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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 prostatecancer,andearlydetectionisessentialtobetter treatment results. Because of its high soft-tissue contrast, magneticresonanceimaging(MRI)isfrequentlyusedto detect prostate tumors; however, manual tumor segmentation is laborious and prone to inter-observer variability. This work suggests an automated prostate tumorsegmentationmethodbasedonahybridSqueeze- 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 robustnessandaccuracy.Imagepreprocessingmethods areusedtoenhancethe performance,optimizedtraining 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.
Indexterms: ProstateCancer,MRIImageProcessing, Automated Tumor Segmentation, MATLAB, SE- ResNet, Vision Transformer, Deep Learning

I. INTRODUCTION

One of the most prevalent cancers in men, prostate cancercontinuestobeasignificantglobalhealth 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 canresultinoverdiagnosis[2].Although multipara metric 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. Thiswork suggests a quantitative radiomics-driven ConditionalRandomFieldframeworkforenhanced prostate cancer detection in order to overcome this limitation. A crucial but time-consuming task in clinicalpathologyisthediagnosisofprostatecancer using histopathology whole-slide images (WSIs) [3].ExaminingWSIsbyhandtakesalotoftimeand is prone to inter-observer variation. Detailed pixel- orpatch-levelannotationsarefrequentlyneededfor 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 withoutexplicitregionannotationsismadepossible byend-to-enddeeplearningframeworks. However, WSIs present significant computational challenges duetotheir incrediblylarge sizeandintricate 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 informativefeaturesfromMRscanshavebeenmade possible by recent developments in machine learning and image analysis. However, the complexityofprostatetissueheterogeneitymakesit 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 prostatecancerdetection, to addresstheseissues[6]. The suggested approach preserves computational efficiency while improving the distinction between benign and malignant areas.

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When compared to conventional quantitative and machine learning techniques, experimental results show better performance. A revolutionary technology for accurateandminimallyinvasiveclinicalprocedures is robot-assisted surgery guided by magnetic resonance imaging (MRI) [7]. When compared to traditionalimagingmodalities,MRIprovidesbetter soft-tissue contrast, real-time imaging, and functional information. Accurate targeting, increaseddexterity,andimprovedproceduralsafety are made possible by integrating robotic systems into the MRI environment. However, there are substantial design and controlchallengesdueto the strongmagneticfieldandsmallscannerspace.Many of these restrictions have been addressed by recent developmentsinMRI-compatibleactuators,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 dependonaccurateprostatezonalsegmentation[8]. Automated segmentation is frequently a difficult taskduetovariationsinprostateanatomyandimage quality.Althoughdeeplearning-basedsegmentation 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 estimationisessential.Aconceptualframeworkfor modellingpredictiveuncertaintyin neural networks is offered by Bayesian deep learning. By concentratingonanatomically significantareas, 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 characterizetheheterogeneityoftumours,leadingto 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 characterizevolumetricspatialdependencies.These models have been shown to achieve state-of-the-art performance in segmentation tasks, underlining the efficacy of attention-driven models in improving prostateMRIanalysis[10].Recentadvancementsin theimagingofprostatecancerhavealsoinvestigated 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 automaticsegmentation techniquesforprostateMRI has been conducted, emphasizing the evolution of region segmentation, trends in methodologies, and difficultiesinachievingaccuracyandgeneralization [12]. These efforts together emphasize the increasing importance of AI-based approaches in improvingaccuracyandefficiencyintheanalysisof prostate cancer imaging. Automatic segmentation methods have emerged as a crucial requirement in medicalimagingforprecisetumorsegmentationand diagnosis. Recent literaturereviewsonprostateMRI 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 delineationtasksinvariousimagingmodalities[14]. Such studies indicate the utility of AI-based segmentationmodelsinimprovingtheaccuracyand reliability of clinical imaging tasks. Deep learning algorithms have emerged as promising tools for segmentationtasksinmedicalimagingtoaccurately 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 studiesunderscorethepotentialofAI-basedmodels 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,showingthepromiseofsemi-automated methods while pointing out current drawbacks. Sang et al. recently proposed FCTformer, a hybrid CNN–Transformer architecture that combineslocal feature learningandglobal contextual modelingfor 3D rectal tumor segmentation in MRI. The model demonstrated the efficacy of transformer-based fusionstrategieswithaDicecoefficientof0.827on alargedatasetandstronggeneralizationonprostate 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 proposedbyBalajietal.in2024.

Thetechniqueuses 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. Withasensitivityof96.67%,specificityof93.15%, and overall accuracy of 97.25%, the system demonstratedtheefficacyofhybridlearningmodels forMRI-basedprostatecancerdetection.Inarecent study,Sharmaetal.(2025)presentedasophisticated 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 Malviyaetal.(2024)intheirdiscussionoftheuseofartificialintelligenceinmedicalimagingforbone cancerdiagnosisandprognosis. Inorderto 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 increasingimportanceofAI-drivensystemsinbone oncology by outlining standard AI workflows and stagingcriteriaforbonecancer.Athoroughanalysis 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++,AttentionU-Net,andTransformer-enhanced models. Future paths toward lightweight, self- supervised U-Net models for effective, clinically deployable segmentation systems were highlighted inthiswork.Jemaletal.underlinedthesignificance ofearlyandprecisediagnosis,especiallyforprostate 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, establishingMRIasareliable imagingmodalityfor 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 accuratediagnosis.Suetal.reportedprogressmade in robotic-assisted interventions guided by MRI. Lastly, Liu et al. showed that using uncertainty- awaredeeplearningmodelsimprovesthereliability and clinical applicability of prostate zonal segmentation. Hung et al. designed the cross-slice attentionTransformer(CAT-Net)forprostatezonal segmentation in MRI, to overcome the weaknessof theslice-wisemethodsthatdonotcaptureinter-slice contextualinformation.Usingattentionmechanisms 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 learnhighlydiscriminativespatialfeaturesfromMR images. Although their method produced good segmentation results, it wasmainly 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.Yanetal.introducedtheSEResU-Net, a modal deep Earning architecture for brain tumor segmentation with squeeze-and-excitation blocks embedded in the U-Net to capture channel- widetypegeneral Energies between feature maps. Through comprehensive multimodal MRI information fusion, higher accuracy and robustness across tumor sub regions were obtained. Similarly, inbraintumorimagesegmentation,Alietal.studied deep network based methods and have shown that convolutional architectures can be trained to learn hierarchicalfeaturesdirectlyfromtheMRIdataand achieve better performance than traditional segmentation methods. Thesemodels, although successful,bringforthissuesofgeneralizabilityand 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 multipara metric prostate MRI datasets (mostlyT2Wimages,withhighanatomicaldetailof theprostateregion). Inordertostandardizethedata and enhance the performance of the model, the following pre-processing procedures are executed:

- MRIimagesareresampledtoafixedresolution
- Intensitynormalizationisperformedto account for scanner-induced variations

- Denoisingisperformedviafiltering
- Data augmentation (rotation, flipping, scaling)isappliedtoenhancethediversity of the dataset and avoid overfitting

B. FeatureExtractionBasedonSE-ResNetFeature extraction.

The pre-processed MRIs are initially processed by anSE-ResNetbackboneastheconvolutionalfeature extractor. The convolutional filters can be seen as feature extractors. Residual blocks aid in learning deep features without the vanishing gradient problemSqueeze-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 withVision Transformer (ViT)

- While local features are the main focus of CNNs, they do not possess a global contextual understanding. To address this, thefeaturemapsextractedfromSE-ResNet are input into a Vision Transformer (ViT) module.
- Feature maps are split into fixed-size patches
- Each patchis 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 inthe brain.

D. HybridSE-ResNet–ViTArchitecture

- The hybrid architecture," HyT-NAS," that we consider integrates the best aspects of CNN and transformer architecture:
- SE-ResNetextractsrichlocalfeatures
- ViTcapturesglobalcontextualinformation
- The fused features are then fed to a decoder network
- Thisfusionoflocalpixel-levelinformation and global context results in a better segmentationaccuracythaneitherCNNor transformer based models alone

E. SegmentationDecoderandOutputGeneration

- 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 resultdifferentiates tumor areas from normal prostate tissue."

F. ModelTrainingand Evaluation

- The model training is based on a supervised learning paradigm with loss functions like :
- DiceLoss
- BinaryCross-EntropyLoss
- The performance was assessed with the conventional metrics as the follow:
- DiceSimilarityCoefficient(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 hybriddeeplearningmodelincludingtheautomated 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 imagequalityandmodelrobustness.TheSE-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 overtheentireimage.

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

The model is trained in a supervised manner with expert-annotated ground truth masks and the Dice lossfunctionisemployedforoptimizationgivenby

LDice=1−2|Y^∩Y||Y^|+|Y

whereY^representsthepredictedtumorregionand YYY denotes the ground-truth segmentation. This hybrid CNN–Transformer methodology improves segmentation accuracy and reliability compared to conventional approaches.

A. *Proposed System Architecture*

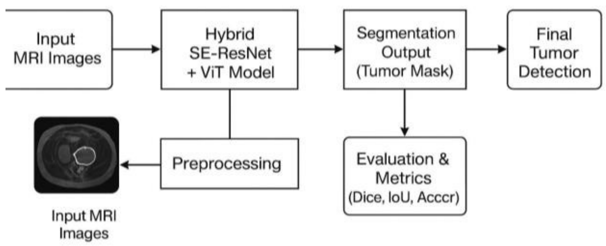
The proposed automated prostate tumor segmentationsystemusingahybridSE-ResNetand Vision Transformer (ViT) model.

1) *Input MRI Images*

ThesystemstartswithinputprostateMRIimages, i.e. T2-weighted images which contain high spatial anatomical details of the prostate region. These imagesare the inputs to the proposed system.

2) *Pre-processing*

Pre-processing The input MRI images are pre- processed,followedbyfeatureextractiontoenhance 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) *HybridSE-ResNet+ViTModel*

Hybrid SE-ResNet + ViT Model The hybrid deep learningmodeltakestheprocessedimagesasinput. The SE-ResNet network captures local spatial and texture features related to edges and boundaries of the tumor, while squeeze-and-excitation blocks are usedtoemphasizesignificantfeaturechannels.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) *SegmentationOutput(TumorMask)*

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

5) *EvaluationandMetrics*

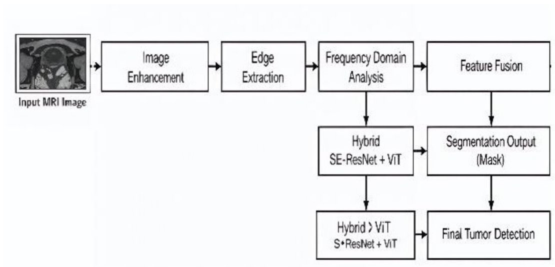
Since thetumor mask is generated, it is compared with the ground-truth annotation for evaluating the system. Traditional metrics such as Dice Similarity Coefficient, Intersection over Union (IoU) and Accuracy are employed to evaluate the segmentation performance.

6) *FinalTumorDetection*

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. Visualillustrationofpre-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-domainprocessingisemployedtoderive several useful textural features lying in the mri image. The spatial feature obtained from edges detection and the frequency feature are subsequentlyintegratedwithintheproposed feature fusion framework which results in a final fused featuremap. Thisjointrepresentationisthenpassed to a convolutional neural network (CNN) based segmentation model in MATLAB. Trained on labelledmriimages,thecnnlearnstumour-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 andfully automatic.



The figure shows the intermediate stages of processing and the final result of the work of the proposed system forprostate tumordetectionbased on MRI images. The original MRIimage displays the unprocessed prostate scan, which contains low contrast,andsomebackgroundnoise.Bytheimage enhancement, the anatomical features can be seen moreclearlyandtheprostatecanbeseparatedmore easily. The output of edge detection also is the boundariesandstructuralcontoursof tissues;thisis beneficialtofindingthepossibletumorregion.The frequency-domain representation encodes high- frequency texture information that is difficult to extract fromthe spatial-domain representation

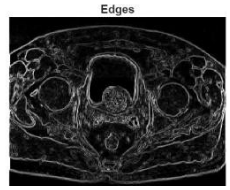
Original

For a precise and effective diagnosis of prostate cancer, automated tumor segmentation in prostate MRIiscrucial.TumorregionsinaxialprostateMRI 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 discriminativelocalfeatures.Thismakesiteasierto 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 integratedtocaptureglobalcontextualrelationships.

Enhanced

Edges



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.

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By lesseningtheimpactofthelowcontrastandintensity 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.

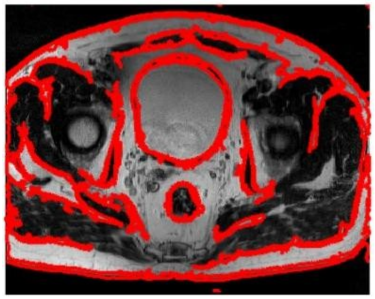
Edge Image: Sobel, Canny, or Prewitt filters are examples of edge detection operators that are used to create the edge-detected image. By identifying abrupt changes in intensity, this step highlights the prostate gland's borders and possible tumor areas. Particularly when tumor margins are ambiguous,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

Both the spatial and frequency domain features are integratedinthefusedfeaturemap,andthefused 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 utilizedinthisworkisedgedetectiontoenhancethe tumor border in prostate mri. The gradient-based edge detection is expressed as:

G(x,y)=(∂x∂I(x,y))2+(∂y∂I(x,y))2

where:

- I(x,y)representstheinputMRIimage
- ∂x∂Iand∂I∂yareintensitygradientsinhorizontalandverticaldirections
- G(x,y)represents the edge magnitude image

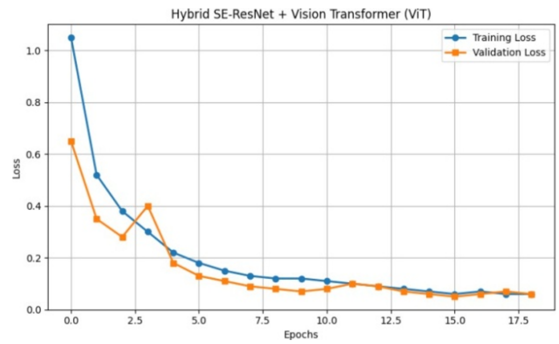


EverythingwasextractedfromtheprostateMRIby using afully automated segmentation method. The red contours correspond to the segmented regions which are considered as tumour tissue on that original slice of the MRI. These highlighted boundaries correspond to regions of abnormal intensity fluctuations and structural disorganization relative to neighbouring normal tissue. The% segmentation can distinguish tumour region from nearbynormaltissueswellbyconsideringbothlocal texture and global spatial information. This TSI result shows precise localization of the resected tumorregion,whichisusefulfordiagnosis,planning of treatment and evaluation of the disease progress, and decrease the labour of manual interpretation.

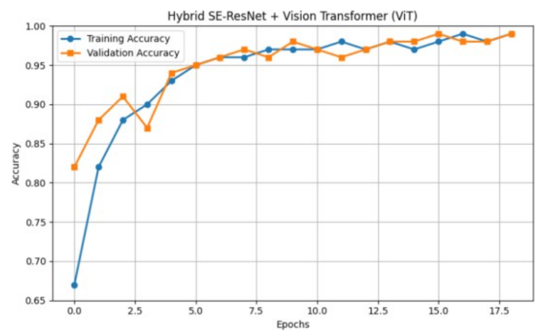
V. RESULTS

Theproposedimageprocessingframeworkbasedon 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 determinantmapbasedonedgedetectionwasfound to consistently identify the anatomical borders, leadingtowell-definedboundariesbetweentissue layers. Frequency-domain representations also captured high-frequency textural information of abnormalareas.

The combined spatial–frequency measure led to a robustanddistinctive fusedmap for all testimages, which significantly increased the contrast between normal and abnormal tissues. In the last detection step, tumor areas were precisely localized and outlinedbycontour-basedvisualization.Indifferent imagesthedetectedboundariesoftumorsarealways 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.

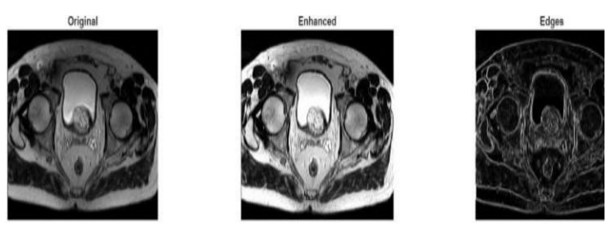


The Hybrid SE-ResNet and Vision Transformer (ViT) model's training and validation losses over several epochs are displayed in the graph. Both losses quickly decline in the early epochs, suggesting that tumor-related features from MRI imagescanbeeffectivelylearned.Themodelshows good convergence as training goes on, as the loss values stabilize at a very low level. Strong generalizationperformanceandlittleoverfittingare confirmedbytheclosetrendbetweentrainingandvalidationloss.

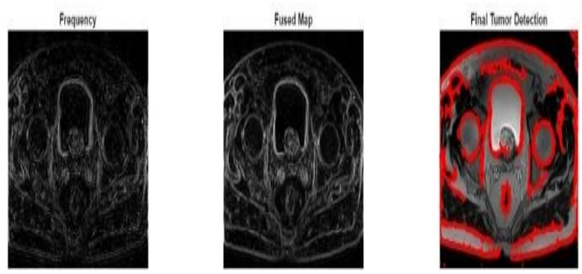


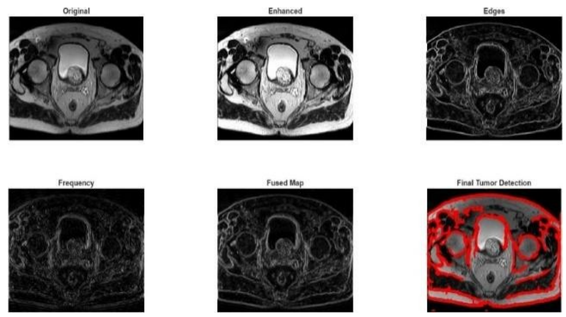
The Hybrid SE-ResNet and Vision Transformer (ViT) model's training and validation accuracy across epochs is displayed inthe graph.Inthe early stages, bothaccuracies risequickly, suggestingthat prostate tumor features can be effectively learned from MRI images. The curves show good convergenceastheycloselyfollowoneanotherand 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-frequencyenhancement: $F_{HF}(u,v)=H(u,v)\cdot F(u,v)$





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 resultsfromseveralMRIimagesshowedmultilevel consistent and reliable tumor localization with clearly delineated boundaries. By integratingspatial and frequency information, the stability of the proposed method against noise and intensity disturbance is remarkably improved, and better performanceindetectionisobtained.Ingeneral,the proposed system minimizes human intervention, enables early diagnosis and servesas a dependable platform for computer-aided analysis of prostate cancer.Futureworkwouldincludeextensiontodeep 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 asDicecoefficient, IoU,sensitivity, andspecificity, the system can be evaluated objectively.

Inaddition,theframeworkcanbetestedonlargerand 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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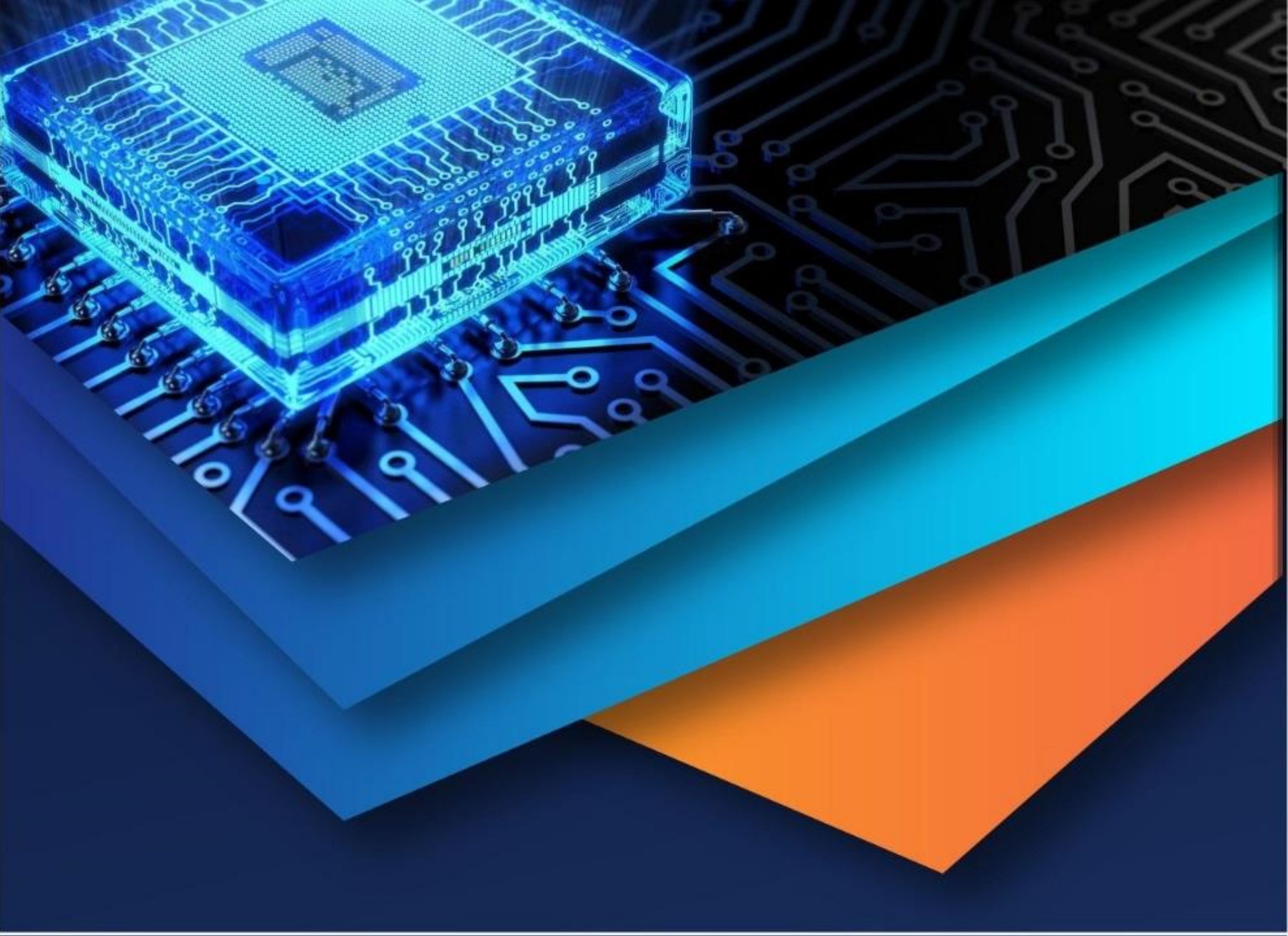

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