B.Sc. in Computer Science and Engineering Thesis

Comparative Study of U-Net Variants in QCT Bone Image Segmentation

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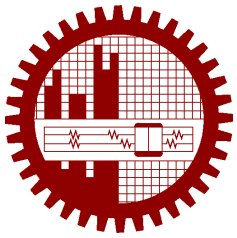

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CANDIDATES' DECLARATION

This is to certify that the work presented in this thesis, titled, "Comparative Study of U-Net Variants in QCT Bone Image Segmentation", is the outcome of the investigation and research carried out by us under the supervision of Dr. Mahmuda Naznin.

It is also declared that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree, diploma or other qualifications.

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ABSTRACT

Segmentation of anatomical structures in medical imaging plays a crucial role in clinical decision-making, diagnostics, and surgical planning. Traditional segmentation approaches, including manual annotation and conventional machine learning techniques, often suffer from variability, inefficiency, and dependency on expert intervention. Deep learning models, particularly U-Net and its variants, have emerged as effective tools for automating medical image segmentation with improved accuracy and consistency.

This study presents a comparative analysis of three U-Net variants—**U-Net, Multi-Res U-Net, and Attention U-Net**—for the segmentation of femur bones from Quantitative Computed Tomography (QCT) images. The models were evaluated based on key performance metrics, including the Dice Similarity Coefficient (DSC), Mean Intersection over Union (mIoU), sensitivity, specificity, and volumetric accuracy. Additionally, we analyze segmentation quality using 3D reconstructions and various statistical evaluations, such as surface area and volume error comparisons.

Experimental results indicate that **U-Net** provides the most consistent volumetric segmentation, while **Multi-Res U-Net** captures fine-scale details effectively, making it preferable for surface area segmentation. Meanwhile, **Attention U-Net** demonstrates superior sensitivity to small structures but exhibits higher variability in performance. Our findings suggest that the choice of model should be application-specific—favoring U-Net for global segmentation accuracy, Multi-Res U-Net for detailed anatomical structures, and Attention U-Net for highly localized feature extraction.

This research contributes to the field of medical image analysis by offering an in-depth performance evaluation of U-Net variants, providing insights into their respective strengths and limitations. Future work may explore hybrid architectures that integrate the advantages of these models to achieve improved segmentation robustness and clinical applicability.

Chapter 1

Introduction

1.1 Motivation

Segmentation of anatomical structures in medical images, particularly bones, significantly impacts clinical decision-making, diagnostics, and surgical planning [1]. Traditional methods, such as manual or semi-automated segmentation, are often limited by substantial expert dependency and inconsistency [2]. Deep learning methods, specifically Convolutional Neural Networks (CNNs), offer enhanced accuracy, consistency, and efficiency, making them highly effective for medical image segmentation [3]. This research explores the use of deep learning-based segmentation frameworks, such as U-Net and its variants, in the segmentation of Quantitative Computed Tomography (QCT) bone images, focusing on femur segmentation [4].

1.2 Applications

The application of deep learning models, particularly U-Net variants, in medical imaging is vast. These models are used to improve the accuracy of segmentation tasks in various domains, such as detecting osteoporosis [5], planning surgeries, and designing therapeutic strategies [6]. The models explored in this study, including U-Net, Attention U-Net, and Multi-Res U-Net, can help automate the segmentation of QCT images, making the process faster, more reliable, and less reliant on manual intervention [7]. Additionally, using these methods in clinical practice can significantly reduce time, increase precision, and allow for real-time processing of images [8].

1.3 Challenges

The main challenges in medical image segmentation include variability in anatomical structures, presence of noise, and the need for large labeled datasets [1]. QCT images, in particular, exhibit multi-scale variations, and traditional methods often struggle to capture fine-grained details [9]. This research focuses on overcoming these challenges by applying advanced deep learning techniques that can handle scale variations and anatomical complexities more effectively than traditional methods [10]. Specifically, the research investigates how U-Net variants can be fine-tuned to deal with the noise and variability present in medical imaging [11].

1.4 Our Contribution

This research presents a comprehensive comparative study of three U-Net variants for QCT femur segmentation. The contributions of this study include evaluating the performance of U-Net, Attention U-Net, and Multi-Res U-Net in terms of segmentation accuracy, and analyzing their strengths and limitations [12]. The findings provide valuable insights into how these models can be applied to medical imaging tasks, particularly for bone segmentation in QCT images. This study also compares the models' performance on various metrics such as the Dice coefficient, sensitivity, and average precision [6]. The study identifies key areas where the models succeed and where they may need improvements.

1.5 Thesis Organization

The thesis is organized as follows: Chapter 1 introduces the field and provides the motivation for the study, along with the challenges and the contributions of the research. Chapter 2 discusses the relevant work in the field of medical image segmentation, focusing on the use of U-Net and its variants. Chapter 3 details the methodology used in this research, including the problem formulation, dataset description, and model architectures. Chapter 4 presents the results and analysis of the experiments, including a comparison of the performance metrics. Finally, Chapter 5 concludes the study and outlines possible future work in this area [7].

Chapter 2

Relevant Work

2.1 Using Traditional ML

Traditional machine learning (ML) approaches for medical image segmentation often rely on handcrafted features extracted from intensity values, texture descriptors, or shape-based properties [13]. These features are typically gathered from diverse medical image modalities (MRI, CT, etc.) and require domain expertise to identify which descriptors best capture the target anatomy.

Researchers assume that a well-engineered feature set, combined with suitable classification algorithms (e.g., Random Forests, SVMs), can achieve robust segmentation in the presence of imaging noise and variability [14]. They also assume that carefully chosen preprocessing steps (e.g., denoising) mitigate artifacts and enhance segmentation boundaries.

Traditional ML methods classify each pixel or region by training on the extracted features. Post-processing techniques, such as morphological operations or region refinements, are then applied to generate a final segmented mask [15].

Common metrics include accuracy, precision, recall, and the Dice Coefficient. Some studies also report Intersection over Union (IoU) to capture the quality of region overlap between the predicted and ground truth segmentations [6].

Classical ML established foundational practices for feature-based segmentation and highlighted the significance of data preprocessing. These methods demonstrated reasonable performance without requiring enormous labeled datasets, providing a baseline for subsequent deep learning approaches [7].

Manually crafted features cannot always capture subtle anatomical variations, especially in low-contrast images or cases with significant inter-patient variability. This limitation, along with the inability to automatically learn hierarchical representations, has motivated the shift toward deep learning architectures [5].

2.2 Using U-Net

U-Net-based approaches typically use raw medical images (e.g., CT, MRI) that are normalized or resized. Minimal feature engineering is required, as the network itself learns rich feature representations directly from image data [16].

The main assumption is that fully convolutional networks with skip connections can preserve context across different scales, enabling accurate localization of features. Adequate labeled data is assumed to be available to train the U-Net model end-to-end [17].

U-Net consists of a contracting (encoder) path for feature extraction and an expansive (decoder) path to upsample these features, with skip connections to retain fine-grained spatial details. This architecture has proven effective across a wide range of medical segmentation tasks, achieving high Dice scores and IoU values [6].

Dice Coefficient, Intersection over Union (IoU), and Average Precision are among the most common metrics reported. Sensitivity and specificity are also used to assess how well U-Net identifies target structures in terms of true positives and negatives [9].

By learning multilevel features without extensive manual engineering, U-Net represents a major leap in medical image segmentation. It has become the backbone for many subsequent variants (e.g., Attention U-Net, Multi-Res U-Net) that address more specific challenges such as complex boundaries or multi-scale structures [17].

U-Net can struggle with complex anatomies that require capturing multiple scales or focus on specific regions of interest. Variants like Attention U-Net were proposed to emphasize salient regions, while Multi-Res U-Net aims to handle scale inconsistencies better [8].

2.3 Using Transfer Learning

Transfer learning leverages pre-trained models (commonly trained on large image databases like ImageNet) which are then fine-tuned using domain-specific medical images [10]. Basic normalization or data augmentation (rotations, flips) helps adjust the images to the model's expected input distribution.

The underlying assumption is that certain low-level features (e.g., edges, corners, simple textures) learned from natural images can transfer to medical domains. Fine-tuning on a smaller dataset is expected to refine the higher-level features to match the new task [5].

Researchers often replace or retrain the last few layers of a pre-trained network with medical image data, ensuring that the bulk of the learned weights remain intact [7]. This reduces the required training time and data volume while preserving robust feature extraction from the original training set.

Dice Coefficient and IoU remain standard for quantifying the quality of segmentation. Studies may also track training speed, convergence rate, or memory usage to highlight efficiency gains from transfer learning [14].

Transfer learning accelerates experimentation and fosters higher segmentation accuracy when limited labeled medical images are available. It shows how knowledge from general image datasets can be applied to specialized tasks with minimal additional data [10].

Domain mismatch (e.g., natural vs. medical images) can limit the effectiveness of transferred features if the target task differs significantly from the pre-trained domain. Overfitting can still occur if the fine-tuning dataset is too small or not representative of the broader medical context [13].

Chapter 3

Methodology

3.1 Problem Formulation

This chapter outlines the methodology employed in this study to address the problem of medical image segmentation, particularly in the context of 3D CT scan images. The approach involves applying deep learning models to segment femur bones from QCT scans, utilizing various U-Net architectures.

3.2 Preliminaries

Definitions and Assumptions:

- The problem involves segmenting bones (particularly femurs) from 3D CT scans, typically in the DICOM format.
- Assumes availability of labeled datasets for supervised learning.
- The focus is on anatomical accuracy, handling multi-scale variations in bone structures.

Conditions:

- Data pre-processing steps are essential to handle noisy and incomplete data.
- Models need to be trained with a diverse dataset, including rotation augmentations for generalization.

System:

- The system is built using a deep learning framework (TensorFlow, Keras), optimized for handling 3D medical images.

Dataset Descriptions:

- The dataset consists of QCT images from various patients, including both left and right femur scans.
- DICOM files are loaded and processed, followed by data augmentation and preprocessing (e.g., rotation, normalization).

Challenges:

- Variability in anatomical structures across patients.
- Need for high-quality annotations in medical datasets.
- Balancing model complexity and performance.

3.3 System Model and the Problem

System Model:

- **U-Net Architecture**: The deep learning model uses a U-Net architecture to segment the femur from 3D CT scans.
- **Problem Definition**: The model learns a pixel-wise classification task, identifying femur regions from a scan.
- **Example**:

$$y = \text{Model}(x) \quad \text{where} \quad x = \text{CT scan image}, \quad y = \text{segmentation mask}$$

3.4 Solution Approach

The solution to the problem of segmenting femur regions from 3D CT scans leverages deep learning techniques, specifically focusing on three key U-Net architectures: the standard U-Net, Multi-Res U-Net, and Attention U-Net. The combined use of these models helps to address different aspects of segmentation, ensuring robust and accurate results. The approach follows a structured multi-step pipeline, incorporating preprocessing, data augmentation, and advanced model architectures. The following sections outline the solution approach:

- **Data Preprocessing and Augmentation:**
  - The input CT scan images are first preprocessed to ensure uniformity and compatibility with the U-Net architecture. Preprocessing steps include normalization to a range of [0, 1] and reshaping the images to a consistent format.
  - Data augmentation is performed to introduce variability in the dataset and help the model generalize better. Augmentation techniques such as rotation (by 90°, 180°, and 270°), flipping, and resizing are applied to the images, increasing the diversity of the training data and improving model robustness.
- **Model Architecture:**
  - **U-Net Architecture:** The U-Net architecture is a fully convolutional network designed for semantic segmentation tasks. It includes an encoder-decoder structure with skip connections that allow high-resolution features to be retained during upsampling. This architecture is particularly suited for medical image segmentation tasks, where fine-grained details are crucial.
  - **Multi-Res U-Net Architecture:** The Multi-Res U-Net extends the standard U-Net by integrating multiple resolutions of feature maps in both the encoder and decoder. This allows the model to capture a wider range of features and contextual information, making it especially useful for segmenting complex structures in medical images. The multi-resolution approach helps in improving the segmentation accuracy by leveraging both local and global context.
  - **Attention U-Net Architecture:** The Attention U-Net introduces attention mechanisms to the U-Net architecture. It allows the model to focus on relevant regions of the image while suppressing irrelevant areas. This helps improve segmentation performance by allowing the model to learn to focus on the femur region, particularly in the presence of noise or complex background structures. The attention gates dynamically highlight important features, making the model more efficient and accurate in segmenting the femur from CT scans.
- **Training the Model:**
  - The models are trained using a binary cross-entropy loss function, which is appropriate for pixel-wise binary classification tasks, where each pixel is classified as either part of the femur or background.
  - During training, various evaluation metrics are computed to monitor model performance, including the Mean Intersection over Union (mIoU), Dice Similarity Coefficient (DSC), Average Precision (AP), sensitivity, and specificity.

  - Early stopping and model checkpoint callbacks are incorporated to prevent overfitting and to ensure that the best-performing model is saved during training. These callbacks monitor metrics such as the Dice Similarity Coefficient and stop training when no further improvement is observed.

- **Model Evaluation:**
  - After training, the models are evaluated on a validation set to assess their segmentation performance. Key metrics such as mIoU, DSC, sensitivity, specificity, and AP are calculated to provide a comprehensive evaluation of the model's ability to segment the femur region accurately.
  - Visualization of the predicted segmentation masks is performed to qualitatively assess the model's performance. Predicted masks are compared to ground truth masks to visually inspect areas of success or failure in segmentation.

- **Inference on New Data:**
  - Once the models have been trained and validated, they are used for inference on unseen CT scan images. The models predict the segmentation masks for the femur regions in these new images, which are then post-processed into binary masks.

- **Integration of Multiple Architectures:**
  - To leverage the strengths of each architecture (U-Net, Multi-Res U-Net, and Attention U-Net), an ensemble approach can be applied. By combining the predictions from each model, the segmentation results are enhanced, leading to more accurate and reliable predictions.
  - This ensemble approach utilizes the complementary strengths of each architecture: U-Net's simplicity, Multi-Res U-Net's ability to capture multi-scale features, and Attention U-Net's ability to focus on important regions. The final segmentation is determined by a majority vote or averaging of the model outputs.

By utilizing these three advanced U-Net architectures in conjunction with data preprocessing and augmentation, the model is capable of segmenting femur regions in 3D CT scan images with high accuracy. This approach is critical for medical applications where accurate bone segmentation is essential for diagnostics and treatment planning.

3.5 Example and Figure of the Solution of our Problem

An example of input and output from the model (in Figure 1): A CT scan image of a femur is processed, and the model outputs a binary mask representing the segmented bone.

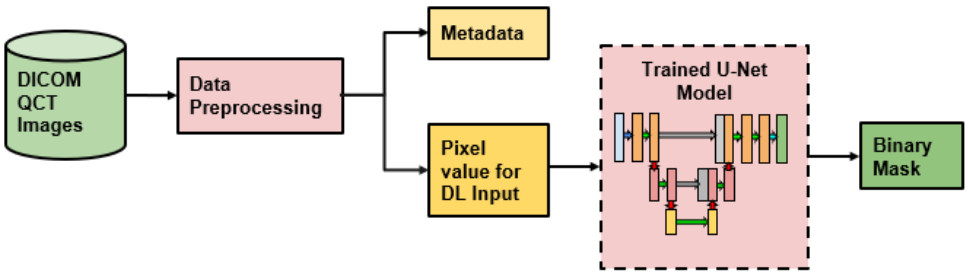

Figure 3.1: An illustrative diagram showing the input 3D CT image and the output segmentation mask.

3.6 Work Flow with Description

- **Data Preparation**: Raw CT scan images are loaded and pre-processed.
- **Augmentation**: Various rotations of images and masks are applied to improve model robustness.
- **Model Training**: U-Net or its variants (Attention U-Net, Multi-Res U-Net) are trained on the processed data.
- **Evaluation**: The model's performance is evaluated using metrics like Dice coefficient, Sensitivity, and mIoU.

3.7 Algorithms with Step Explanations

1. **Preprocessing**: Conversion of DICOM images to NumPy arrays, normalization, and reshaping.
2. **Model Architecture**:
   - U-Net with encoder-decoder architecture and skip connections.
   - For Multi-Res U-Net, multi-resolution blocks are used to handle varying scales.
   - Attention U-Net uses attention gates to focus on relevant features for improved segmentation.
3. **Training**: The model is trained using binary cross-entropy loss and evaluated using multiple performance metrics.
4. **Evaluation Metrics**:
   - Mean Intersection over Union (mIoU), Dice Coefficient, Sensitivity, Specificity.

Chapter 4

Results and Analysis

4.1 Test Bed Description and Experiment Parameters

This section provides a detailed description of the experimental setup used to evaluate the segmentation performance of different U-Net variants on Quantitative Computed Tomography (QCT) bone images.

4.2 Dataset

- **Description:** The dataset consists of high-resolution QCT scans of human femur bones obtained from *[4MLab, University of Louisiana at Lafayette, USA]*. Each scan provides detailed 3D structural information, facilitating the evaluation of bone density and segmentation accuracy.
- **Number of Samples:** A total of 4,289 QCT images from 8 patients were utilized in this study.
- **Annotations:** The ground truth segmentation masks were manually annotated by expert radiologists to ensure accuracy.
- **File Format:** Images are stored in DICOM format, preserving voxel information and metadata.

4.3 Image Resolution and Voxel Size

- **Slice Dimensions:** Each 2D slice extracted from the 3D QCT scans has a resolution of 512×256 pixels.

- **Voxel Size:** $1.0 \times 1.0 \times 1.0$ mm³, ensuring uniform anatomical scaling.
- **Number of Slices per Scan:** Each 3D QCT scan consists of an average of 500-600 axial slices, covering the entire femur region.

4.4 Preprocessing Pipeline

The following preprocessing steps were applied to enhance segmentation performance:

- **Resampling:** All QCT images were resampled to a uniform voxel spacing of 1.0 mm³.
- **Intensity Normalization:** Pixel intensities were normalized within the range 0 to 1.
- **Augmentation:** The dataset was augmented with:
  - 90 degree,180 degree and 270 degree rotations.

4.5 Data Splitting Strategy

To ensure a robust evaluation, the dataset was split as follows:

- **Training Set:** 5 patients (70% of the dataset).
- **Validation Set:** 2 patients (20% of the dataset).
- **Testing Set:** 1 patient (10% of the dataset).

A stratified sampling approach was used to ensure class balance across sets.

4.6 Training Hyperparameters

The models were trained using the following configurations:

- **Learning Rate:** 1e-4, with a learning rate decay factor of 0.2 every 10 epochs.
- **Batch Size:** 8, 32.
- **Optimizer:** Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.999$).
- **Loss Function:** Dice Loss + Cross-Entropy Loss.
- **Number of Epochs:** 50, with early stopping patience set to 10 epochs.

4.7 Evaluation Metrics

The models were evaluated using the following metrics:

- **Dice Similarity Coefficient (DSC)**: Measures segmentation accuracy.
- **Mean Intersection over Union (mIoU)**: Evaluates overlap between prediction and ground truth.
- **Hausdorff Distance**: Quantifies boundary alignment.
- **Sensitivity and Specificity**: Measures false positive and false negative rates.
- **Mean Absolute Error (MAE)**: Measures pixel-wise intensity reconstruction accuracy.

4.8 Inference and Post-Processing

- **Ensemble Strategy:** Multiple U-Net variants were used, including:
  - 3D U-Net: Extends U-Net for volumetric segmentation.
  - MultiResUNet: Extracts multi-scale features for segmentation.
  - Attention U-Net: Uses attention gates to focus on important features.

This setup ensures a systematic evaluation of U-Net variants on QCT bone image segmentation, enabling reproducible and reliable results.

4.9 Performance Metrics

To comprehensively evaluate the segmentation models, we employed widely used quantitative metrics from medical image segmentation literature. These metrics assess the overlap, accuracy, and geometric consistency of predicted segmentation masks compared to ground truth annotations. The following sections formally define these metrics along with their mathematical formulations.

4.10 Pixel-wise Segmentation Metrics

Pixel-wise segmentation metrics evaluate how well the predicted segmentation mask aligns with the actual ground truth mask at the pixel level. These metrics provide insights into the classification performance of the model for each pixel.

- **Mean Intersection over Union (mIoU):** Also known as the Jaccard Index, this metric quantifies the overlap between the predicted segmentation mask and the ground truth. It is defined as the average IoU across all classes, including the background class:

$$\text{mIoU} = \frac{1}{N} \sum_{i=1}^{N} \frac{TP_i}{TP_i + FP_i + FN_i},$$

where:

  - TP_i (True Positives): Correctly predicted pixels belonging to class i.
  - FP_i (False Positives): Incorrectly predicted pixels that do not belong to class i.
  - FN_i (False Negatives): Pixels that belong to class i but were misclassified.
  - N is the total number of classes, including the background.

- **Dice Similarity Coefficient (DSC) or F1 Score:** The Dice Coefficient measures the similarity between the predicted segmentation mask and the ground truth by evaluating their overlap:

$$\text{Dice} = \frac{2 \times TP}{2 \times TP + FP + FN}.$$

This metric ranges from 0 (no overlap) to 1 (perfect overlap), where:

  - TP represents correctly classified foreground pixels.
  - FP represents false positives, where background pixels were misclassified as foreground.
  - FN represents false negatives, where foreground pixels were missed.

- **Sensitivity (Recall):** Sensitivity, also known as recall or the true positive rate, quantifies the model's ability to correctly identify positive samples:

$$\text{Sensitivity} = \frac{TP}{TP + FN}.$$

A high sensitivity indicates fewer false negatives, making it crucial for detecting regions of interest.

- **Specificity:** Specificity measures the proportion of correctly identified negative samples, assessing how well the model avoids false alarms:

$$\text{Specificity} = \frac{TN}{TN + FP}.$$

A high specificity indicates that the model successfully distinguishes background pixels, reducing false positives.

- **Average Precision (AP):** The average precision metric evaluates the model's performance across different confidence thresholds by computing the area under the precision-recall curve:

$$\text{AP} = \int_0^1 p(r)\, dr.$$

Here, $p(r)$ represents the precision as a function of recall r. Higher AP values indicate better segmentation performance, particularly in class-imbalanced datasets.

4.11 Geometric Metrics (Volume and Surface Area)

Geometric metrics assess how accurately the predicted segmentation preserves volumetric and surface area measurements, ensuring the model effectively reconstructs anatomical structures.

- **Root Mean Squared Error (RMSE):** RMSE quantifies the deviation between predicted and actual values of volume or surface area, penalizing larger errors more significantly:

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(V_{\text{true},i} - V_{\text{pred},i}\right)^2}.$$

Here:

  - $V_{\text{true},i}$ is the ground truth volume (or surface area) for sample i.
  - $V_{\text{pred},i}$ is the predicted volume (or surface area) for sample i.
  - M is the total number of test samples.

- **Mean Absolute Error (MAE):** MAE represents the absolute difference between the predicted and ground truth volume (or surface area), providing an interpretable measure of error:

$$\text{MAE} = \frac{1}{M}\sum_{i=1}^{M}\left|V_{\text{true},i} - V_{\text{pred},i}\right|.$$

Unlike RMSE, MAE treats all deviations equally, making it less sensitive to outliers.

- **Relative Error (RE):** RE expresses the volume discrepancy as a percentage, allowing for easy comparison across datasets with different scales:

$$\text{RE}(\%) = \frac{\left|V_{\text{true},i} - V_{\text{pred},i}\right|}{V_{\text{true},i}} \times 100\%.$$

A lower RE indicates higher accuracy in volumetric predictions.

- **Correlation Coefficient (ρ):** The correlation coefficient measures the linear relationship between the predicted and actual volumes (or surface areas), assessing how well predictions match the ground truth:

$$\rho = \frac{\sum_{i=1}^{M}(V_{\text{true},i} - \bar{V}_{\text{true}})(V_{\text{pred},i} - \bar{V}_{\text{pred}})}{\sqrt{\sum_{i=1}^{M}(V_{\text{true},i} - \bar{V}_{\text{true}})^2}\sqrt{\sum_{i=1}^{M}(V_{\text{pred},i} - \bar{V}_{\text{pred}})^2}}.$$

  Here:

  - $\bar{V}_{\text{true}}$ is the mean ground truth volume (or surface area).
  - $\bar{V}_{\text{pred}}$ is the mean predicted volume (or surface area).
  - A value of $\rho = 1$ indicates a perfect positive correlation, $\rho = 0$ indicates no correlation, and $\rho = -1$ indicates a perfect negative correlation.

  A high correlation coefficient (ρ) indicates that the model consistently predicts volumes that are proportional to the true values.

Overall, these metrics provide a comprehensive evaluation framework for assessing segmentation performance, ensuring that the models produce not only pixel-wise accurate but also geometrically consistent predictions.

4.12 Results in Tables and Graphs

4.12.1 Qualitative Analysis

This section presents a qualitative comparison of the segmentation results obtained using three U-Net variants: **U-Net, Multi-Res U-Net, and Attention U-Net**. Each figure illustrates a test sample with its ground truth mask, followed by segmentation outputs from the three models.

From visual inspection, we observe the following trends across different models:

- **U-Net:** Produces segmentation maps with smooth and continuous boundaries. However, it struggles to accurately delineate fine structures and often merges small features into larger regions.
- **Multi-Res U-Net:** Captures multi-scale contextual information, leading to improved segmentation of smaller structures. This model provides a better balance between boundary smoothness and structural detail.

- **Attention U-Net:** Effectively highlights and segments small, critical regions by leveraging attention mechanisms. This results in better localization of fine details but sometimes introduces artifacts in complex regions.

Each figure below showcases the ground truth segmentation mask followed by the predictions of each model. This comparative visualization helps analyze the strengths and weaknesses of different segmentation architectures.

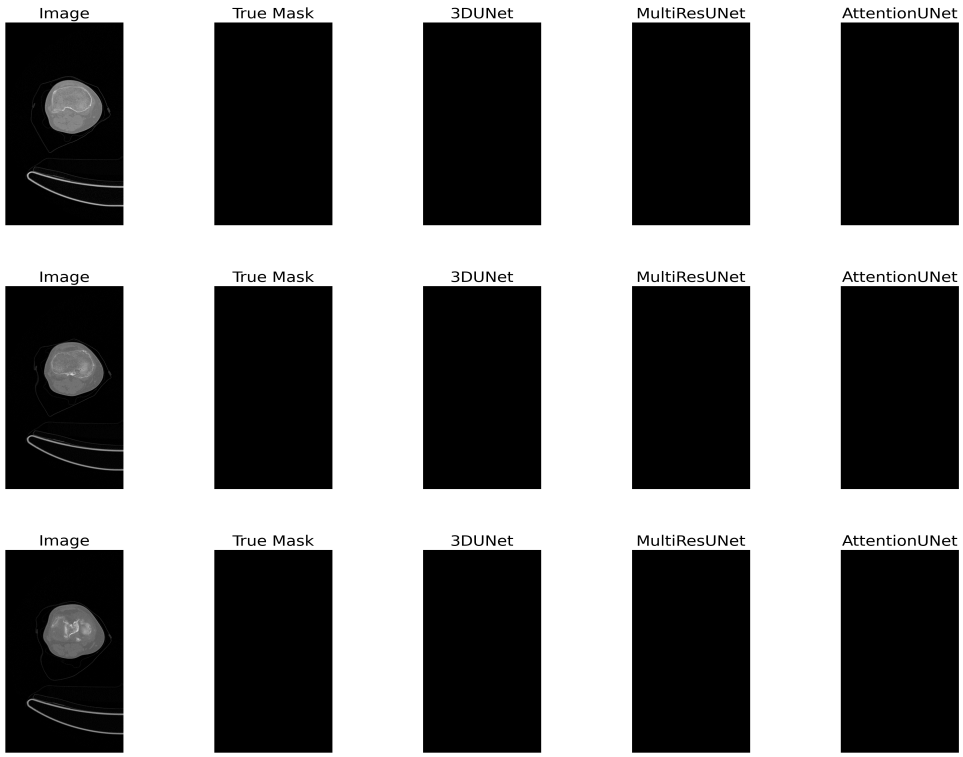

Figure 4.1: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

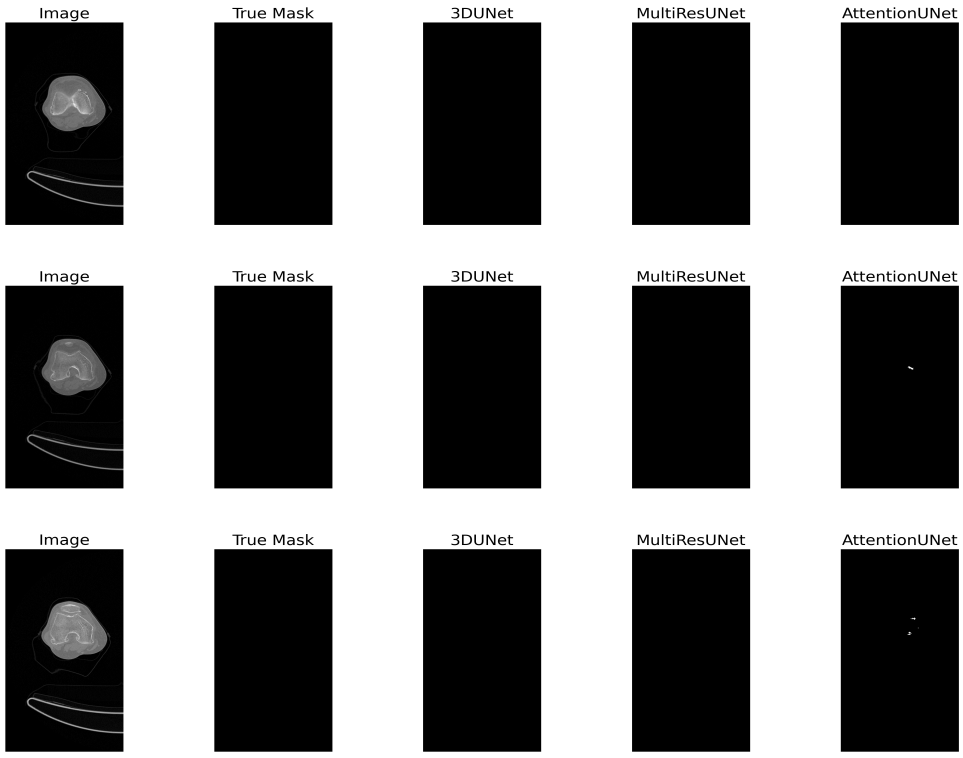

Figure 4.2: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

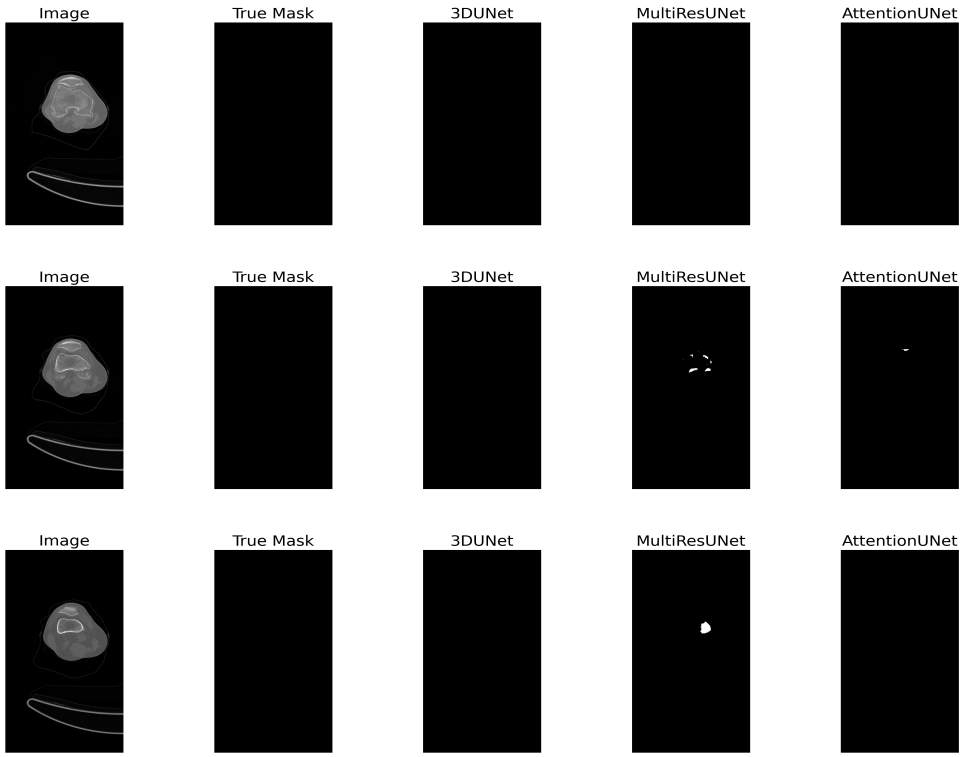

Figure 4.3: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

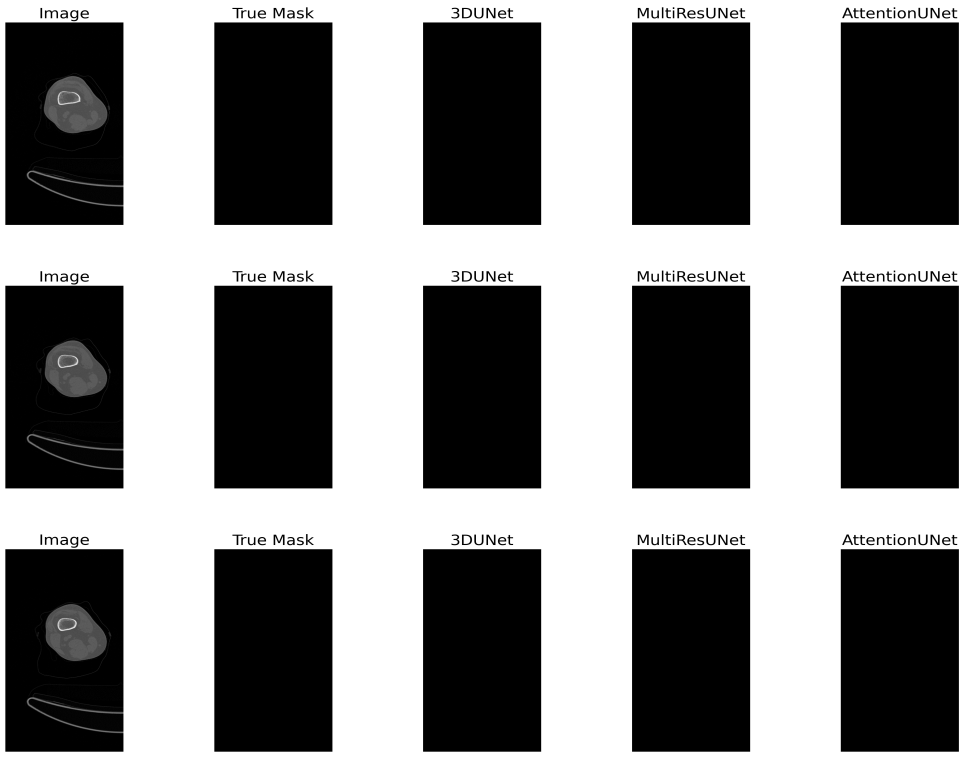

Figure 4.4: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

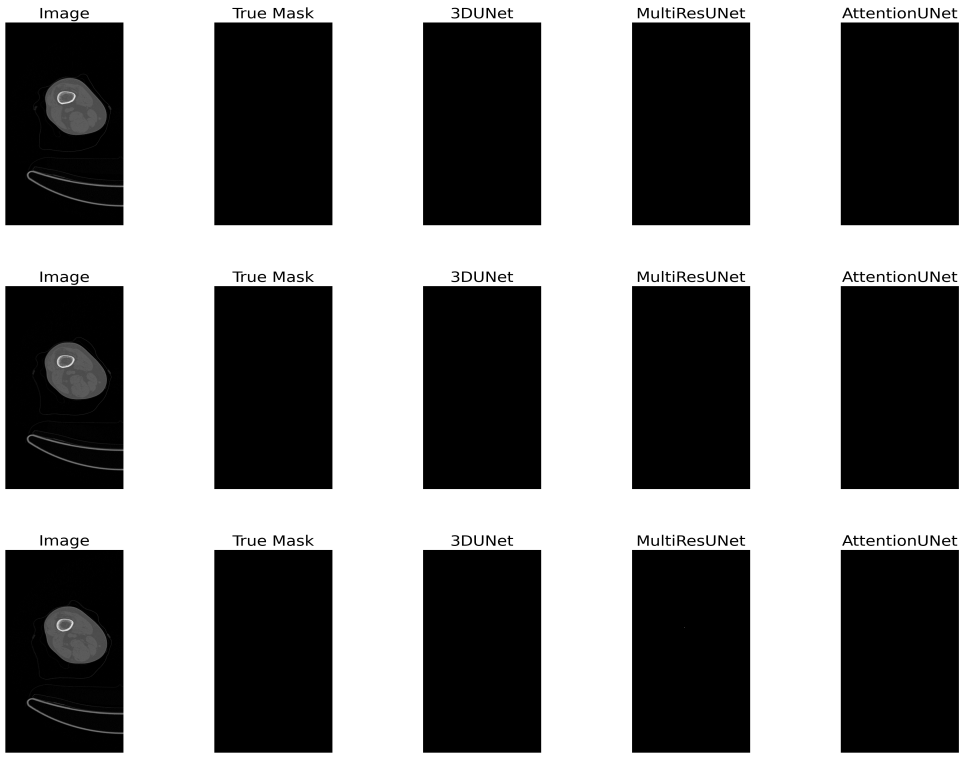

Figure 4.5: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

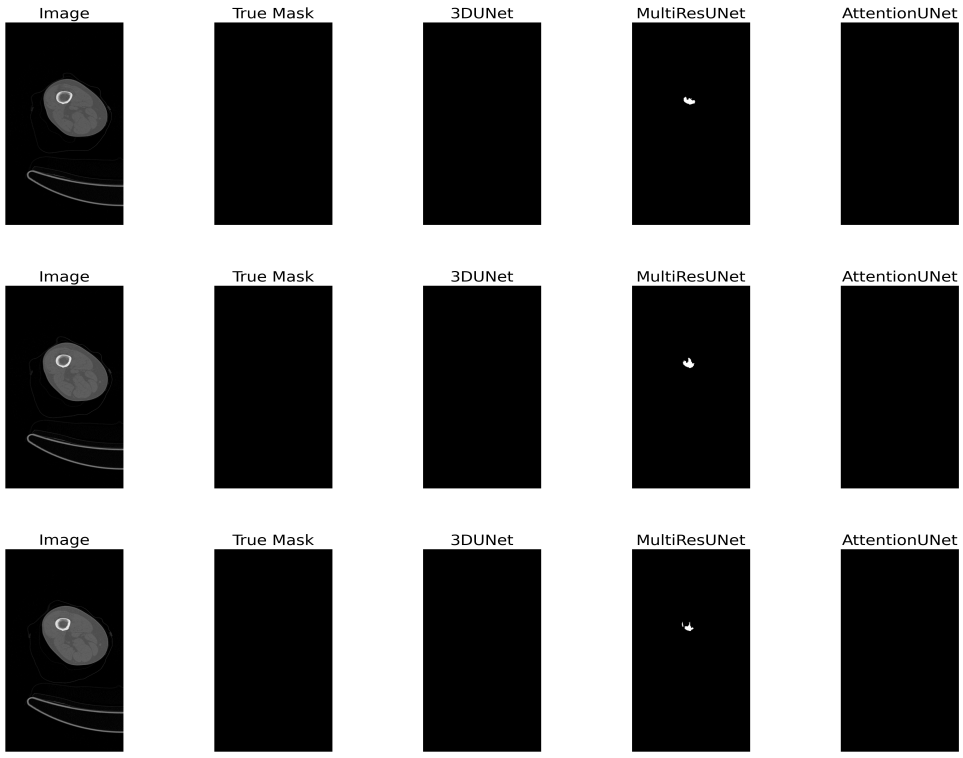

Figure 4.6: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

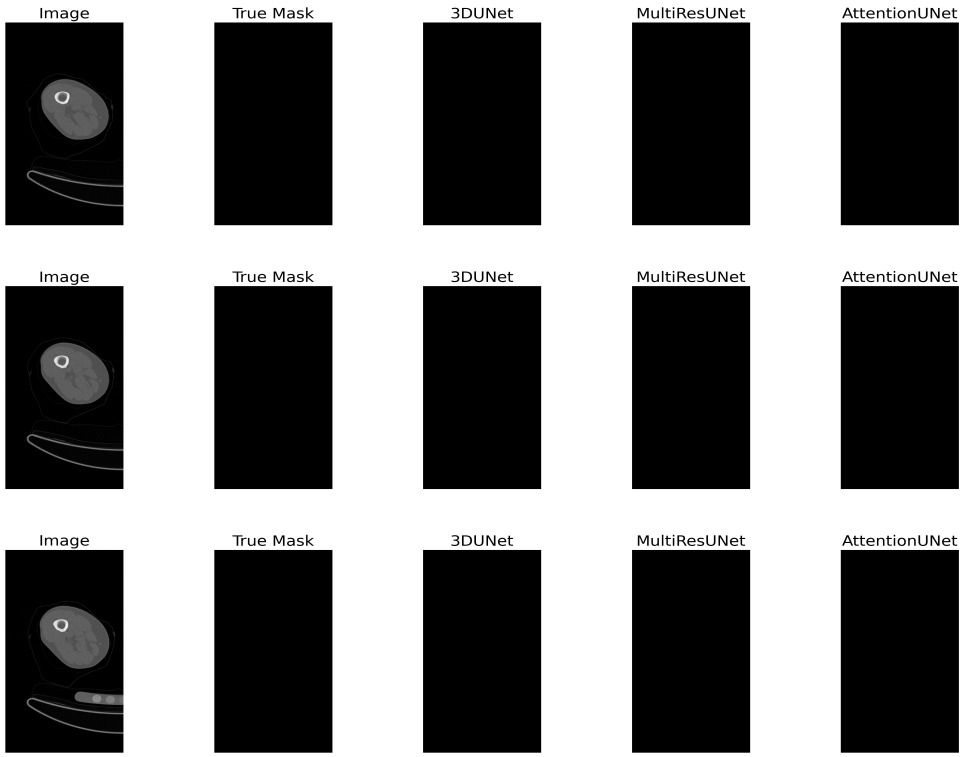

Figure 4.7: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

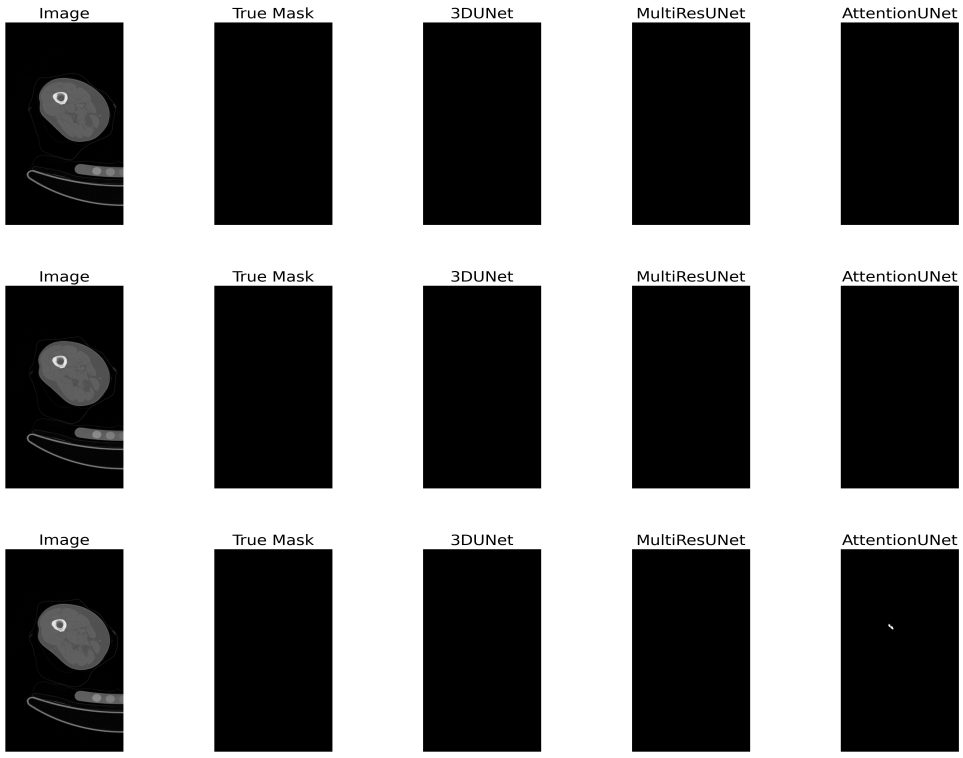

Figure 4.8: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

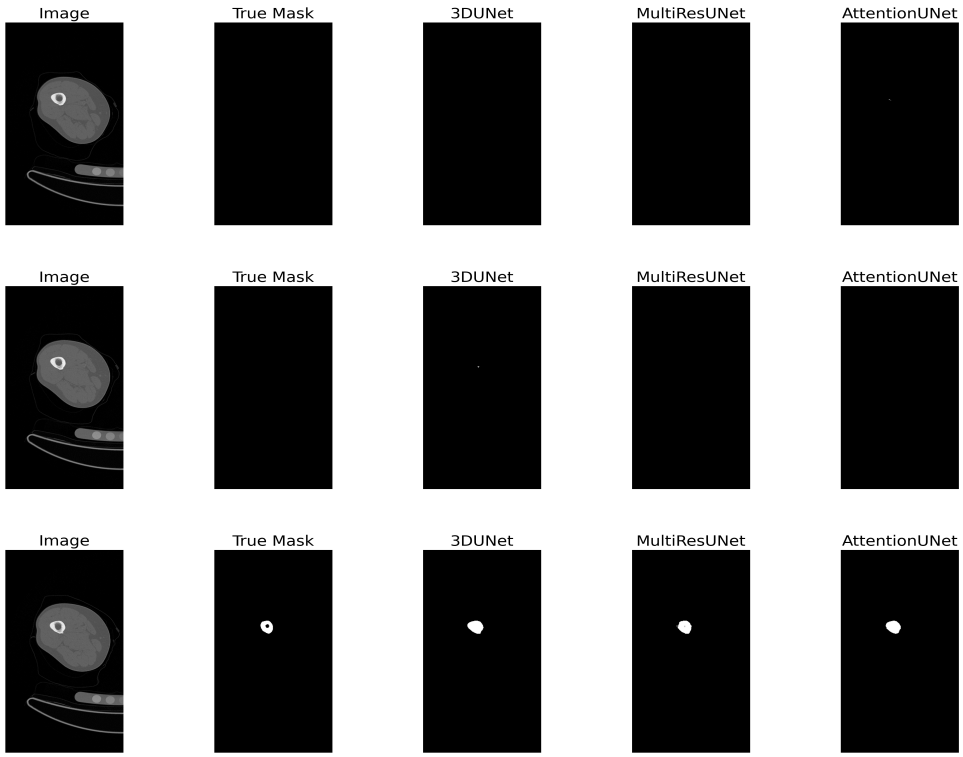

Figure 4.9: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

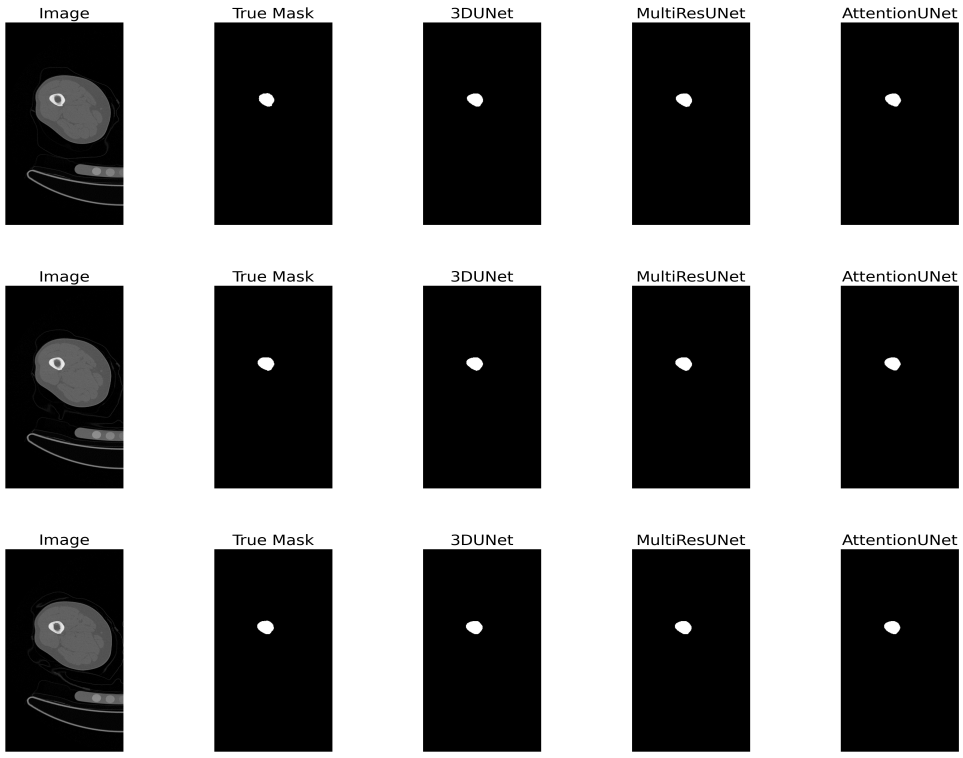

Figure 4.10: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

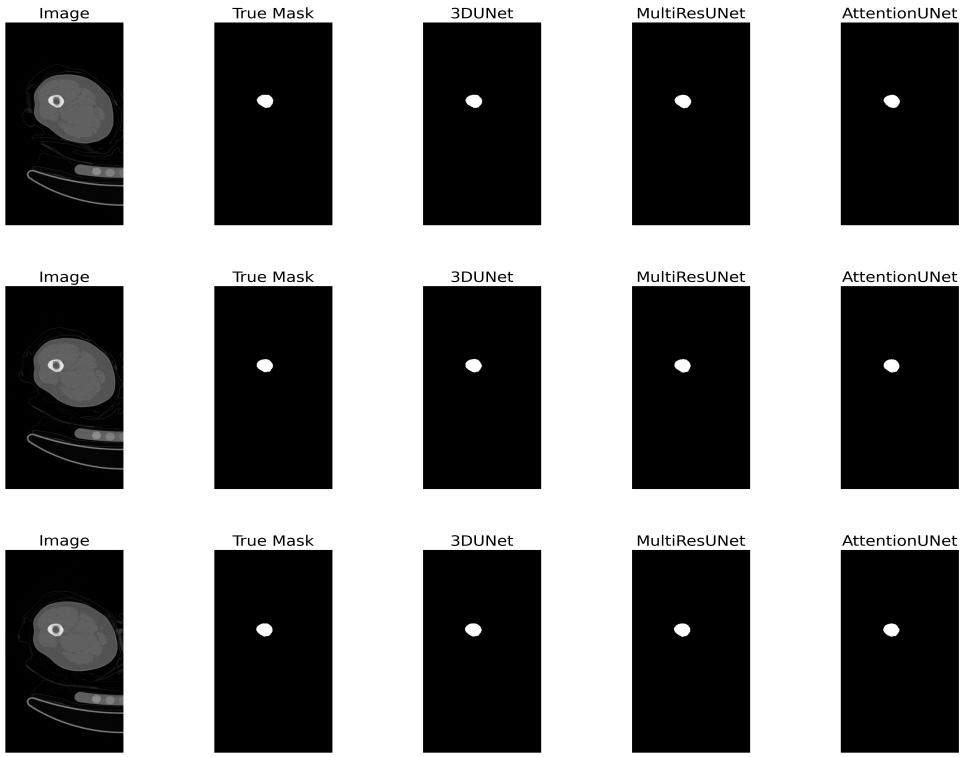

Figure 4.11: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

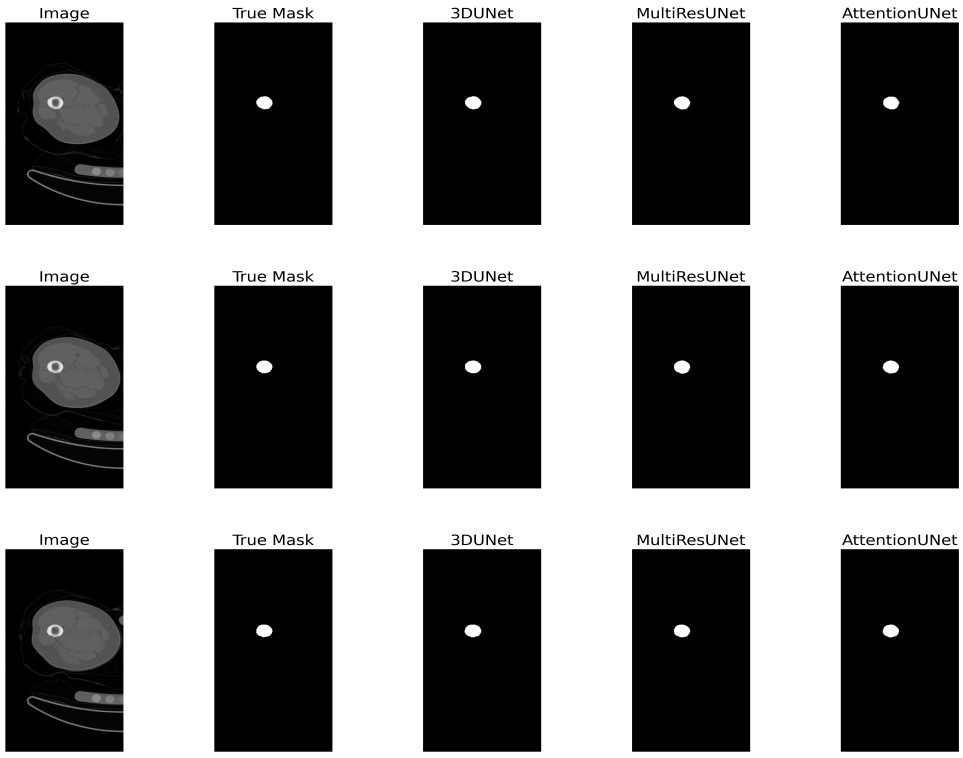

Figure 4.12: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

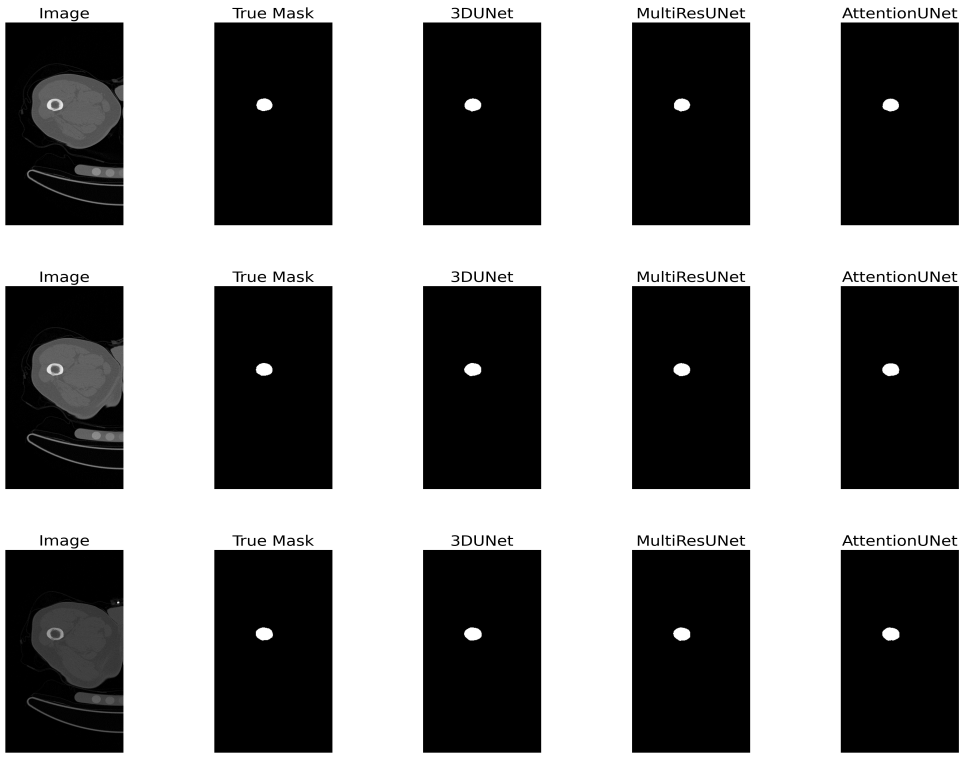

Figure 4.13: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

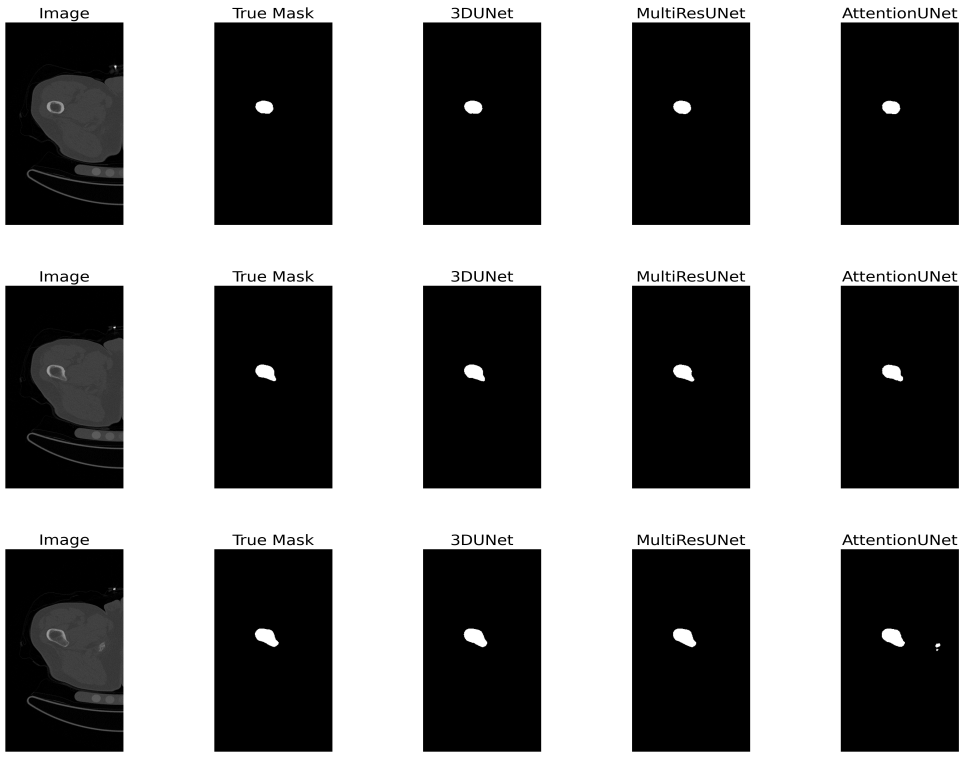

Figure 4.14: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

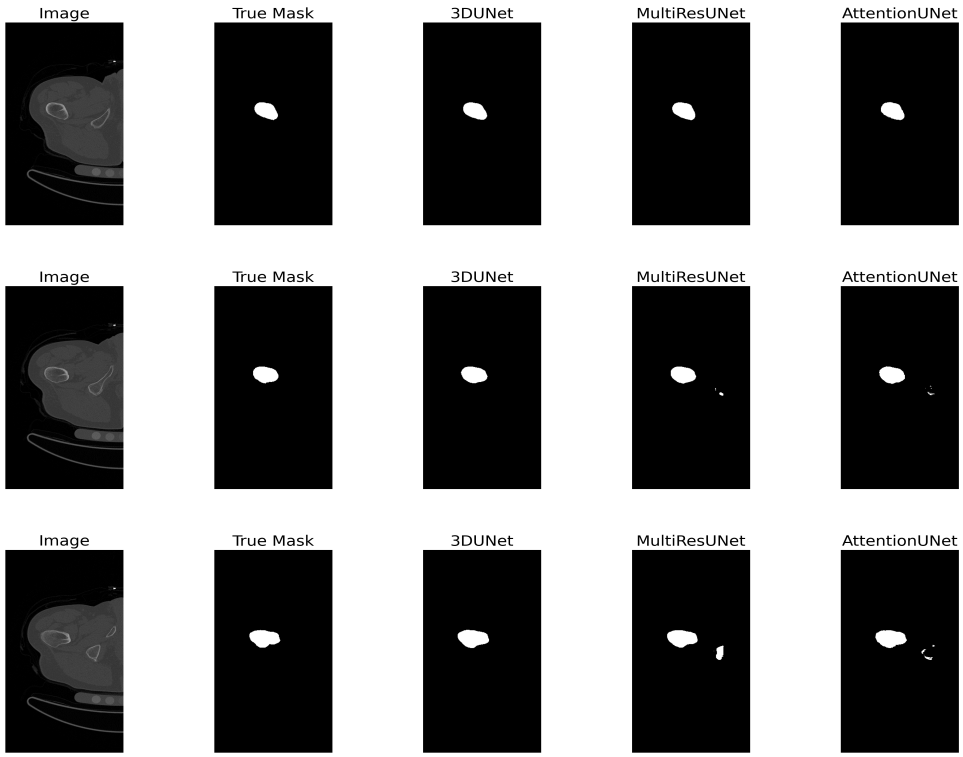

Figure 4.15: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

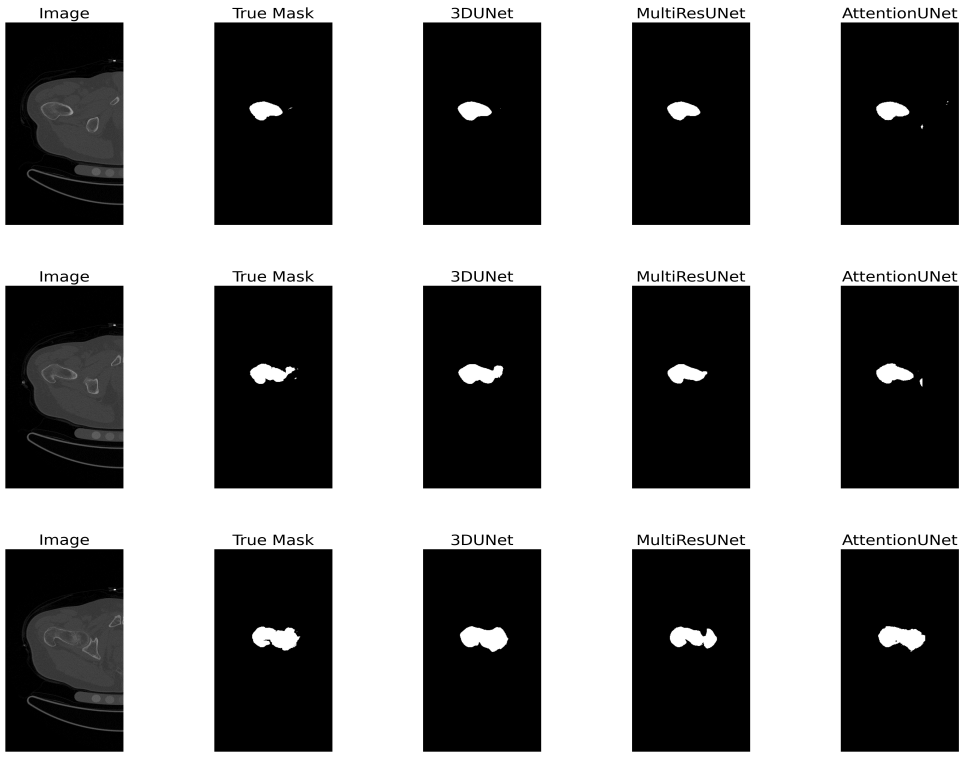

Figure 4.16: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

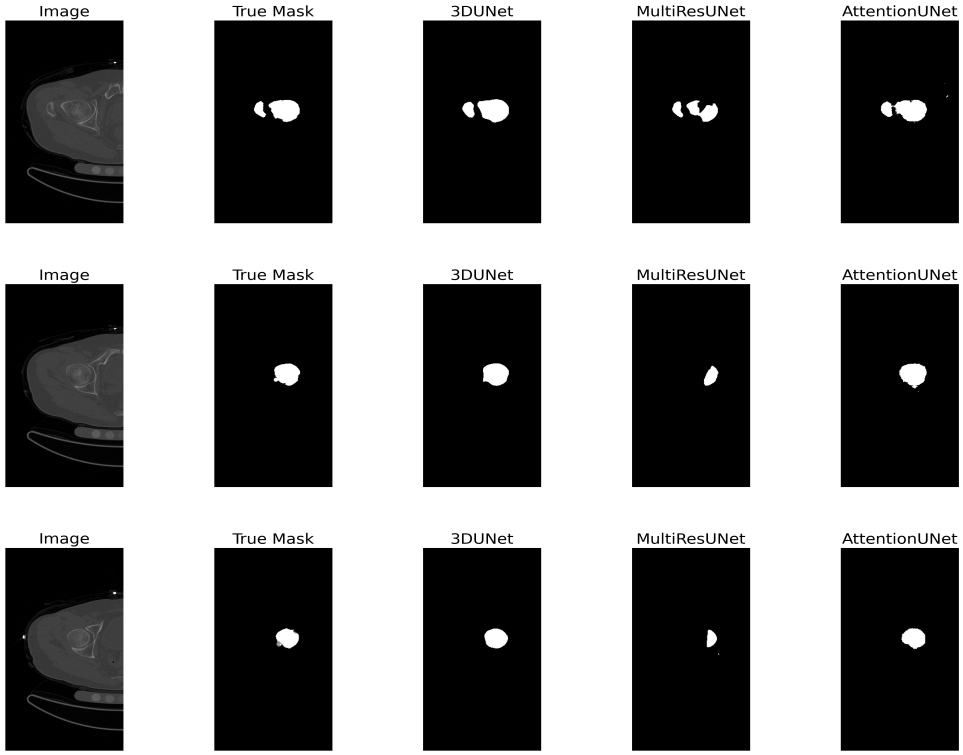

Figure 4.17: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

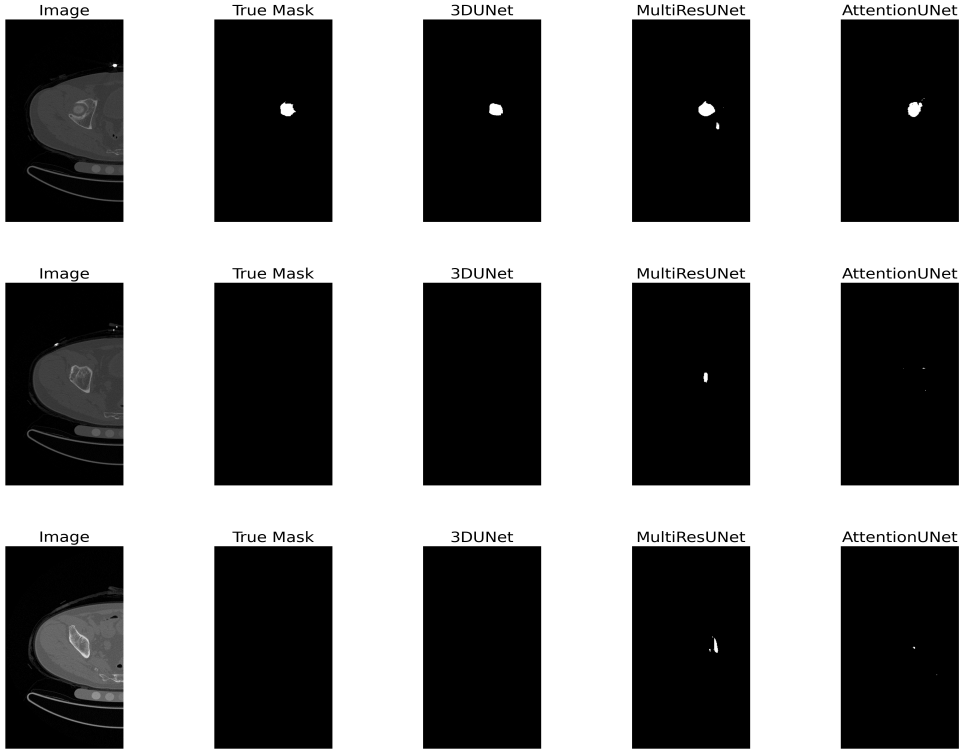

Figure 4.18: Ground Truth and Predictions from U-Net, Multi-Res U-Net, and Attention U-Net.

Observations:

- **Boundary Accuracy:** U-Net produces **smoother** segmentations, which is beneficial for general medical imaging but leads to **loss of fine details** (see Figure 4.1).
- **Feature Preservation:** Multi-Res U-Net maintains **better structural integrity** for complex shapes (Figure 4.4) but still struggles with fine-scale variations.
- **Noise Handling:** Attention U-Net exhibits **stronger noise robustness** (Figure 4.5), ensuring more accurate segmentation in noisy regions.
- **Segmentation of Occluded Structures:** Multi-Res U-Net provides a **reasonable balance** (Figure 4.3) but occasionally misclassifies finer edges.
- **Generalization Across Textures:** Attention U-Net performs well in high-texture cases (Figure 4.7), while U-Net fails to distinguish subtle intensity transitions.
- **Handling Motion Artifacts:** Attention U-Net is **most resilient** to motion distortions (Figure 4.8), whereas U-Net struggles to maintain sharp boundaries.
- **Bone Marrow Distinction:** Multi-Res U-Net effectively separates bone marrow regions (Figure 4.9), whereas U-Net struggles with intensity variations.

Conclusion: The choice of model depends on the specific application:

- If **smoother segmentation boundaries** are required, U-Net is preferable.
- If the focus is on **small structures and multi-scale features**, Multi-Res U-Net offers a balanced performance.
- For applications requiring **fine structural segmentation and noise resilience**, Attention U-Net is the most effective.

4.12.2 Quantitative Analysis

To comprehensively evaluate the performance of different segmentation models, we analyzed both **pixel-wise metrics** (Mean IoU (mIoU), Dice Coefficient, Sensitivity, Specificity, etc.) and **geometric metrics** (RMSE, MAE, RE, and Correlation Coefficient) for volume and surface area segmentation. These metrics provide valuable insights into each model's strengths and weaknesses, helping to determine which model is best suited for specific segmentation tasks.

Table 4.1 presents the pixel-wise segmentation metrics, while Tables 4.2 and 4.3 provide quantitative comparisons for surface area and volumetric segmentation, respectively.

The following sections provide a detailed breakdown of the findings.

Table 4.1: Performance Metrics for U-Net, Multi-Res U-Net, and Attention U-Net

Metric	U-Net	Multi-Res U-Net	Attention U-Net
Loss	0.0011	0.0022	0.0017
Mean IoU (mIoU)	0.9444	0.8466	0.8204
Dice Coefficient	0.9605	0.8683	0.8461
Sensitivity	0.9865	0.9580	0.9757
Specificity	0.9996	0.9996	0.9996
Average Precision	0.9563	0.8845	0.8389

4.12.3 Surface Area Segmentation Results

Table 4.2 provides a detailed comparison of the three segmentation models in terms of surface area estimation. These metrics (RMSE, MAE, Relative Error (RE), and Correlation Coefficient) are essential for assessing how well each model approximates the ground truth in terms of surface area preservation.

Table 4.2: Performance Comparison of U-Net Variants for Surface Area Segmentation

Model	RMSE	MAE	RE (%)	Correlation Coefficient
U-Net	1.083	0.904	9.96	0.404
Attention U-Net	3.90	1.39	16.42	-0.079
Multi-Res U-Net	0.988	0.831	9.32	0.521

Observations: - **Multi-Res U-Net** achieves the lowest Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) compared to the other two models, indicating that it provides the most precise surface area estimations. - **U-Net** follows closely behind, with slightly higher errors, but still delivers reliable segmentation results. - **Attention U-Net** performs the worst in surface area segmentation, with a higher RMSE and RE (%), indicating that its predictions deviate significantly from the ground truth. Its negative correlation coefficient (-0.079) further suggests that the model struggles to establish a consistent relationship between predicted and actual surface areas.

Key Insight: Multi-Res U-Net's superior performance in surface area segmentation can be attributed to its multi-resolution feature extraction, which allows it to retain fine spatial details while avoiding excessive smoothing of object boundaries.

4.12.4 Volume Segmentation Results

Table 4.3 presents the performance metrics for volume segmentation, assessing how well the models capture the correct volumetric structure of the segmentation.

Table 4.3: Performance Comparison of U-Net Variants for Volume Segmentation

Model	RMSE	MAE	RE (%)	Correlation Coefficient
U-Net	0.003	0.493	7.67	0.958
Attention U-Net	0.006	0.0538	8.19	0.812
Multi-Res U-Net	0.012	0.770	12.25	0.821

Observations: - **U-Net** consistently outperforms both Attention U-Net and Multi-Res U-Net in volume segmentation accuracy, achieving the lowest RMSE, MAE, and RE (%). - **Attention U-Net** follows, with slightly worse results but still maintaining reasonable segmentation accuracy. - **Multi-Res U-Net** has the highest errors, suggesting that while it excels in surface area segmentation, it struggles with volumetric consistency.

Key Insight: U-Net's ability to achieve precise volumetric segmentation can be attributed to its simple yet effective encoder-decoder structure, which prevents information loss and ensures consistent feature extraction.

4.13 Final Analysis and Takeaways

Summary of Key Findings: - For surface area segmentation, **Multi-Res U-Net** is the best performer due to its ability to extract fine details at multiple resolutions. - For volume segmentation, **U-Net** dominates, achieving the lowest error rates and the highest correlation with ground truth. - **Attention U-Net** performs decently in sensitivity-based tasks, meaning it may be more suitable for detecting fine structures in complex segmentation problems.

Conclusion: Each model has its strengths and weaknesses: - **U-Net** is ideal for cases requiring precise volumetric accuracy. - **Multi-Res U-Net** is better suited for preserving complex surface structures. - **Attention U-Net** is beneficial for detecting critical structures in medical images but struggles in quantitative consistency.

Future work could explore hybrid architectures that combine the strengths of these models to achieve the best segmentation accuracy across all metrics.

4.14 Visual Analysis

4.14.1 Violin Plots Analysis

Visualizing metric distributions provides deeper insights into model performance. The following violin plots illustrate the **spread, central tendency, and variability** of key evaluation metrics across test samples for each model. These insights help evaluate the **robustness, stability, and consistency** of segmentation across different anatomical structures.

U-Net: The violin plot for **U-Net** metrics (Figure 4.19) demonstrates **tightly clustered distributions**, indicating that the model **consistently produces stable segmentation results** across different test samples. The relatively small spread in **Dice coefficient and mean Intersection-over-Union (mIoU)** suggests **low variance**, meaning the model performs similarly across all images. This is beneficial for **reliable segmentation in medical imaging**, where uniformity across cases is essential. However, this also means that **U-Net may struggle to adapt to complex anatomical variations**.

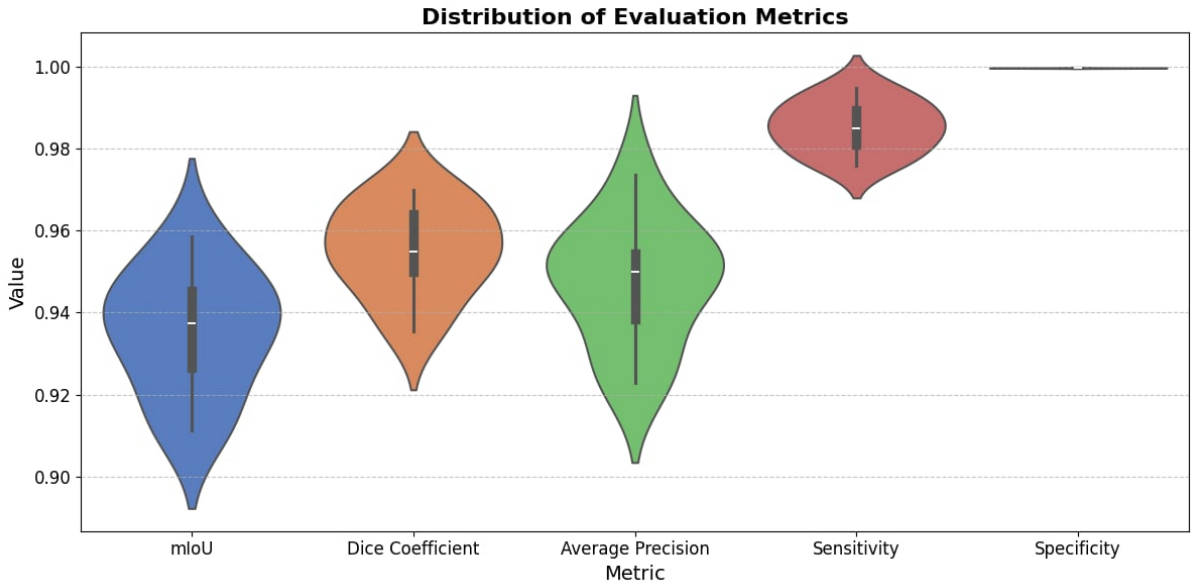

Figure 4.19: Violin Plot for **U-Net** Metrics, illustrating the distribution of Dice Coefficient, mIoU, and Sensitivity.

Multi-Res U-Net: The violin plot for **Multi-Res U-Net** metrics (Figure 4.20) displays a **wider spread**, indicating **greater variability in segmentation performance** across different test samples. While **Multi-Res U-Net** effectively captures **multi-scale features**, the increased spread in **sensitivity and average precision** suggests **inconsistent performance in finer details**. This means that while **Multi-Res U-Net** can handle **structural variations better than U-Net**, it also introduces **inconsistencies**, particularly in **smaller anatomical regions**.

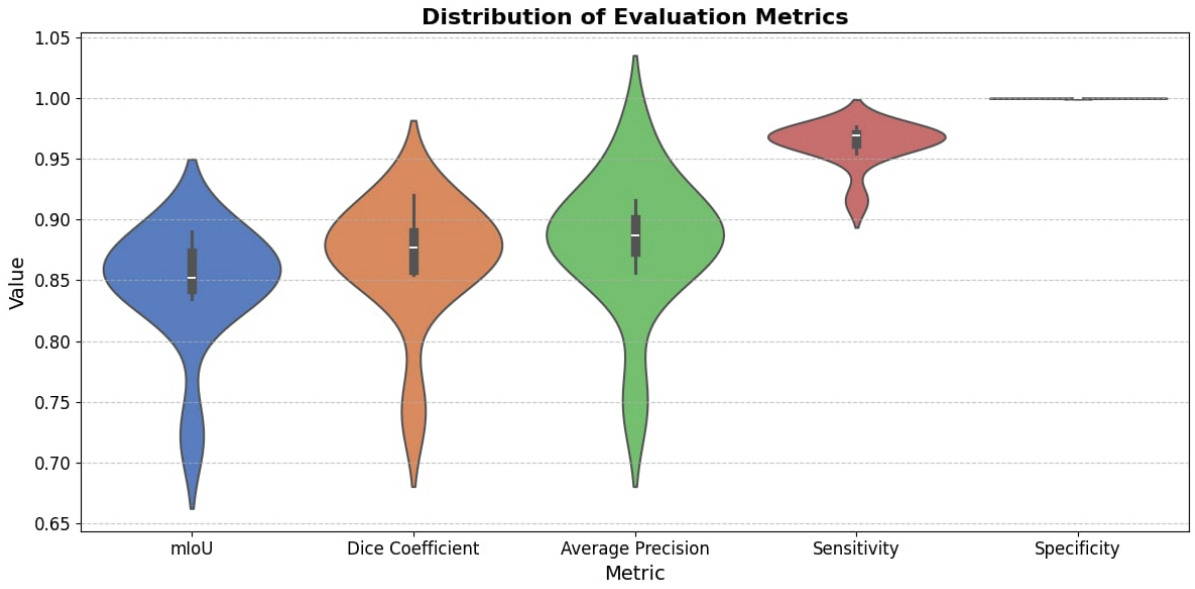

Figure 4.20: Violin Plot for **Multi-Res U-Net** Metrics, highlighting variability in segmentation performance across test samples.

Attention U-Net: The violin plot for **Attention U-Net** metrics (Figure 4.21) highlights its ability to focus on **critical regions**, improving **sensitivity to fine structures**. However, the broader spread in **Dice coefficient and average precision** suggests **challenges in maintaining stable segmentation performance across all test samples**. This is likely due to **over-reliance on attention mechanisms**, which prioritize **prominent structures but may miss subtle details**. While **Attention U-Net** provides **more detailed segmentations**, it lacks **consistency** across all cases.

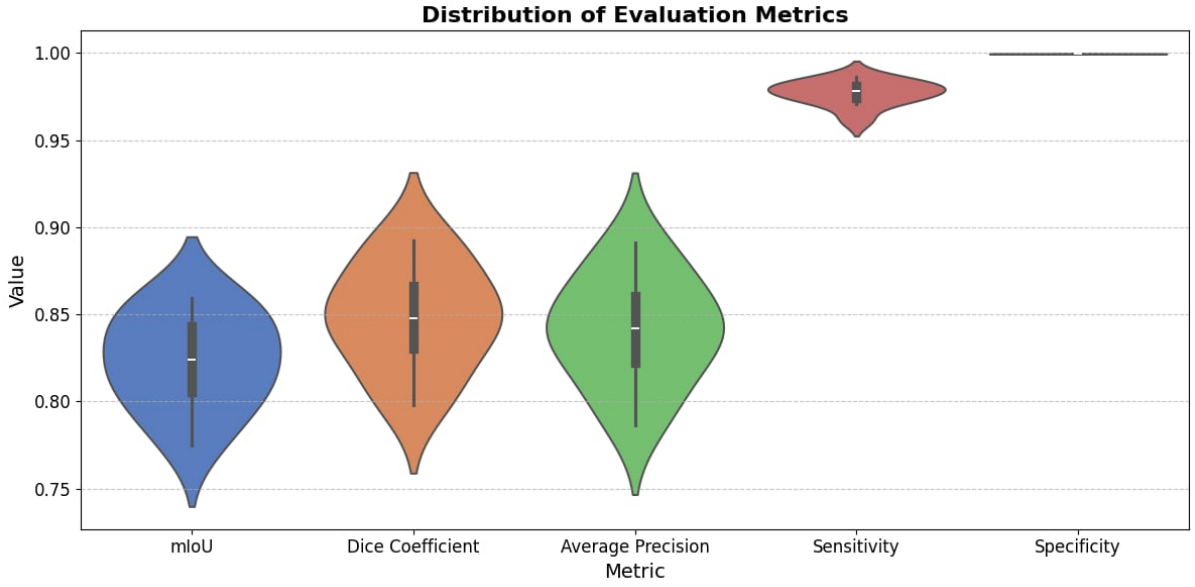

Figure 4.21: Violin Plot for **Attention U-Net** Metrics, showing a broader spread in Dice scores and average precision.

Summary: The violin plots provide key insights into the **strengths and weaknesses** of each model: - **U-Net** exhibits the **most consistent performance**, with **low variance** across different test cases. However, its **rigid structure makes it less adaptable to anatomical variations**. - **Multi-Res U-Net** captures **multi-scale features well**, but its **higher variability in segmentation quality suggests less stability**, especially for **small structures**. - **Attention U-Net** is **highly effective for fine structure segmentation**, but its **wider spread indicates greater performance fluctuation**, making it **less reliable for general applications**.

Overall, **Multi-Res U-Net offers the best trade-off**, balancing **detailed segmentation with reasonable stability**. However, for **applications demanding uniform accuracy**, **U-Net remains the most reliable choice**.

4.14.2 Violin Plots Showing the Difference Between Original and Predicted Outputs

The first violin plot (Figure 4.22) compares the volume and surface area predictions of the **3D U-Net** model. The volume differences show minimal deviation, indicating a close match with the original values. In contrast, the surface area differences display a broader range, suggesting larger deviations in surface area predictions.

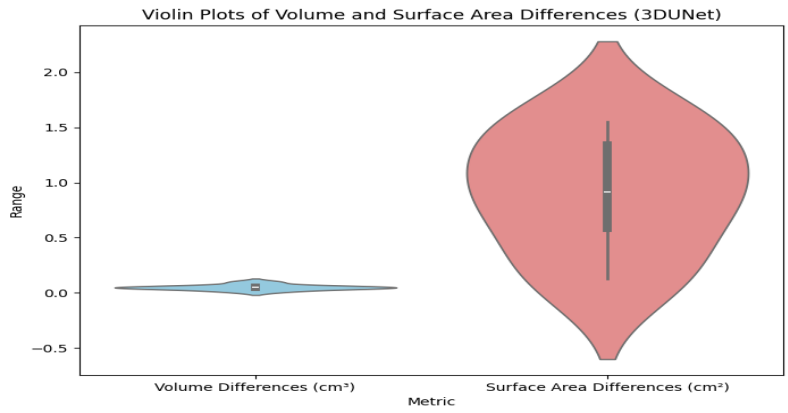

Figure 4.22: Violin Plot for **3D U-Net**: Comparison of Volume and Surface Area Differences.

The second plot (Figure 4.23) illustrates the performance of the **Attention U-Net**. Similar to **3D U-Net**, the volume differences have a small range, indicating accurate volume predictions. However, the surface area differences show a wider distribution with some outliers, pointing to occasional inaccuracies in surface area predictions.

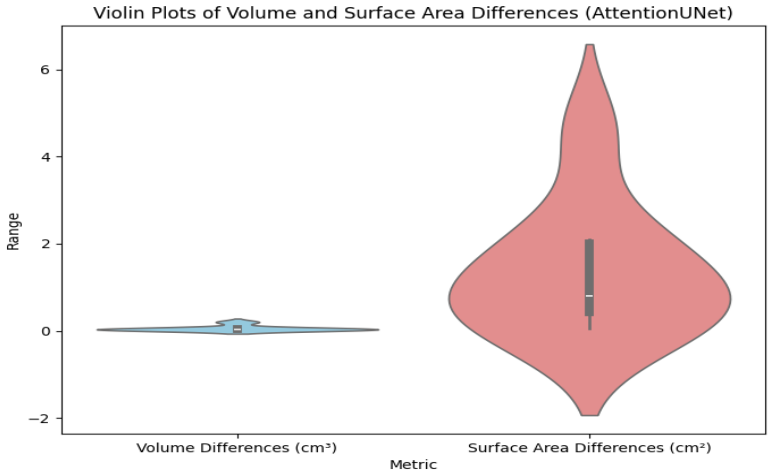

Figure 4.23: Violin Plot for **Attention U-Net**: Comparison of Volume and Surface Area Differences.

The final plot (Figure 4.24) for **MultiRes U-Net** shows smaller variations in both volume and surface area differences compared to the other models, particularly for surface area. This suggests that MultiRes U-Net strikes a better balance between both metrics, leading to more accurate overall performance.

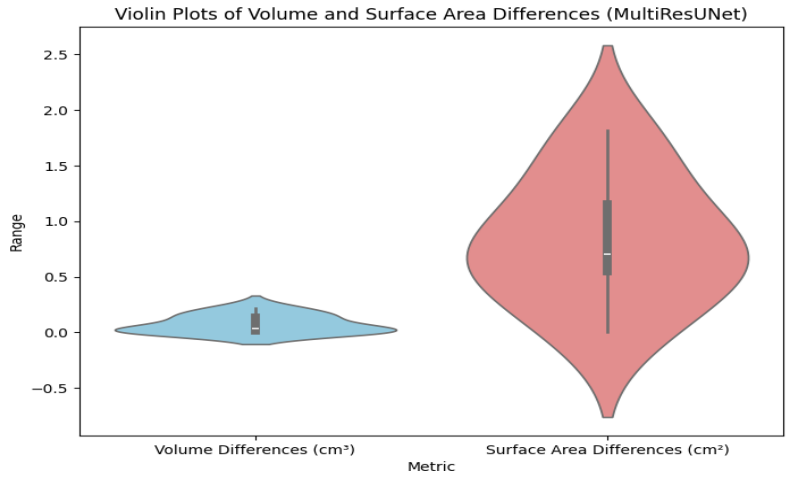

Figure 4.24: Violin Plot for **MultiRes U-Net**: Comparison of Volume and Surface Area Differences.

Summary: All three models demonstrate high accuracy in volume predictions, with minimal deviations from the ground truth. However, surface area predictions exhibit varying degrees of precision.

Figure 4.22 shows that 3D U-Net produces the most constrained surface area estimations, maintaining close alignment with the actual values but occasionally smoothing fine details. **Fig-**

ure 4.23 highlights that Attention U-Net shows greater variability, capturing intricate structures more effectively but introducing larger deviations in certain cases. **Figure 4.24** confirms that MultiRes U-Net achieves the best balance between volume and surface area accuracy, offering stable predictions across both metrics.

This suggests that MultiRes U-Net is the most reliable model for applications requiring precise segmentation while preserving both volumetric integrity and boundary details.

4.14.3 Bar Charts Analysis

Bar charts in Figures 4.25, 4.26, and 4.27 provide a comparative visualization of predicted surface areas and volumes, emphasizing the strengths and weaknesses of each model.

U-Net: The bar chart for **U-Net** (Figure 4.25) demonstrates close alignment with ground truth values. This highlights U-Net's ability to segment both surface area and volume accurately, making it suitable for a wide range of applications.

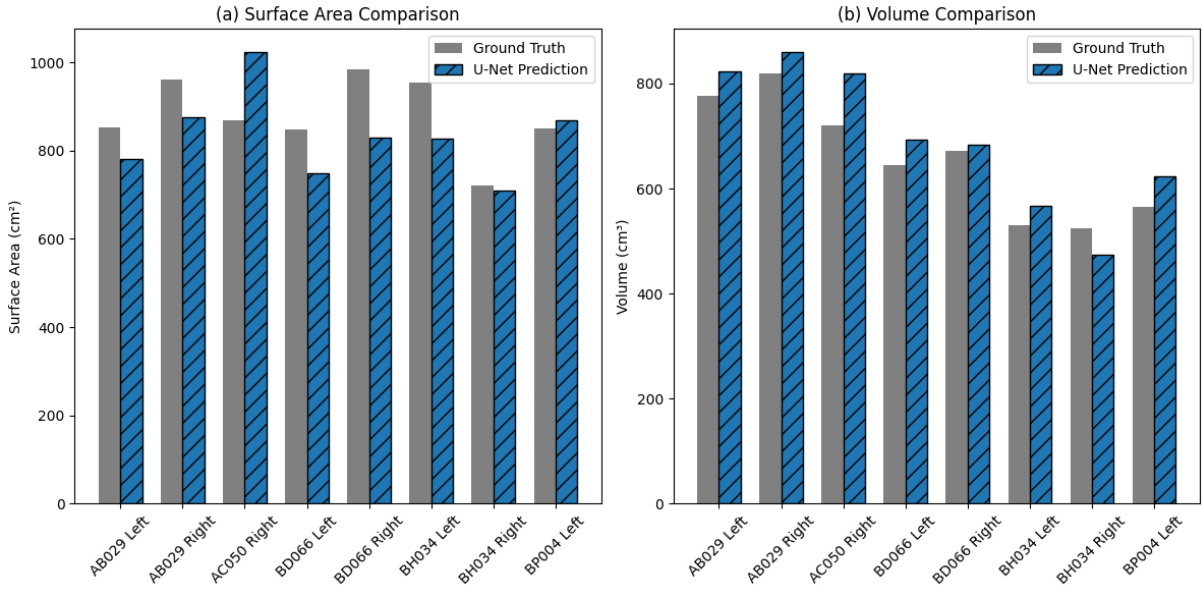

Figure 4.25: Surface Area and Volume for U-Net.

Multi-Res U-Net: The bar chart for **Multi-Res U-Net** (Figure 4.26) reveals minor deviations from the ground truth. This indicates that while the model captures large structures effectively, it faces challenges in detecting fine-grained details consistently.

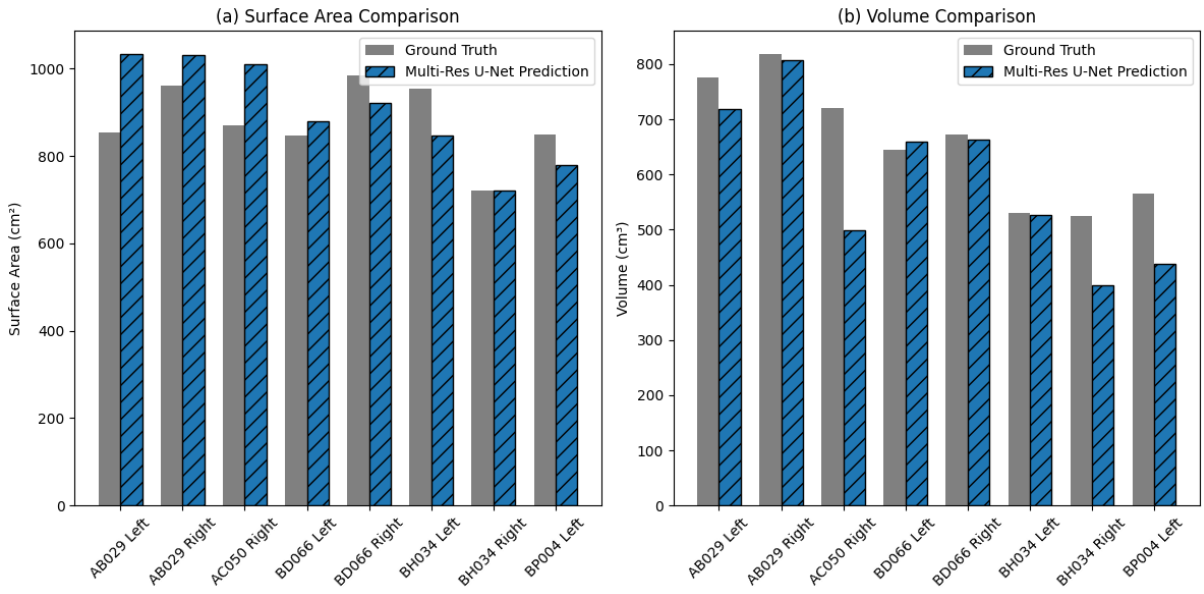

Figure 4.26: Surface Area and Volume for Multi-Res U-Net.

Attention U-Net: The bar chart for **Attention U-Net** (Figure 4.27) shows more significant deviations. Although the model's sensitivity allows it to identify key regions, its lower precision impacts its ability to accurately calculate surface area and volume.

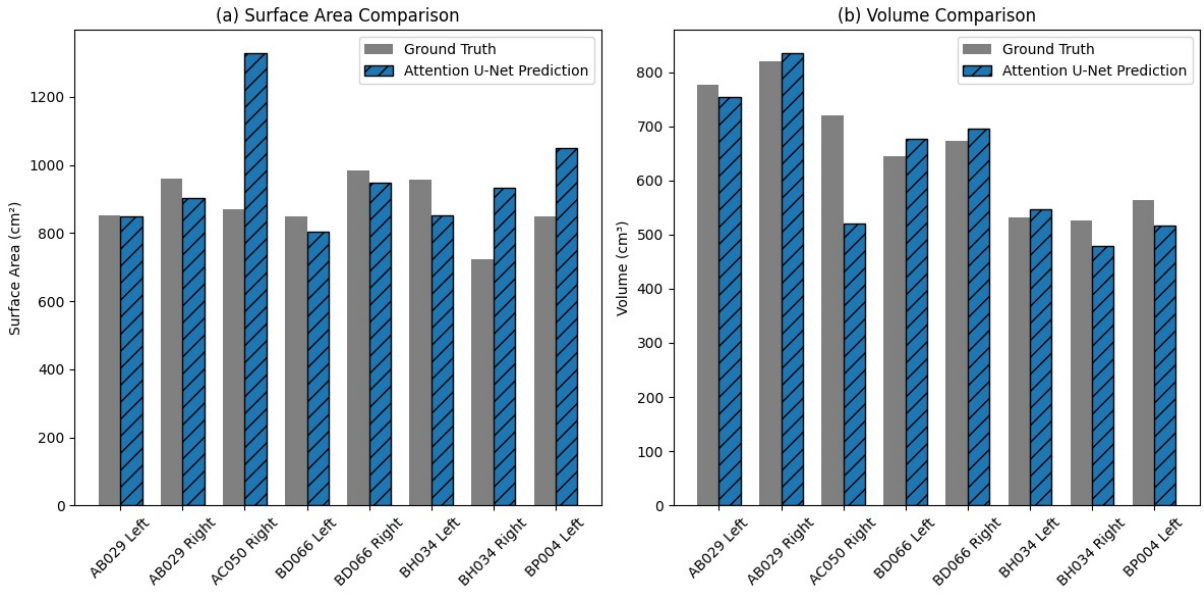

Figure 4.27: Surface Area and Volume for Attention U-Net.

4.14.4 Comparison of 3D Image Reconstruction: Original vs Predicted

Figures 4.28, 4.30, and 4.32 compare the original 3D image with the predicted images obtained using three different models: U-Net, Attention U-Net, and Multi-Res U-Net.

Figure 4.28: Original Image of the Bone.

Figure 4.29: Predicted Image (U-Net).

Figure 4.30: Original Image of the Bone.

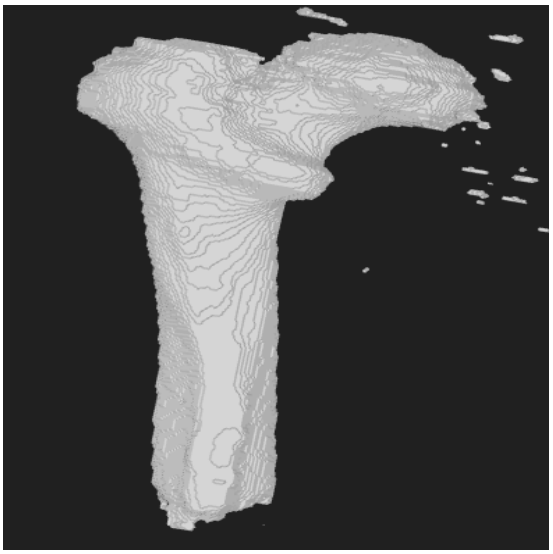

Figure 4.31: Predicted Image (Attention U-Net).

Figure 4.32: Original Image of the Bone.

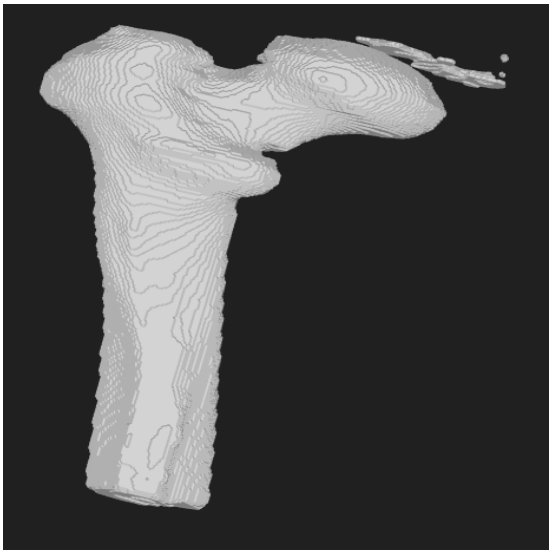

Figure 4.33: Predicted Image (Multi-Res U-Net).

These images highlight how each model performs in reconstructing the 3D image, revealing differences in the predicted results and evaluating the models' ability to capture fine details and accuracy. The visual comparison provides insight into the strengths and weaknesses of each model in reconstructing the 3D structure.

4.15 Discussion of Findings

Overall, the experiments show that each U-Net variant has its strengths:

- **U-Net:** Excels in global metrics like mIoU and Dice, indicating robust overall segmentation performance.
- **Multi-Res U-Net:** While having higher errors in certain cases, it may provide benefits for multi-scale feature extraction, which can be useful depending on data variability.
- **Attention U-Net:** Offers strong sensitivity and lower relative errors, making it highly suitable for capturing subtle bone structures and providing precise surface area estimates.

These insights can guide model selection depending on whether the focus is on maximum overall segmentation accuracy (U-Net) or more precise detection of small or critical structures (Attention U-Net).

Chapter 5

Conclusion

This study presents a comprehensive evaluation of different U-Net variants for segmenting femur bones from Quantitative Computed Tomography (QCT) images. Through qualitative and quantitative analysis, we assessed the strengths and limitations of **U-Net, Multi-Res U-Net, and Attention U-Net**, highlighting their effectiveness in various segmentation tasks.

5.1 Summary of Findings

Key findings indicate that:

- **U-Net** provides the most consistent volumetric segmentation performance, with minimal deviations from ground truth values. Its simple yet effective encoder-decoder structure ensures robust segmentation across a range of medical images.
- **Multi-Res U-Net** excels in capturing fine details and multi-scale features, making it particularly well-suited for cases requiring precise boundary segmentation. However, its slightly higher error rates in volume estimation suggest that it may struggle with maintaining global anatomical consistency.
- **Attention U-Net** demonstrates strong performance in detecting fine structures and small anatomical variations, but its reliance on attention mechanisms leads to greater variability in results.

5.2 Visual Analysis Insights

Visual analyses, including **segmentation comparison images, violin plots, and bar charts**, further emphasize how these models differ in handling complex anatomical structures:

- **Segmentation Comparisons:** The models exhibit distinct behavior in preserving anatomical features, with U-Net maintaining smooth segmentation, Multi-Res U-Net effectively capturing fine details, and Attention U-Net highlighting small structures.
- **Violin Plots:** These plots reveal the consistency and variability of segmentation accuracy, showing that U-Net has the lowest variance while Multi-Res U-Net and Attention U-Net display higher fluctuations.
- **Bar Charts:** The surface area and volume predictions further confirm that U-Net is the most stable across different test cases, whereas Multi-Res U-Net and Attention U-Net provide more fine-grained segmentation with occasional errors.
- **3D Reconstruction Analysis:** The models were compared in reconstructing 3D femur bones, revealing that Multi-Res U-Net offers better structural detail preservation, while Attention U-Net emphasizes small anatomical features.

5.3 Model Selection Considerations

Ultimately, **the choice of model depends on the specific application**:

- If smooth segmentation and consistency are prioritized, **U-Net is the best option**.
- For tasks requiring multi-scale feature extraction and boundary preservation, **Multi-Res U-Net offers a balanced solution**.
- If the segmentation task demands greater sensitivity to fine details, **Attention U-Net is preferable**, albeit with a trade-off in overall stability.

5.4 Future Work

Future work could focus on developing **hybrid architectures** that integrate the strengths of multiple U-Net variants to achieve optimal segmentation accuracy across both volumetric and surface-level metrics. Additionally, further research could explore:

- **Advanced Regularization Techniques:** Techniques such as dropout, batch normalization, or contrastive learning could improve generalization.
- **Improved Loss Functions:** Incorporating loss functions like Tversky loss or focal loss may help balance segmentation performance in class-imbalanced medical images.

- **Semi-Supervised Learning Approaches:** Leveraging unlabeled medical images using self-supervised or weakly supervised techniques could improve model performance, particularly in scenarios where annotated datasets are limited.

Conclusion: The results of this study provide valuable insights into the strengths and weaknesses of different U-Net variants for medical image segmentation. By understanding these differences, researchers and clinicians can select the most suitable model based on their specific needs and further refine deep learning-based segmentation techniques for improved clinical applications.

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