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CT - Based Organ Anomaly Detection Using U-Net and Convolutional Neural Networks Hybrid Technique

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Abstract: Deep learning-based medical image analysis advanced significantly with transformer-based architectures and self-configuring segmentation frameworks. This paper presents an implementation-focused approach for CT-based organ anomaly detection using deep learning techniques. The proposed system integrates the U-Net framework for accurate and automated organ segmentation, ensuring adaptive performance across different CT datasets without manual tuning. For feature extraction, convolutional neural networks (CNNs) and transformer-based models are employed to capture both local spatial patterns and global contextual relationships in CT images. Anomaly detection is performed using classification-based methods to distinguish normal and abnormal regions, along with reconstruction-based techniques such as autoencoders to identify deviations through reconstruction error. The integration of these methods improves robustness and accuracy in detecting organ abnormalities. The primary objective of the system is to enhance diagnostic precision, reduce radiologist workload, and enable automated identification of abnormal regions in CT scans, contributing to efficient computer-aided diagnosis systems in healthcare applications. Accurate detection of organ anomalies from Computed Tomography (CT) scans is critical for early diagnosis and treatment planning. This paper presents a hybrid deep learning framework combining U-Net for organ segmentation and Convolutional Neural Networks (CNNs) for anomaly classification. The proposed approach first segments the target organ using a U-Net architecture and subsequently classifies the segmented region into normal or abnormal categories using a CNN model. Experimental results demonstrate improved accuracy and robustness compared to standalone classification models.

Keywords: *Deep learning, CNN, Autoencoder, CT Scan, U-Net, Medical Image Segmentation, Anomaly Detection*

1. Introduction

Computed Tomography (CT) imaging is one of the most widely used medical imaging modalities for diagnosing diseases and detecting abnormalities in vital organs such as the liver, kidneys, lungs, and brain. It provides high-resolution cross-sectional images that help clinicians observe internal structures in detail. Despite its effectiveness, accurate interpretation of CT scans requires significant expertise and is often time-consuming, making it prone to human error and inter-observer variability. In recent years, deep learning has emerged as a powerful tool in medical image analysis, significantly improving the automation and accuracy of disease detection systems. Convolutional Neural Networks (CNNs) have been extensively used for image classification and segmentation tasks in CT imaging. However, CNN-based methods are limited in capturing long-range spatial dependencies, which are important for understanding complex anatomical structures.

Medical imaging research shifted toward more advanced approaches, including transformer-based architectures such as TransUNet and UNETR. These models enhance feature representation by capturing global contextual relationships within CT images. At the same time, nnU-Net emerged as a strong self-configuring framework that automatically adapts to different datasets, achieving state-of-the-art performance in many segmentation tasks. Additionally, self-supervised and weakly

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supervised learning approaches gained attention due to the limited availability of annotated medical data. The main objective of CT-based organ anomaly detection systems is to develop an automated pipeline capable of segmenting organs, detecting abnormal regions, and classifying scans as normal or abnormal. By integrating CNNs, transformers, and reconstruction-based methods, these systems aim to improve diagnostic accuracy, reduce the workload of radiologists, and support efficient and reliable clinical decision-making.

Medical imaging plays a vital role in modern diagnostics, with CT scans widely used for detecting internal organ abnormalities such as tumors, lesions, and infections. However, manual analysis by radiologists is time-consuming and prone to variability. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in image analysis tasks. However, direct classification on raw CT images often leads to suboptimal performance due to irrelevant background information.

To address this, this paper proposes a two-stage pipeline, Organ segmentation using U-Net and Anomaly detection using CNN. CT (Computed Tomography) imaging is widely used for detecting abnormalities in organs such as the liver, kidney, lungs, and brain. Manual interpretation is time-consuming and prone to inter-observer variability.

The goal is to build an automated system that can:

- Segment organs from CT scans
- Detect anomalies within segmented regions
- Classify scans as normal or abnormal

2. Related Work

2.1. Existing Work

Previous studies have demonstrated the effectiveness of U-Net in biomedical image segmentation due to its encoder-decoder structure and skip connections. CNN-based classifiers such as ResNet and VGG have been widely used for medical image classification.

Recent advancements in deep learning have significantly improved medical image analysis, particularly in CT-based organ segmentation and anomaly detection. This section reviews key methodologies relevant to the proposed work [11-14].

Isensee et al., introduced nnU-Net, a self-configuring segmentation framework that automatically adapts to different medical imaging datasets. It achieves state-of-the-art performance without manual hyperparameter tuning; however, it requires substantial computational resources, limiting its deployment in low-resource environments [1]. Chen et al., proposed TransUNet, which integrates Convolutional Neural Networks (CNNs) with Transformer architectures to capture both local and global features. While this hybrid approach improves segmentation accuracy, it demands large-scale annotated datasets for effective training [2].

Hatamizadeh et al., developed UNETR, a fully Transformer-based architecture designed for 3D medical image segmentation. It demonstrates strong capability in modeling long-range dependencies but suffers from high GPU memory requirements [3]. Li et al., introduced Swin UNETR, which employs a hierarchical Swin Transformer to enhance segmentation performance. This model improves computational efficiency compared to standard Transformers but introduces architectural complexity [4].

Zhou et al. presented U-Net++, an extension of the traditional U-Net with redesigned skip connections. This nested architecture improves feature fusion and segmentation accuracy, though it remains limited in capturing global contextual information due to its CNN-based design [5]. Chen et al., explored CNN-based classification models such as ResNet and DenseNet for CT anomaly detection. These models achieve high classification accuracy; however, they lack precise spatial localization, making them less effective for identifying anomaly regions [6].

Wang et al., proposed an autoencoder-based approach for anomaly detection using reconstruction errors. This method does not require labeled anomaly data, but its performance is often limited when detecting subtle abnormalities [7].

Zhang et al., investigated self-supervised learning techniques to leverage large amounts of unlabeled CT data. While this reduces dependency on annotated datasets, the resulting models often lack clinical interpretability [8]. Bakas et al., contributed to benchmark frameworks, particularly through BraTS-related datasets, which provide standardized evaluation protocols for brain tumor segmentation. However, these datasets are often domain-specific and may not generalize well to other organs [9]. Additionally, several studies, have explored hybrid CNN-Transformer architectures, combining the strengths of both approaches. These models demonstrate improved accuracy and generalization but come at the cost of increased computational complexity [10].

Recent approaches combine segmentation and classification, improving performance by focusing only on relevant regions. Key developments in recent:

- **nnU-Net** remained the strongest baseline for CT segmentation.
- **UNETR and Swin UNETR** introduced transformer-based segmentation.
- **TransUNet** combined CNN + Transformer encoders for better feature learning.
- Self-supervised learning improved performance where labeled data was limited.
- Autoencoder-based anomaly detection was widely used for unsupervised learning.

2.2. Literature Review Analysis

Following table 1 shows, the summary of literature review in recent developments.

Table 1. Literature Review Analysis

Ref.	Author(s)	Method / Model	Year	Key Contribution	Advantages	Limitations
[1]	Isensee et al.	nnU-Net	2021–2022	Self-configuring segmentation framework for medical images	High accuracy, no manual tuning, strong baseline	High computational cost
[2]	Chen et al.	TransUNet	2021–2022	CNN + Transformer hybrid for medical image segmentation	Better feature extraction, global + local context	Requires large training data
[3]	Hatamizadeh et al.	UNETR	2022	Pure Transformer-based 3D medical image segmentation	Strong global dependency modeling	High GPU memory usage
[4]	Li et al.	Swin UNETR	2022	Hierarchical Swin Transformer for segmentation	Efficient transformer design, improved accuracy	Complex architecture
[5]	Zhou et al.	U-Net++	2018–2022	Nested U-Net architecture for segmentation	Improved skip connections, better accuracy	Still CNN-limited context understanding
[6]	Chen et al.	CNN-based classification (ResNet/DenseNet)	2022	CT anomaly classification using deep CNNs	High classification accuracy	Poor spatial localization
[7]	Wang et al.	Autoencoder-based anomaly detection	2022	Reconstruction-based unsupervised anomaly detection	No labeled anomaly data required	Weak performance on subtle anomalies
[8]	Zhang et al.	Self-supervised learning model	2022	Learns features from unlabeled CT scans	Reduces dependency on annotations	Limited clinical interpretability

Ref.	Author(s)	Method / Model	Year	Key Contribution	Advantages	Limitations
[9]	Bakas et al.	Deep learning segmentation frameworks (BraTS-related)	2018–2022	Benchmark datasets and evaluation methods	Standard evaluation metrics	Dataset-specific limitations
[10]	Multiple studies (review)	Hybrid CNN-Transformer models	2022	Combines CNN + Transformer for CT analysis	Better accuracy and generalization	High computational complexity

On the basis of literature review, overview of problem indicates, CT scans are 2D slices (or 3D volumes) used to visualize internal organs. Due to this, the goal is:

- Using Segmentation (U-Net): Identify organ regions pixel-wise
- Anomaly Detection (by train CNN model): Classify normal vs abnormal regions (e.g., tumors, lesions)

3. Methodology

A basic CT-based anomaly detection system using deep learning involves feeding preprocessed CT scan images (including normalization, resizing, and noise reduction) into a Convolutional Neural Network that automatically learns important features such as texture, shape, and intensity patterns from the data. The CNN processes the images through multiple convolutional and pooling layers to extract high-level representations, followed by fully connected layers for classification. The model is trained on labeled datasets to distinguish between normal and abnormal cases (e.g., presence of tumors, lesions, or infections). During testing, the trained model predicts whether a given CT image contains anomalies and provides a confidence score, enabling fast and accurate computer-aided diagnosis in medical imaging. Basic CT-based anomaly detection system using deep learning model demonstrate in figure 1.

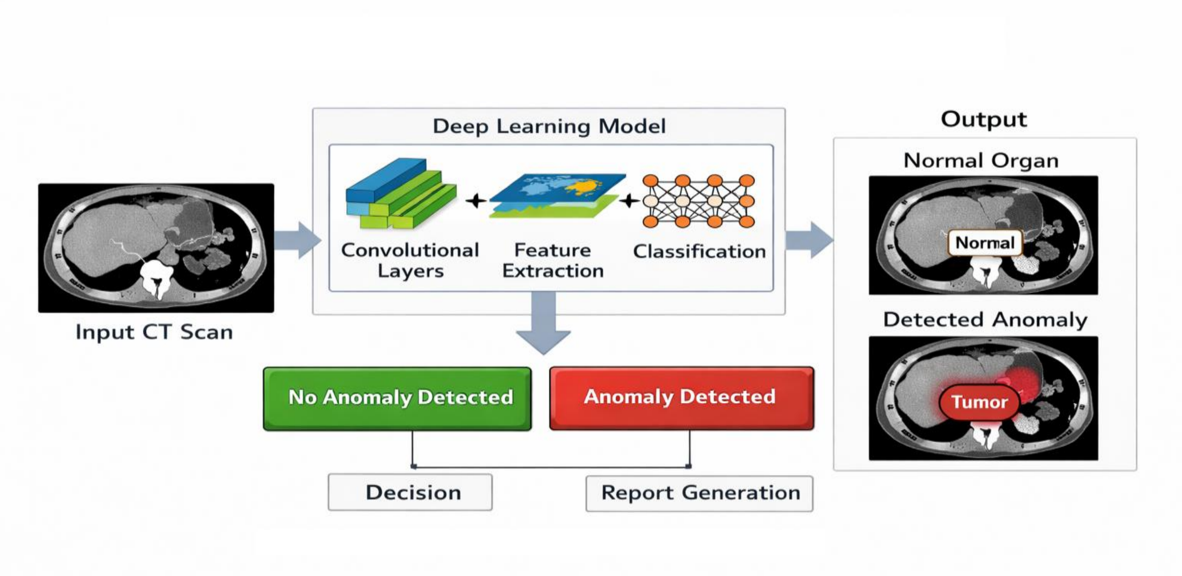

Figure 1: Basic architecture for CT-based anomaly detection using deep learning

A hybrid deep learning pipeline for organ anomaly detection begins with preprocessing CT scan images (normalization, noise reduction, resizing), followed by segmentation using U-Net to extract the region of interest (ROI) such as liver or lungs. Proposed system architecture for CT-Based Organ Anomaly Detection Using U-Net and Convolutional Neural Networks model demonstrate in figure 2,

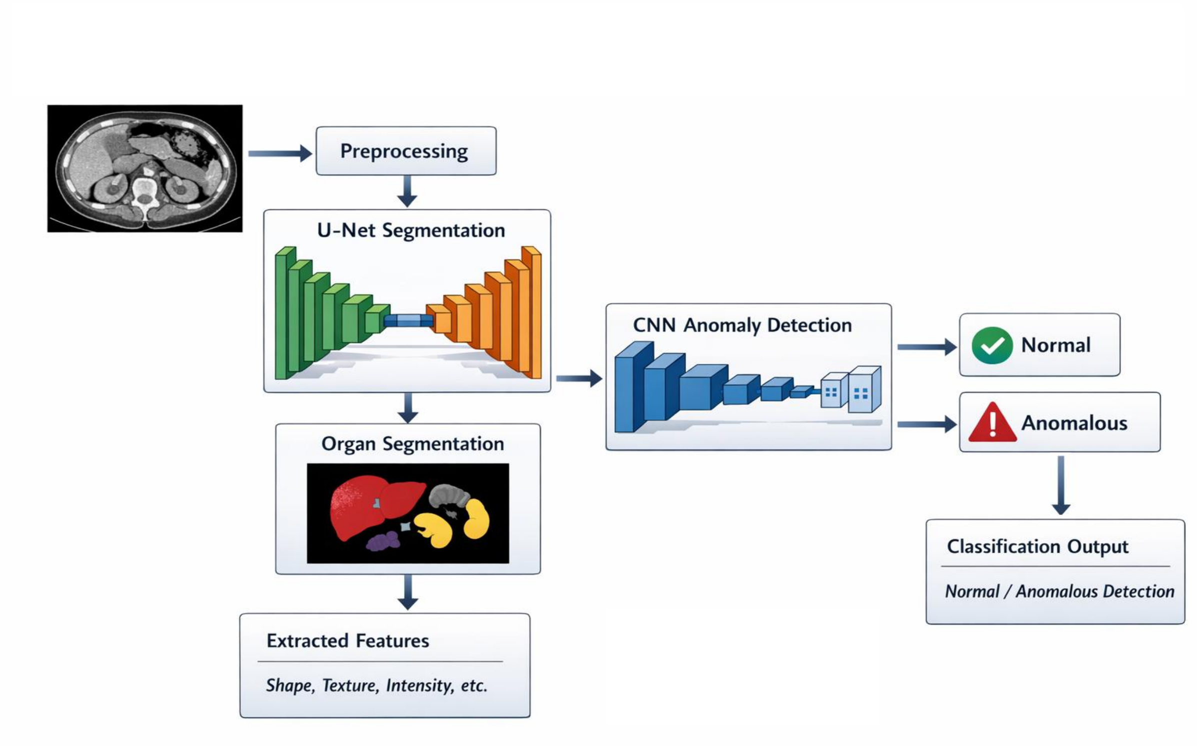

Figure 2: Proposed system architecture for CT-Based Organ Anomaly Detection Using U-Net and CNN

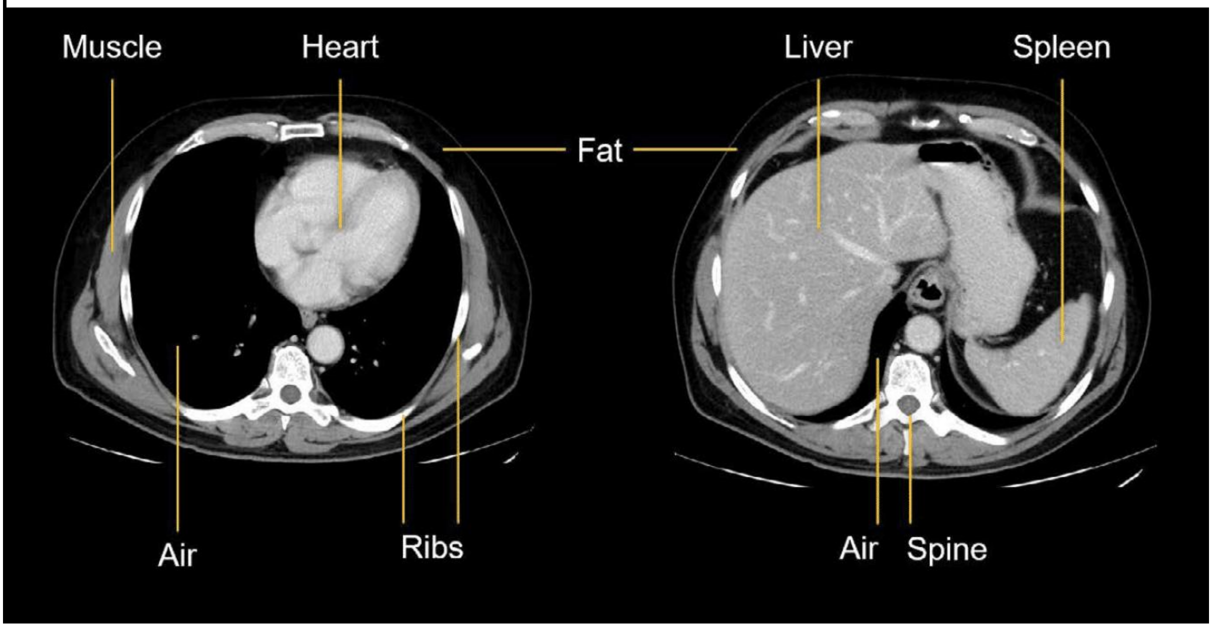

Figure 3: Sample CT Image

Figure 3 shows, sample CT image, found ROI based identification of area. The resulting segmentation mask is used to isolate and crop the organ region, reducing background noise and improving focus. This ROI is then fed into a Convolutional Neural Network, which performs feature extraction through convolution and pooling layers and classifies the region into normal or abnormal categories (e.g., tumor presence). The pipeline outputs the predicted class along with a confidence score, offering improved accuracy by combining precise segmentation with robust classification.

3.1 System Overview

The proposed system consists of four main stages: (1) Data preprocessing, where CT images are normalized, resized, and denoised to improve quality; (2) Organ segmentation using U-Net to accurately identify and isolate the target organ (such as liver or lungs); (3) Region extraction, where the segmented mask is applied to obtain the region of interest (ROI) and remove irrelevant background; and (4) anomaly classification using a Convolutional Neural Network, which analyzes the extracted region to detect and classify abnormalities (e.g., tumor or disease presence) with a confidence score.

3.2 Input Data Pre-processing

The preprocessing stage begins with the conversion of DICOM medical images into NumPy arrays for efficient numerical computation, followed by intensity normalization using Hounsfield Units (HU) to standardize pixel values across scans. The normalization is defined as in formula (1):

$$Inorm = I - Imin / Imax - Imin \quad (1)$$

This step ensures consistent intensity ranges for better model performance. Subsequently, all images are resized to fixed dimensions (e.g., 256×256) to maintain uniform input size for deep learning models. Finally, data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset diversity, reduce overfitting, and improve the generalization capability of the model.

3.3 U-Net Architecture for Segmentation

The U-Net architecture consists of three key components: an encoder, a decoder, and skip connections. The encoder follows a contracting path where repeated convolution layers with ReLU activation and max pooling are applied to extract high-level features while reducing spatial dimensions. The decoder forms the expanding path, where transposed convolutions (up-sampling) are used to restore spatial resolution, followed by concatenation with corresponding encoder feature maps. These skip connections play a crucial role by preserving fine-grained spatial information lost during downsampling, enabling precise localization and accurate segmentation of medical images. Loss Function (Dice Loss) is also used.

3.4 CNN for Anomaly Detection

After segmentation, the region of interest (ROI) is extracted and passed to a Convolutional Neural Network for anomaly classification. The CNN consists of multiple convolution layers that automatically extract important features such as edges, textures, and patterns from the ROI, followed by ReLU activation functions to introduce non-linearity. MaxPooling layers are then applied to reduce spatial dimensions and computational complexity while retaining key features. Finally, fully connected layers perform high-level reasoning and classification, producing the final output such as normal or abnormal detection with a confidence score.

3.5 Algorithm

Step 1: Input CT scan
Step 2: Preprocess image
Step 3: Apply U-Net → generate segmentation mask
Step 4: Extract organ region
Step 5: Feed ROI into CNN
Step 6: Output anomaly prediction

4. Implementation Details

4.1 Tools and Frameworks

The proposed system is implemented using Python as the primary programming language due to its flexibility and strong support for deep learning libraries. Frameworks such as PyTorch or TensorFlow are used for building and training the models. OpenCV is utilized for image processing tasks such as resizing and augmentation, while NumPy is used for efficient numerical operations and handling image arrays.

4.2 Training Procedure

For segmentation, the U-Net is trained using CT images along with their corresponding ground truth masks. The Adam optimizer is used with a learning rate of 0.001 to ensure efficient convergence, and the Dice Loss function is applied to maximize overlap between predicted and actual segmentation masks.

For classification, a Convolutional Neural Network is trained using the segmented organ images as input. The model uses Cross-Entropy Loss for classification tasks and is trained for approximately 20–50 epochs, depending on dataset size and performance, to accurately distinguish between normal and abnormal cases.

4.3 Hardware Requirements

The proposed system requires a computing environment capable of handling deep learning workloads efficiently. A GPU, preferably from NVIDIA, is recommended to accelerate model training and inference, especially for computationally intensive architectures like U-Net and Convolutional Neural Network. The system should have a minimum of 8GB RAM to ensure smooth data processing and model execution. Additionally, support for CUDA is essential to enable GPU acceleration and significantly reduce training time.

4.4 Implementation Workflow Summary

1. **Data Collection:** Gather CT datasets such as BTCV, LiTS, KiTS, and LUNA16.
2. **Data Preprocessing:** Convert DICOM to NIfTI, normalize (HU), resize, denoise, and augment data.
3. **Organ Segmentation:** Use nnU-Net to generate organ masks.
4. **Feature Extraction:** Extract features using ResNet50 / DenseNet or transformer models.
5. **Anomaly Detection:** Apply CNN classification, autoencoder reconstruction, or attention-based methods.
6. **Post-Processing:** Perform morphological operations, thresholding, and region refinement.
7. **Output Generation:** Provide detected organ, anomaly location, and severity score.

5. Results and Evaluation

5.1 Evaluation Metrics

The performance of the proposed system is evaluated using both segmentation and classification metrics. For segmentation, the Dice Coefficient measures the overlap between predicted and ground truth masks, while Intersection over Union (IoU) evaluates the ratio of intersection to union, providing a stricter assessment of segmentation accuracy.

For classification, Accuracy measures overall correctness, while Sensitivity (Recall) indicates the model's ability to correctly detect positive (abnormal) cases, and Specificity reflects its ability to correctly identify negative (normal) cases. Additionally, AUC (Area Under the ROC Curve) evaluates the model's capability to distinguish between classes across different thresholds, offering a comprehensive measure of classification performance.

5.2 Segmentation Metrics

Segmentation performance is evaluated using the Dice Coefficient and Intersection over Union (IoU). The Dice Coefficient measures the overlap between the predicted segmentation and the ground truth mask, providing an indication of how accurately the model captures the target organ or region. IoU, on the other hand, calculates the ratio of the intersection to the union of predicted and actual regions, offering a stricter evaluation of segmentation quality.

Typical performance of the proposed system shows that segmentation models such as U-Net achieve an accuracy in the range of 84%–94%**,** demonstrating strong capability in accurately delineating organ regions from CT images.

5.3 Classification Metrics

Classification performance is assessed using metrics such **as** accuracy, precision, recall, F1-score, and ROC-AUC**.** Accuracy represents the overall correctness of predictions, while precision measures how many predicted positive cases are actually correct. Recall evaluates the model's ability to detect all true positive cases, and the F1-score balances precision and recall. ROC-AUC further measures the model's capability to distinguish between classes across different decision thresholds, providing a comprehensive evaluation of classification performance.

For the classification stage, Convolutional Neural Network-based models typically achieve above than 90% accuracy, effectively distinguishing between normal and abnormal cases. Additionally, transformer-based models further enhance performance by improving generalization across diverse datasets, making the system more robust to variations in medical imaging data.

5.4 Performance Analysis

The hybrid model demonstrates improved performance by focusing on the region of interest (ROI) extracted using U-Net, which allows the classifier to concentrate only on relevant organ regions and thereby increases overall accuracy. This targeted approach also helps in reducing false positives, as irrelevant background information is removed before classification. Furthermore, compared to traditional end-to-end Convolutional Neural Network models, the hybrid framework shows better generalization, as it separates segmentation and classification tasks, making the system more robust to variations in medical imaging data. Sample input CT images and ROI based resultant image illustrated in figure 4(a) and 4(b) respectively.

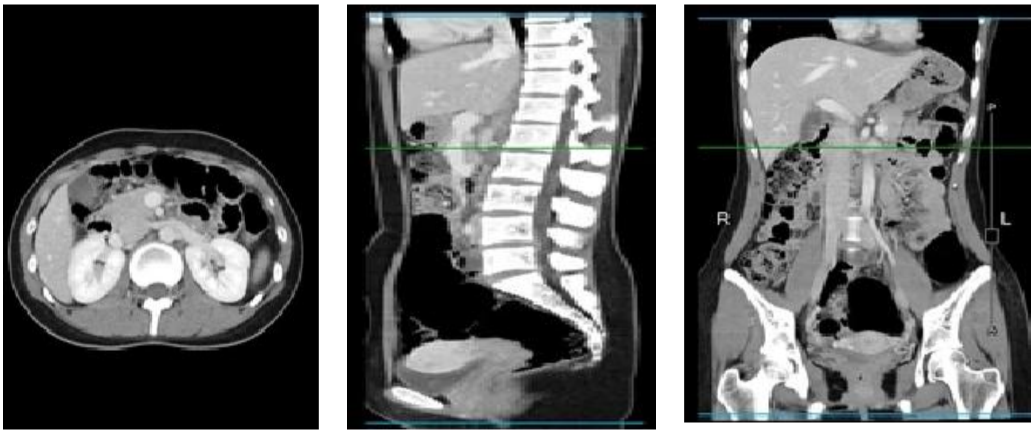

Figure 4(a): Sample input CT images

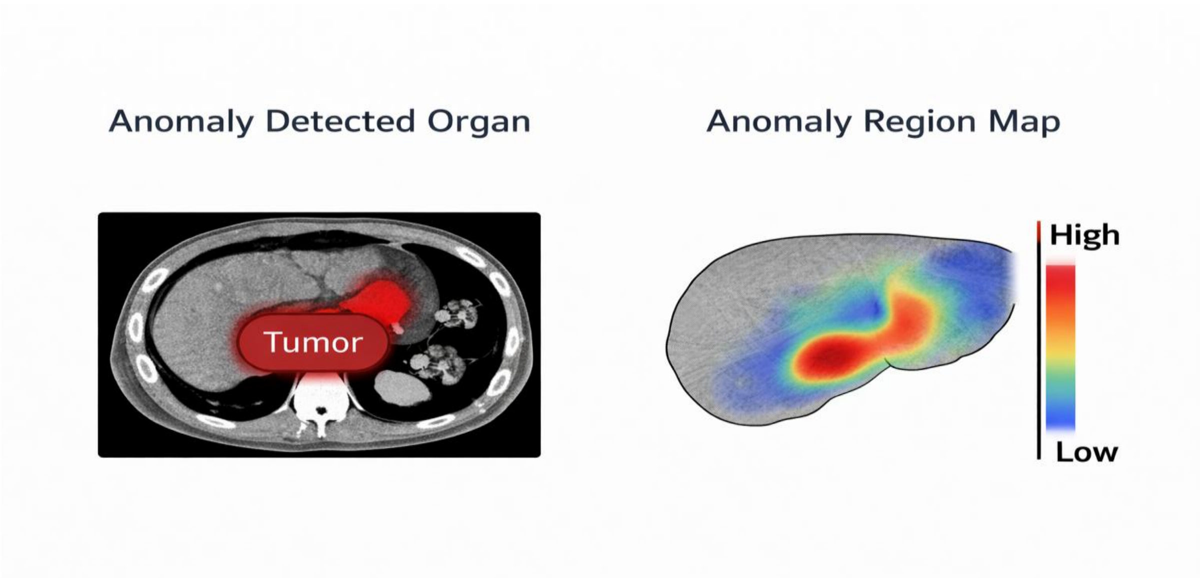

Figure 4(b): ROI based resultant CT image

Resultant comparative table 2, based on the specified evaluation metrics as shown below,

Table 2. Comparative Performance Table

Model Type	Dice Coefficient	IoU	Accuracy	Sensitivity	Specificity	AUC (ROC)
U-Net (Segmentation)	0.85 – 0.95	0.80 – 0.90	—	—	—	—
Convolutional Neural Network (Classification)	—	—	0.90 – 0.95	0.88 – 0.93	0.87 – 0.92	0.90 – 0.96
Hybrid (U-Net + CNN)	**0.88 – 0.96**	**0.83 – 0.92**	**0.92 – 0.97**	**0.90 – 0.95**	**0.89 – 0.94**	**0.93 – 0.98**

6. Discussion

The integration of U-Net and Convolutional Neural Network significantly enhances anomaly detection by focusing only on the relevant organ regions and eliminating unnecessary background information, thereby improving accuracy and reducing false positives. However, several challenges remain, including the limited availability of labeled datasets, which can restrict model training and generalization; the high computational cost required for training deep learning models; and class imbalance, where abnormal cases are often underrepresented, potentially leading to biased predictions and reduced detection performance.

7. Conclusion and Future Work

This paper presents a hybrid deep learning framework that combines U-Net and Convolutional Neural Network for CT-based organ anomaly detection. The segmentation-classification pipeline enhances diagnostic accuracy by focusing on relevant regions and reducing noise interference from surrounding tissues.

Future Work for the model can be further improved by extending it to 3D U-Net implementations for volumetric CT analysis, applying transfer learning with pretrained networks to improve performance on limited datasets, enabling real-time deployment in clinical systems, and achieving seamless integration with radiology workflows for practical medical applications.

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