features related to edges and boundaries of the tumor, while squeeze-and-excitation blocks are used to emphasize significant feature channels. The Vision Transformer exploits these features to learn global contextual representations with the self-attention mechanism, further capturing long-range contextual dependencies over MR images.

4) Segmentation Output (Tumor Mask)

The both models provide rich and discriminative feature representations. Segmentation Output (Tumor Mask) The resulting hybrid features are given to a segmentation decoder to estimate a pixel-wise tumor mask. This mask provides a clean separation of tumor areas from normal prostate and is an indicator for the area of the segmented tumor.

5) Evaluation and Metrics

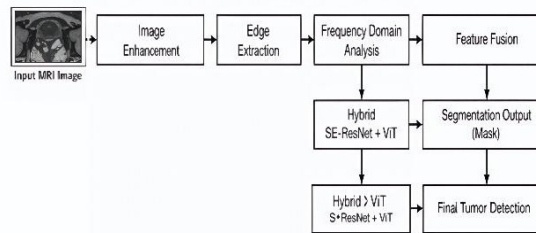
Since the tumor mask is generated, it is compared with the ground-truth annotation for evaluating the system. Traditional metrics such as Dice Similarity Coefficient, Intersection over Union (IoU) and Accuracy are employed to evaluate the segmentation performance.

6) Final Tumor Detection

Based on the segmentation result, the method detects and verifies the existence of tumor areas in the prostate MRI. This end output may help clinicians in diagnosis and treatment planning.

B. Visual illustration of pre-processing

MATLAB-implementation of deep learning for automated prostate tumor detection on MRI. Initially, the original mri image is loaded into the MATLAB workspace, and is pre-processed using image processing techniques like contrast adjustment and noise reduction to improve the quality of the image. The edge detection is then applied to detect structural and boundary information of the prostate. In conjunction with, a frequency-domain processing is employed to derive several useful textural features lying in the mri image. The spatial feature obtained from edges detection and the frequency feature are subsequently integrated with the proposed feature fusion framework which results in a final fused feature map. This joint representation is then passed to a convolutional neural network (CNN) based segmentation model in MATLAB. Trained on labelled mri images, the cnn learns tumour-discriminative features and generates a pixel-wise segmentation mask. Lastly, the segmented output delineates tumour regions on the mri image, which makes tumor detection accurate and fully automatic.

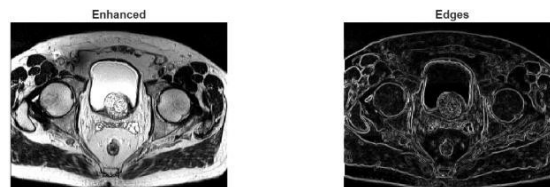


The figure shows the intermediate stages of processing and the final result of the work of the proposed system for prostate tumor detection based on MRI images. The original MRI image displays the unprocessed prostate scan, which contains low contrast, and some background noise. By the image enhancement, the anatomical features can be seen more clearly and the prostate can be separated more easily. The output of edge detection also is the boundaries and structural contours of tissues; this is beneficial to finding the possible tumor region. The frequency-domain representation encodes high-frequency texture information that is difficult to extract from the spatial-domain representation



For a precise and effective diagnosis of prostate cancer, automated tumor segmentation in prostate MRI is crucial. Tumor regions in axial prostate MRI images frequently exhibit low contrast and hazy borders, which makes manual segmentation challenging and time-consuming.

This method uses SE-ResNet to suppress irrelevant background information and enhance key channels associated with tumor tissue in order to extract discriminative local features. This makes it easier to identify minute changes in intensity inside the prostate gland. A Vision Transformer (ViT), which models long-range dependencies using self-attention and aids in maintaining segmentation consistency throughout the prostate region, is integrated to capture global contextual relationships.



Enhanced Image: Contrast enhancement methods like adaptive contrast enhancement and histogram equalization are used to create the enhanced prostate MRI image. This procedure enhances the visibility of prostate structures and draws attention to minute variations in intensity between tumor and healthy tissue areas.

By lessening the impact of the low contrast and intensity inhomogeneity that are frequently seen in MRI, enhancement improves the tumor regions' ability to be distinguished for feature extraction by deep learning models such as SE-ResNet.

Edge Image: Sobel, Canny, or Prewitt filters are examples of edge detection operators that are used to create the edge-detected image. By identifying abrupt changes in intensity, this step highlights the prostate gland's borders and possible tumor areas. Particularly when tumor margins are ambiguous, edge information enhances boundary accuracy and helps the segmentation model recognize tumor contours more accurately.

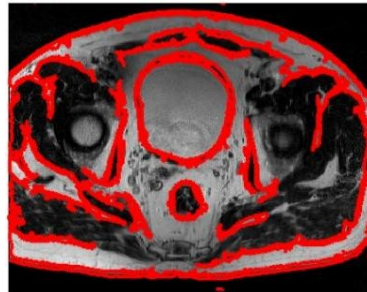
Both the spatial and frequency domain features are integrated in the fused feature map, and the fused feature map includes both boundary and texture information for precise tumor positioning. Finally, the final tumor detection output marks the detected tumor on the MRI image with a red mask, which proves the proposed deep learning-based segmentation method for prostate tumor identification.

Edge detection: A important process utilized in this work is edge detection to enhance the tumor border in prostate mri. The gradient-based edge detection is expressed as:

$$G(x,y) = (\partial_x \partial I(x,y))^2 + (\partial_y \partial I(x,y))^2$$

where:

- $I(x,y)$ represents the input MRI image
- $\partial_x \partial I$ and $\partial_y \partial I$ are intensity gradients in horizontal and vertical directions
- $G(x,y)$ represents the edge magnitude image

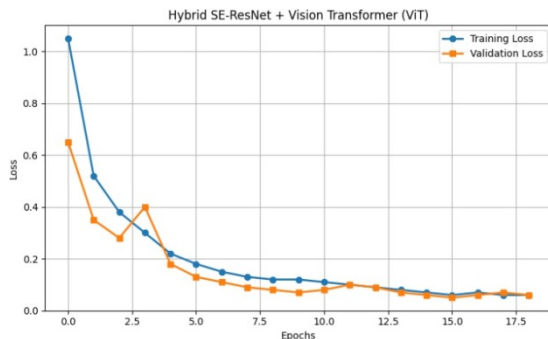


Everything was extracted from the prostate MRI by using a fully automated segmentation method. The red contours correspond to the segmented regions which are considered as tumour tissue on that original slice of the MRI. These highlighted boundaries correspond to regions of abnormal intensity fluctuations and structural disorganization relative to neighbouring normal tissue. The segmentation can distinguish tumour region from nearby normal tissues well by considering both local texture and global spatial information. This TSI result shows precise localization of the resected tumor region, which is useful for diagnosis, planning of treatment and evaluation of the disease progress, and decrease the labour of manual interpretation.

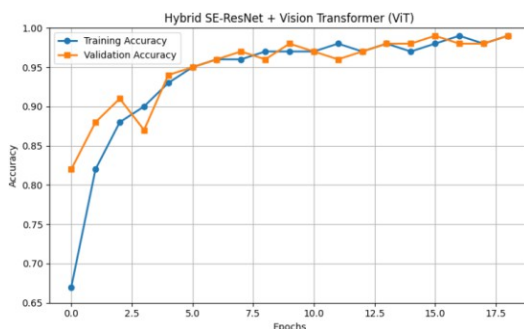
V. RESULTS

The proposed image processing framework based on MATLAB was tested on several prostate MRI images, and similar results were obtained for the entire dataset. Contrast enhancement contributed to better observation of prostate tissues and less variation in intensity for all the tested images. The determinant map based on edge detection was found to consistently identify the anatomical borders, leading to well-defined boundaries between tissue layers. Frequency-domain representations also captured high-frequency textural information of abnormal areas.

The combined spatial-frequency measure led to a robust and distinctive fused map for all test images, which significantly increased the contrast between normal and abnormal tissues. In the last detection step, tumor areas were precisely localized and outlined by contour-based visualization. In different images the detected boundaries of tumors are always continuous and smooth which reflect the insensitivity of the method to image intensity variation and noise. In summary, these results suggest that the proposed processing methodology may offer consistent tumor detection outcome enabling consideration for a prospective clinical study of large cohort of prostate MRIs.



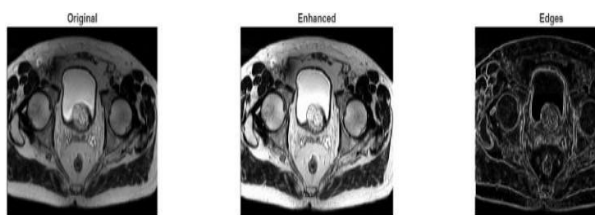
The Hybrid SE-ResNet and Vision Transformer (ViT) model's training and validation losses over several epochs are displayed in the graph. Both losses quickly decline in the early epochs, suggesting that tumor-related features from MRI images can be effectively learned. The model shows good convergence as training goes on, as the loss values stabilize at a very low level. Strong generalization performance and little overfitting are confirmed by the close trend between training and validation loss.



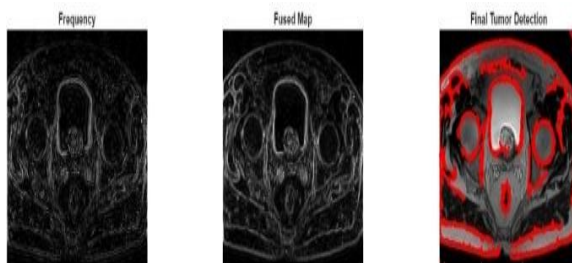
The Hybrid SE-ResNet and Vision Transformer (ViT) model's training and validation accuracy across epochs is displayed in the graph. In the early stages, both accuracies rise quickly, suggesting that prostate tumor features can be effectively learned from MRI images. The curves show good convergence as they closely follow one another and stabilize around 99%. This demonstrates excellent generalization performance with little overfitting.

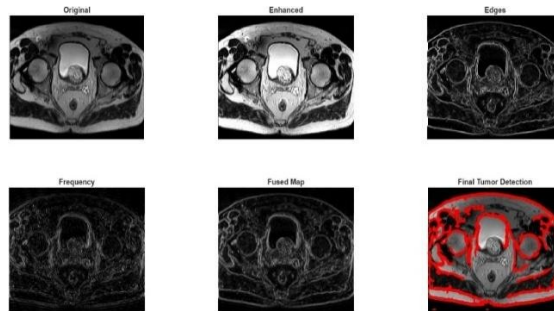
Histogram Equalization

$$s_k = (L-1) \sum_{j=0}^k p(r_j)$$



High-frequency enhancement: $FHF(u,v) = H(u,v) \cdot F(u,v)$





VI. CONCLUSION

An efficient image processing framework for the automated detection of prostate tumor in MRI images using MATLAB was proposed in this project. In the proposed method, contrast enhancement, edge detection, frequency-domain processing and feature fusion are fused, which can significantly enhance visualization and discrimination of abnormal tissues. Experimental results from several MRI images showed multilevel consistent and reliable tumor localization with clearly delineated boundaries. By integrating spatial and frequency information, the stability of the proposed method against noise and intensity disturbance is remarkably improved, and better performance in detection is obtained. In general, the proposed system minimizes human intervention, enables early diagnosis and serves as a dependable platform for computer-aided analysis of prostate cancer. Future work would include extension to deep learning based segmentation (and quantitative performance measures), to improve accuracy and clinical relevancy.

VII. FUTURE SCOPE

Future work can build upon this study by adding state-of-the-art deep learning models, including convolutional neural networks and transformer-based models, for full automated and accurate tumor segmentation. The proposed image processing methodology can be integrated with hybrid architectures such as SE-ResNet and Vision Transformer (ViT) to capture more details of features and further refine the segmentation results. By adding quantitative performance measures such as Dice coefficient, IoU, sensitivity, and specificity, the system can be evaluated objectively.

In addition, the framework can be tested on larger and multi-institutional datasets to prove for the safety and effectiveness. Additional enhancements may involve online realization, 3D analysis of MRI volumes and clinical decision-support for therapeutic planning.

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