MRI-Based Bladder Cancer Staging via YOLOv11 Segmentation and Deep Learning Classification

**Abstract**

Accurate and rapid staging of Bladder Cancer

**[1]** from MRI images, specifically from stages T1 to T4, is paramount for effective treatment planning. This research presents and evaluates a two-stage Artificial Intelligence (AI) framework for cancer staging.

In the first stage, we utilized YOLOv11, a Segmentation Model, to automatically identify and segment the tumor mass within the MRI images. In the second stage, the resulting segmented tumor images were used to train Image Classification Models, namely VGG19**[*4*]**, ResNet50**[*6*]**, ResNet101**[*7*]**, and Vision Transformer (ViT)**[*8*]**, to classify the cancer stage into T1, T2, T3, and T4.

The initial dataset of 1,285 images from Kaggle was curated and confirmed by expert physicians, resulting in a refined dataset of 416 images. Various Data Augmentation techniques were then applied, yielding a new dataset of 1,610 images.

Experimental results indicate that the ResNet50 and ResNet101 models demonstrated the highest performance in cancer staging classification, achieving an accuracy of up to 97%. This highlights the potential of the proposed method as accurate and efficient diagnostic aid for expert physicians.

**1. Introduction**

Bladder cancer is the 10th most common cancer globally. Accurate diagnosis and staging are crucial in clinical decision-making. Staging according to the TNM system, particularly distinguishing non-muscle-invasive cancer (T1) from muscle-invasive cancer (T2-T4), directly impacts treatment selection. MRI-based

**[*1*]** assessment is a widely adopted standard. However, visual analysis by physicians still depends on experience and is susceptible to fatigue, which may lead to discrepancies.

In recent years, Deep Learning technology has emerged as a powerful tool for medical image analysis. CNN models such as VGG19**[*5*]** and ResNet have demonstrated outstanding capability in learning image features for classification and segmentation tasks. Furthermore, the advent of the Vision Transformer (ViT) has opened a new dimension in image analysis by using the Self-Attention mechanism to analyze the image's global context, which differs from CNNs that focus on learning local features.

The main objective of this research is to build and evaluate the effectiveness of a two-stage framework for staging bladder cancer from MRI images. The first stage uses YOLOv11 for accurate tumor segmentation, a critical step to reduce noise and focus on the Region of Interest (ROI). Subsequently, various deep CNN models—VGG19**[*5*]**, ResNet50**[*6*]**, ResNet101**[*7*]**—and ViT**[*8*]** are employed to classify the segmented tumor images, determining which model is most suitable for this task. We systematically conduct comparative experiments on the performance of all models using a data-augmented dataset to enhance the models' robustness and efficacy.

**2. Materials and Methods**

**2.1. Data Acquisition and Preparation**  
This table helps to clearly illustrate the significance of **[4]** Data Augmentation in this research, especially

in addressing the severe data imbalance problem in T3 and T4 stages, which initially had very few images.

**Table 1**

|  |  |  |
| --- | --- | --- |
| Bladder cancer | Original Image Count  (Before Augmentation) | numbers of images after Data Augmentation |
| T1 | 272 | 531 |
| T2 | 76 | 372 |
| T3 | 41 | 365 |
| T4 | 27 | 342 |
| Total | 416 | 1,610 |

The initial dataset originated from the Kaggle platform, comprising a total of 1,285 MRI images. These images were reviewed and confirmed by expert physicians, resulting in a reliable dataset of 416 diagnosed and staged MRI images, distributed as follows: T1 (272 images), T2 (76 images), T3 (41 images), and T4 (27 images). It is evident that the dataset suffers from a significant data imbalance problem.

This table helps to clearly illustrate the significance of Data Augmentation in this research, especially in addressing the severe data imbalance problem in T3 and T4 stages, which initially had very few images. We utilized the Roboflow **[2]** platform for manual tumor mass labeling. Subsequently, the YOLOv11 Segmentation Model was trained on this labeled dataset. The trained model accurately performs segmentation, or the identification and delineation of the tumor mass. This allowed us to extract the cropped tumor images (Cropped Tumors) for use in the subsequent classification stage

**Figure 1**

Segmentation **[2]** The original MRI images were processed using the YOLOv11 model (in conjunction with

DeepLabV3[3]) to accurately detect and segment the tumor mass. This process effectively reduces noise and focuses the analysis on the Region of Interest (ROI).

A diagram of a model

AI-generated content may be incorrect.**Figure 1**

Segmentation **[2]** The original MRI images were processed using the YOLOv11 model (in conjunction with

DeepLabV3 **[3]**) to accurately detect and segment the tumor mass. This process effectively reduces noise and focuses the analysis on the Region of Interest (ROI).

To address the problems of small sample size and data imbalance, we applied Data Augmentation**[4]** techniques to the segmented tumor images. This process increased the size of the dataset to 1,610 images, which is composed of: T1: 531 images, T2: 372 images, T3: 365 images, and T4: 342 images (**Table 1**)

The Augmentation **[*4*]** methods utilized included: Random Rotation (±15∘), Translation (horizontal and vertical shift, ±10%), Shear (±0.1), and Zoom In/Out (±10%).

**2.2. Model Architectures for Classification**

We compared the performance of four types of deep learning models:

**รูปภาพประกอบด้วย ภาพหน้าจอ, ข้อความ, การออกแบบกราฟิก, ออกแบบ

เนื้อหาที่สร้างโดย AI อาจไม่ถูกต้องFigure 2**

**Classification Stage using VGG19**

This section illustrates the Classification stage using the VGG19 **[*5*]** CNN architecture, which constitutes the second part of the AI framework for staging bladder cancer. This diagram details the operation of the VGG19**[*5*]** model in analyzing the tumor images obtained from the Segmentation stage (**Figure 2**).

**2.2.1 Input Image:**

The initial input is the cropped MRI image containing only the tumor region.

**2.2.2 VGG19 Architecture:**

The image is fed into the VGG19 model, a Convolutional Neural Network (CNN) architecture with 19 deep layers.

**2.2.3 Feature Extraction:**

The model repeatedly uses 3×3 Convolutional (Conv) layers followed by Max Pooling layers to reduce spatial size and extract hierarchical features from the image. The channel depth increases progressively (e.g., 64, 128, 256, 512), while the image size decreases (e.g., 224×224, 112×112, 56×56, 28×28, 14×14, 7×7) **Figure** **2**

**2.2.4 Fully Connected Layers (FC):**

The extracted features are fed into the Fully Connected (FC) layers (FC1 and FC2), which have a size of 4096. The final layer (SoftMax) size is equal to the number of classes to be classified (

**[*1*]** in this case, 4 stages: T1, T2, T3, T4) **(  
This** table helps to clearly illustrate the significance of [4] Data Augmentation in this research, especially

in addressing **the severe** data imbalance problem in T3 and T4 stages, which initially had very few images.)

Note on Table 1: This table helps to clearly illustrate the significance of Data Augmentation in this research, especially in addressing the severe data imbalance problem in T3 and T4 stages, which initially had very few images.

**Figure 3**

A diagram of a company

AI-generated content may be incorrect.

Classification Stage using ResNet50 **[*6*]**

This section illustrates the Classification stage using the ResNet50 CNN architecture, which constitutes the second part of the AI framework for bladder cancer staging. The diagram details the operation of the ResNet50 **[*6*]** model in analyzing the tumor images obtained from the Segmentation stage.

**2.3.1 Input Image:**

The initial input is the cropped MRI image (

**Figure 1**.) that has undergone the Segmentation process using the YOLOv11 and DeepLabV3 **[*3*]** models to isolate the tumor mass.

**2.3.2 ResNet50 Architecture:**The image is fed into the ResNet50 **[*6*]** model

(***Figure* *3***.), a Convolutional Neural Network (CNN) architecture with 50 deep layers. This model utilizes the Residual Connection (or Skip Connection) technique to solve the Gradient Vanishing problem prevalent in very deep networks.

**2.3.3 Feature Extraction and Residual Learning:**

The model is divided into several Stages (Stage 1 to Stage 5).

2.3.3.1 Stage 1: Consists of a Convolution (Conv) layer, Batch Normalization (Batch Norm), ReLU activation, and a Max Pooling layer.

2.3.3.2 Stages 2-5: Employ a sequence of Convolutional Blocks (Conv Block) and Identity Blocks (ID Block), which are the core Residual Blocks used for extracting Hierarchical Features.

2.3.4 Fully Connected Layers (FC):

2.3.4.1 The extracted features pass through an Average Pooling (Avg Pool) layer and Flattening.

2.3.4.2 They then enter the Fully Connected (FC) layer for classification.

2.3.4.3 Output: The final layer classifies the cancer stage into one of four stages**[1]**: T1, T2, T3, and T4.

**รูปภาพประกอบด้วย ข้อความ, ภาพหน้าจอ, ออกแบบ

เนื้อหาที่สร้างโดย AI อาจไม่ถูกต้องFigure 4**

This image illustrates the Classification stage using the ResNet101 CNN **[*7*]** architecture, which is the second part of the AI framework for bladder cancer

staging.

Classification Stage using ResNet101 **[*7*]**

The diagram (

***Figure 4***.) details the operation of the ResNet101 model in analyzing the tumor image (Region of Interest - ROI) obtained from the Segmentation stage.

**2.4.1 Input Image and ROI**

2.4.1.1 The process begins with the MRI image of the tumor area.

2.4.1.2 The image undergoes the Segmentation process to separate and highlight the tumor mass (Region of Interest - ROI), resulting in the Cropped Tumors image before being fed into the model.

**2.4.2 ResNet101 Architecture**

2.4.2.1 The ROI image is fed into the ResNet101 model, a Convolutional Neural Network (CNN) architecture with a depth of 101 layers.

2.4.2.2 The model uses the Residual Connection (or Skip Connection) technique to enable efficient training of a very deep network.

**2.4.3 Feature Extraction and Residual Learning**

2.4.3.1 The model is divided into several Stages with varying depths and Channel Depths, utilizing repeated sets of Identity BlocksError! Reference source not found.:

- Stage 2 (Conv2\_x): Consists of 3× Identity Blocks

- Stage 3 (Conv3\_x): Consists of 4× Identity Blocks

- Stage 4 (Conv4\_x): Consists of 23× Identity Blocks (This part accounts for the depth of ResNet101)

- Stage 5 (Conv5\_x): Consists of 3× Identity Blocks 2.4.3.2 Each Stage extracts increasingly complex Hierarchical Features.

2.4.3.2 Each Stage extracts increasingly complex Hierarchical Features.

**2.4.4 Classification Head**

2.4.4.1 The extracted features pass through an Average Pooling (Avg Pool) layer to reduce spatial dimensions.

2.4.4.2 Before entering the Fully Connected (FC) layer for the final classification.

2.4.4.3 Output: The result is the classification of the cancer stage (e.g., T1-T4), which would be displayed on the MRI image.

**Figure 5**

รูปภาพประกอบด้วย ข้อความ, ภาพหน้าจอ, ออกแบบ

เนื้อหาที่สร้างโดย AI อาจไม่ถูกต้อง

We compared the performance of four types of deep learning models

Classification [2] Stage using Vision Transformer (ViT)**[*8*]**

This image illustrates the Classification stage using the Vision Transformer (ViT) **[*8*]** architecture, which is part of the model evaluation for bladder cancer staging. The diagram details the operation of the ViT model, which, unlike traditional CNNs, uses a Self-Attention mechanism to analyze the tumor image (ROI).

**2.5.1 Input Image and Image Patching**

2.5.1.1 The process starts with the tumor image (ROI) obtained from the Segmentation stage.

2.5.1.2 The image is then processed via Generate Image Patches by dividing it into equal-sized, non-overlapping patches.

**2.5.2 Linear Projection and Position Embedding**

2.5.2.1 Each image patch is converted into a vector through a Linear Projection layer.

2.5.2.2 Position Embedding is added to these vectors to preserve the spatial positional information of the different patches (which is crucial since Transformer Blocks inherently lack the position-learning capability of CNNs).

**2.5.3 Transformer Blocks (Feature Extraction)**

2.5.3.1 The resulting patch vectors are fed into a series of Transformer Blocks.

2.5.3.2 Each Transformer Block consists of:

2.5.3.3 Multi-Head Self-Attention: The core mechanism that allows ViT **[*8*]** to analyze the Global Context relationships among all patches in the image, unlike CNNs which focus on Local Features.

2.5.3.4 Feed Forward Neural Network: A layer that processes the features derived from the Self-Attention mechanism.

**2.5.4 Classification Head**

2.5.4.1 The features processed by the Transformer Blocks are fed into a Feed-Forward Network (which serves as the Classification Head).

2.5.4.2 Output: The result is the classification of the cancer stage

**[1]** (e.g., T1, T2, T3, T4)

**2.6 Experimental Setup and Evaluation**

The augmented dataset was split into a Training Set (80%) and a Test Set (20%). All models were trained using the Transfer Learning technique, initialized with pre-trained weights from the ImageNet dataset. Cross-Entropy Loss was utilized as the loss function, and the Adam Optimizer was employed for parameter optimization during training. Accuracy

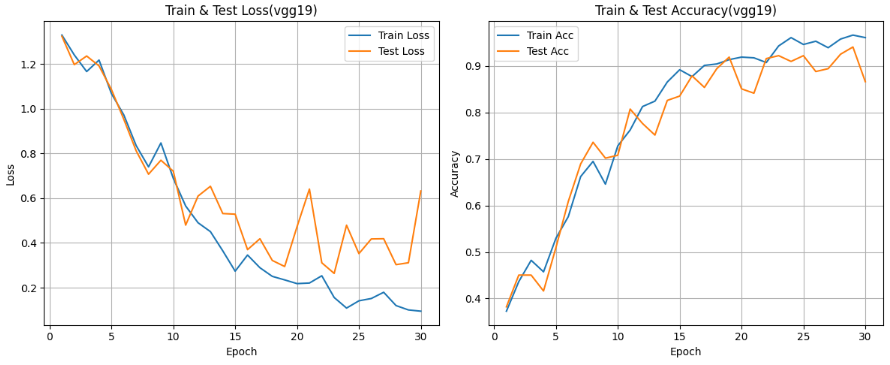
Performance Metrics

Model performance was measured using the following key indicators **[9]**:

**3. VGG19 Results**

**3.1 Training and Evaluation Results**

The results obtained from training and evaluating the VGG19 model for image classification show good performance.

**Figure 6**

**Figure 6** :The image displays the Training and Testing (Train & Test) results of the VGG19 model over 30

Epochs.

**3.2 VGG19 Performance Evaluation Results**

The VGG19 model, a traditional CNN architecture with 19 deep layers, was applied to stage bladder cancer (T1-T4), yielding the following evaluation results:

When tested on the unseen Test Set, the VGG19 model demonstrated a very good level of performance:

* Overall Accuracy: 0.9410
* Average F1-score (Macro Avg): 0.94

**Table 2**

|  |  |  |  |
| --- | --- | --- | --- |
| Bladder cancer | Precision | Recall | F1-score |
| T1 | 0.90 | 0.95 | 0.93 |
| T2 | 0.95 | 0.93 | 0.94 |
| T3 | 0.94 | 0.93 | 0.94 |
| T4 | 1.00 | 0.94 | 0.97 |
| Macro Avg | 0.95 | 0.94 | 0.94 |

**Table *2***: This indicates that the model correctly staged the tumor with an overall accuracy of 94.10% and maintained a high balance between Precision and Recall across all four cancer stages (T1-T4), as reflected by the Macro F1-score.

**3.3 Analysis of the Confusion Matrix**

The Confusion Matrix test kit table shows the details of the different sections.

**รูปภาพประกอบด้วย ข้อความ, ภาพหน้าจอ, แผนภาพ, สี่เหลี่ยมผืนผ้า

เนื้อหาที่สร้างโดย AI อาจไม่ถูกต้องFigure 7**

The critical errors occurred when classifying T1 (non-muscle-invasive cancer) from the invasive stages (T2/T3):

3 T1 examples were misclassified as T3.

2 T1 examples were misclassified as T2.

4 T2 examples were misclassified as T1.

Discriminative Power (AUC)

Despite these cross-class misclassifications, the ROC curve on the test set confirms that VGG19 possesses excellent Discriminative Power with the following AUC values:

AUC of 0.98 for classes T1, T3, and T4. AUC of 0.99 for class T2. (**Figure 8**)

**Figure 7** : Confusion Matrix for VGG19 on the Test Set

**รูปภาพประกอบด้วย ข้อความ, ไลน์, พล็อต, แผนภาพ

เนื้อหาที่สร้างโดย AI อาจไม่ถูกต้อง3.4 Computer graph ROC Curve**

**Figure 8**

**Figure 8** :ROC Curve (Test Set): The AUC values ​​remained high, with T2 having the highest AUC of 0.99 and T1, T3, and T4 having AUCs of 0.98

**4. ResNet50 Results**

**4.1 Training and Evaluation Results**

The results obtained from training and evaluating the ResNet50 model for image classification show good performance. The image below presents the results.

**Figure 9**

รูปภาพประกอบด้วย ข้อความ, ไลน์, พล็อต, แผนภาพ

เนื้อหาที่สร้างโดย AI อาจไม่ถูกต้อง

**Figure *9***:Training and Testing (Train & Test) Results of the ResNet50 Model over 30 Epochs

**4. ResNet50 Results**

**4.1 Training and Evaluation Results**

The results obtained from training and evaluating the ResNet50 model for image classification show good performance. The image below presents the results.

**4.2 ResNet50 Performance Evaluation Results**

ResNet50, a CNN architecture with 50 deep layers utilizing the Residual Connection technique to mitigate the Gradient Vanishing problem, was applied for bladder cancer staging **[1]** (T1-T4). The evaluation results are as follows

When tested on the unseen Test Set, the ResNet50 model continued to demonstrate a very good level of performance:

* Overall Accuracy: 0.9658
* Average F1-score (Macro Avg): 0.97

**Table 3**

|  |  |  |  |
| --- | --- | --- | --- |
| Bladder cancer | Precision | Recall | F1-score |
| T1 | 0.95 | 0.96 | 0.93 |
| T2 | 1.00 | 0.97 | 0.94 |
| T3 | 0.94 | 0.96 | 0.94 |
| T4 | 0.99 | 0.99 | 0.97 |
| Macro Avg | 0.97 | 0.97 | 0.97 |

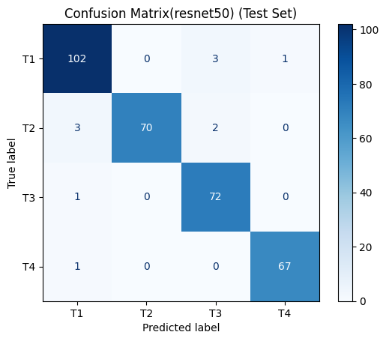
**Table3** : This indicates that the model correctly staged the tumor with an overall accuracy of 96.58% and maintained a high balance between Precision and Recall across all four cancer stages

**[1]** (T1-T4), as reflected by the Macro F1-score.

**4.3 Confusion Matrix Analysis for ResNet50**

The Confusion Matrix on the test set details the classification performance of the ResNet50 model

**Figure 10**

Low Error Rate: Cross-class classification errors were significantly reduced compared to the VGG19 model. Most remaining errors occurred between T1 and T2/T3, and between T4 and T1.

T2 Precision: The model demonstrated a Precision of 1.00 when predicting T2. This means that (**Table *2***) all predictions of T2 were correct.

T4 Misclassification: Only 1 image of T4 was incorrectly classified as T1, while 67 images were correctly classified. This reinforces the high

**Figure 10**: Confusion Matrix for ResNet50 on the Test Set

**4.4 Computer graph ROC Curve**

**A graph with a line

AI-generated content may be incorrect.Figure 11**

**Figure 11** : ROC Curve (Test Set): AUC values ​​are almost perfectly high for all classes with T3 having the highest AUC at 1.00 and T1, T2, T4 having AUC at 0.99.

**5. Model Performance Comparison: ResNet50 vs. ResNet101**

The evaluation on the Test Set revealed that both the ResNet50 and ResNet101 models achieved the exact same Overall Accuracy of 0.9658. Furthermore, both models showed an identical Macro/Weighted Average F1-score of 0.97. This indicates that for this specific classification task, the overall performance of the two models is equivalent.

Per-Class Analysis and Key Metrics

While overall accuracy was the same, minor differences in per-class performance were noted:

- ResNet50 demonstrated superior Precision for class T2 at 1.0000 (meaning every instance predicted as T2 was correct).

- ResNet101 showed superior Precision for class T4 at 1.0000.

- The F1-score was consistently high for both models, with the highest scores for both models being approximately 0.97 to 0.99 across most classes.

**Table 3**

|  |  |  |
| --- | --- | --- |
| Metric | ResNet50 | ResNet101 |
| Overall Accuracy | 0.9658 | 0.9658 |
| Macro Avg F1-score | 0.97 | 0.97 |

Misclassification Analysis (Confusion Matrix)

Analysis of the Confusion Matrices confirms that misclassifications were minimal, but with slightly different patterns:

**Table 4**

|  |  |
| --- | --- |
| Model | Key Misclassifications (True → Predicted) |
| ResNet50 | Misclassified T2 as T1 (3 times) and T3 (2 times). |
| ResNet101 | Misclassified T2 as T1 (3 times). |
| Notable Difference | ResNet50 had zero errors when predicting T4; ResNet101 misclassified T4 as T2 (1 time) and T3 (1 time). |

**Table 4**: In summary, the results suggest that ResNet50, being the less complex architecture, provides an equivalent level of accuracy to the deeper ResNet101 model. Therefore, ResNet50 is the more practical choice as it offers the same high performance while requiring fewer computational resources.

**6. Vision Transformer (ViT) Results**

**6.1 Training and Evaluation Results**

The results obtained from training and evaluating the **Vision Transformer (ViT)** model for image classification show good performance.

A graph of a train loss

AI-generated content may be incorrect.**Figure 12**

**Figure 12** : Training and Testing (Train & Test) Results of the Vision Transformer (ViT) Model over 30 Epochs

**6.2 Vision Transformer (ViT) Performance Evaluation Results**

The Vision Transformer (ViT) model was applied to stage bladder cancer (T1-T4), yielding the following Training Set evaluation results:

When tested on the Training Set (data the model was trained on), the ViT model demonstrated excellent, near-perfect performance:

* Overall Accuracy: 0.9410
* Average F1-score (Macro Avg): 0.94

**Table 5**

|  |  |  |  |
| --- | --- | --- | --- |
| Bladder cancer | Precision | Recall | F1-score |
| T1 | 0.90 | 0.95 | 0.93 |
| T2 | 0.95 | 0.93 | 0.94 |
| T3 | 0.94 | 0.93 | 0.94 |
| T4 | 1.00 | 0.94 | 0.97 |
| Macro Avg | 0.95 | 0.93 | 0.93 |

**Table 5** :This indicates that the model correctly staged the tumor with an overall accuracy of 94.10% and maintained a high balance between Precision and Recall across all four cancer stages (T1-T4), as reflected by the Macro F1-score.

**6.3 Confusion Matrix Analysis for ViT**

Figure 13:The Confusion Matrix details the minimal errors made by the ViT model on the Test Set:

A diagram of a test set

AI-generated content may be incorrect.

Key Error Summary (Clinical Significance): Misclassification between T1 (non-invasive) and T2-T4 (invasive).

**Critical Errors**: T1 → T3 (3 images), T2 → T1 (4 images - risk of under-treatment), and T3 → T1 (5 images - most significant error).

**Conclusion**: Despite high overall accuracy (0.9410), the model shows critical confusion, especially between T1 (non-invasive) and T3 (highly invasive), requiring serious consideration for clinical use.

**Figure 13**:The Confusion Matrix details the minimal errors made by the ViT model on the Test Set: Confusion Matrix for Vision Transformer (ViT) on the Test Set

**6.4 Computer graph ROC Curve**

**A graph of a multi-class curve

AI-generated content may be incorrect.Figure 14**

**Figure 14** : ROC Curve (Test Set): AUC values for T1, T3, and T4 are 0.98, and T2 is 0.99. These results confirm that ViT

**7. Conclusion and Discussion**

This research presented a two-stage Artificial Intelligence framework (Segmentation + Classification) for the accurate staging of bladder cancer from MRI images. The evaluation of four deep learning architectures yielded the following key findings

Summary of Model Performance Comparison

**Table 6**

|  |  |  |
| --- | --- | --- |
| Model | Overall Accuracy | Macro Avg F1-score |
| VGG19 | 0.9410 | 0.94 |
| ResNet50 | 0.9658 | 0.97 |
| ResNet101 | 0.9658 | 0.97 |
| ViT | 0.9410 | 0.94 |

**Table *6***: ResNet family models (ResNet50 and ResNet101) in terms of VGG19 and ViT performance at that time.

Key Discussion Points and Clinical Implications

**Optimal Model Performance**

ResNet Wins: The ResNet50 and ResNet101 models achieved the highest accuracy (96.58%) and F1-score (0.97). This success confirms the Residual Connection is highly effective for

robust feature learning on limited medical datasets.

**Role of Two-Stage Approach**

Segmentation is Crucial: Using YOLOv11 to segment (crop) the tumor was vital. By isolating the Region of Interest (ROI) and removing background noise, this initial step significantly boosted the models' accuracy.

**Model Limitations**

ViT Overfits: The Vision Transformer (ViT) underperformed, matching only the shallower VGG19 (94.10% accuracy) and falling behind ResNet. ViT's failure to generalize efficiently to unseen data highlights the architecture's need for much larger datasets than what was available here, confirming an overfitting issue.

**Clinical Significance**

High Diagnostic Potential: With near-97% accuracy, the ResNet50/101 framework offers a powerful Computer-Aided Diagnosis (CAD) tool. It accurately tackles the most critical clinical challenge: distinguishing T1 (less aggressive surgery) from T2-T4 (radical surgery), ensuring effective treatment planning.

**8.References**

**[1]**

[Role of Multiparametric-MRI in Bladder Cancer( 27 February 2023)](https://link.springer.com/article/10.1007/s40134-023-00412-5)

**[2]**

[Segmentation and classification of skin burn images with artificial intelligence: Development of a mobile application(24 April 2024.)](https://www.sciencedirect.com/science/article/abs/pii/S0305417924000135?via%3Dihub)

**[3]**

[Deep semantic segmentation of natural and medical images: a review(January 2021)](https://www.researchgate.net/publication/342157198_Deep_semantic_segmentation_of_natural_and_medical_images_a_review)

**[4]**

[On Urinary Bladder Cancer Diagnosis: Utilization of Deep Convolutional Generative Adversarial Networks for Data Augmentation](https://www.mdpi.com/2079-7737/10/3/175?trk=organization_guest_main-feed-card-text)

**[5]**

[Deep Fake Detection: Survey of Facial Manipulation Detection Solutions(June 2021)](https://www.researchgate.net/publication/353068723_Deep_Fake_Detection_Survey_of_Facial_Manipulation_Detection_Solutions#pf7)

**[6]**

[Deep learning based Glaucoma Network Classification (GNC) using retinal images(December 2023)](https://www.researchgate.net/publication/376351263_Deep_learning_based_Glaucoma_Network_Classification_GNC_using_retinal_images)

**[7]**

[Abnormal event detection model using an improved ResNet101 in context aware surveillance system(August 2023)](https://www.researchgate.net/publication/372853599_Abnormal_event_detection_model_using_an_improved_ResNet101_in_context_aware_surveillance_system)

**[8]**

[An extensive analysis of artificial intelligence and segmentation methods transforming cancer recognition in medical imaging (June 2024)](https://www.researchgate.net/publication/381276410_An_extensive_analysis_of_artificial_intelligence_and_segmentation_methods_transforming_cancer_recognition_in_medical_imaging)

**[9]**

[Key Evaluation Metrics For AI Model Performance](https://medium.com/gen-ai-adventures/key-evaluation-metrics-for-ai-model-performance-8e372f17a0a2)