Real or fake? Input Optimization for Effective QCT Image Augmentation

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March 18, 2025

Motivation

- **Image augmentation** is necessary for deep learning research since enough medical images are not easily available.
- This research presents a novel method of manipulating input to achieve desired outputs from certain models through input optimization.

Overview

- Introduction
- Problems
- Literary Previews
- Dataset
- Objectives
- Methodology
- Results and Analysis
- Conclusion
- Recommendation
- Appendix

Introduction

- Affine transformations and noise addition are traditional augmentation techniques, but **lack biologically realistic alterations**.
- In input optimization, a gradient-based technique is used to alter images to produce the intended output of the model.

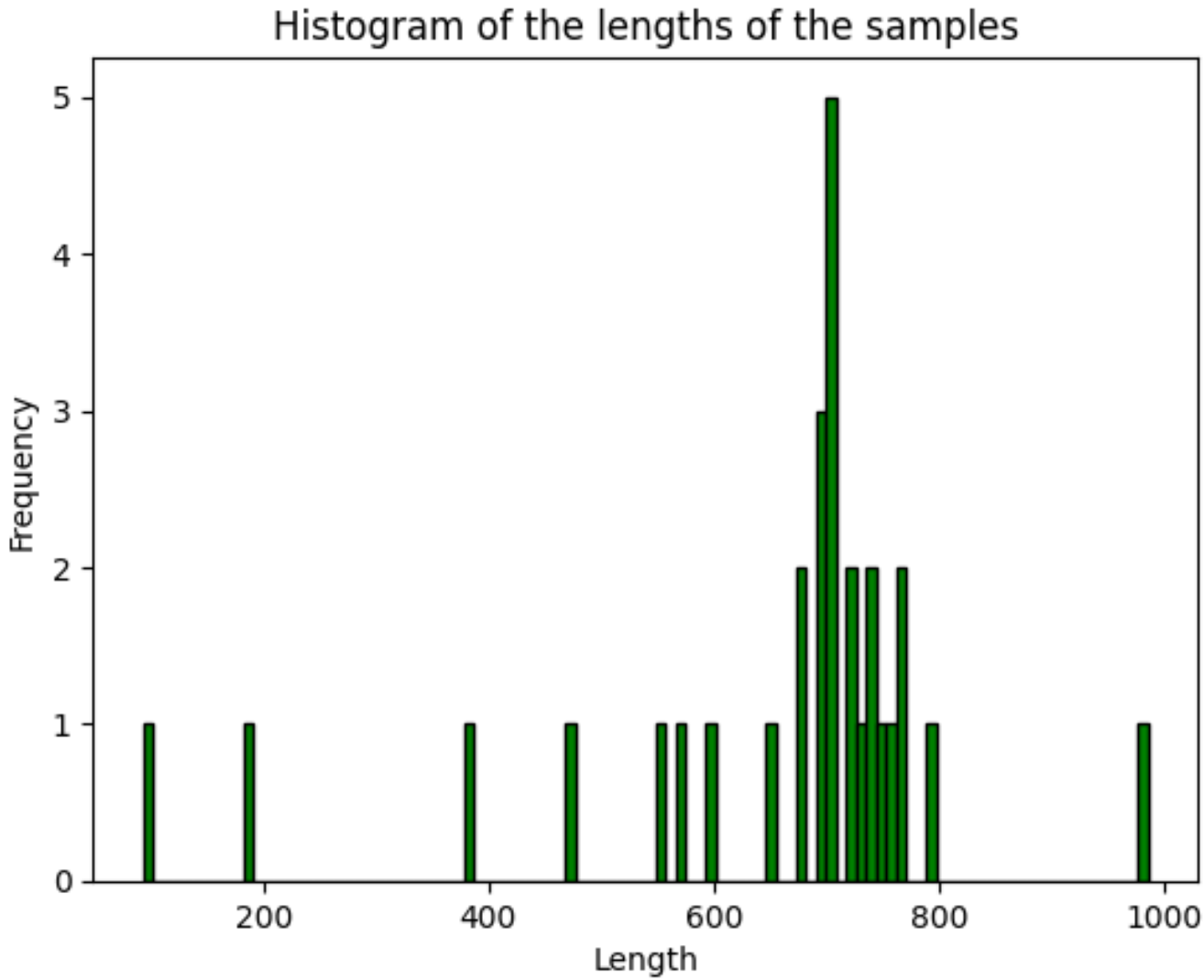
Problems

- To generate data points representing patients of certain age, weight, and gender.
- To modify voxel density while keeping bone structure intact.
- To use quantitative analysis tools for validation.

Literary Previews and Research Gap

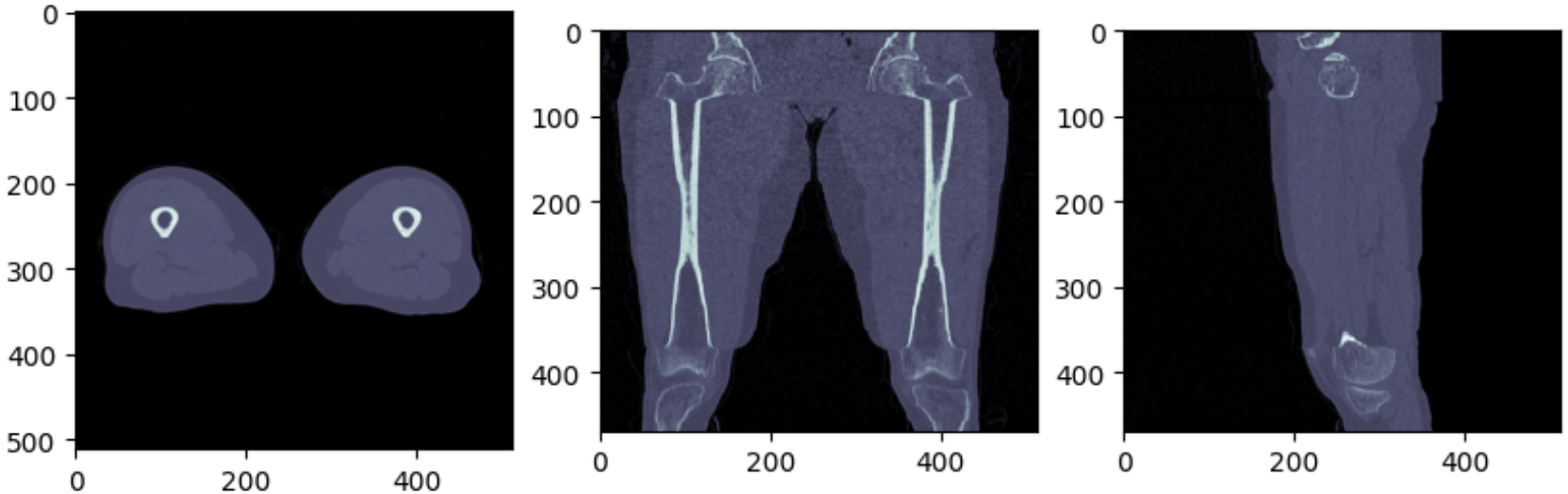
- Sultana et al. (2024) proposed SSDL for 3D femur reconstruction, limited data made their model less generalized.
- Frid-Adar et al. (2018) used GAN-based augmentation in medical imaging, but it works for 2d images rather than 3d images.
- Shorten & Khoshgoftaar (2019) surveyed image augmentation techniques, ignoring gradient-based optimization.
- Litjens et al. (2017) reviewed deep learning applications in medical image analysis but lacked a dedicated discussion on augmentation-driven input optimization.
- Nie et al. (2017) utilized deep convolutional adversarial networks for the synthesis of medical images, but attribute tuning was not available.

Dataset



Consists of 29 QCT scans, each measuring 512x512 pixels with metadata including age, weight, and gender.

Dataset (Contd.)



Idea

- To use input optimization to create dataset variations for diversity.
- To maintain structure while adjusting density to modify patient attributes.

Methodology

- We train gender recognition and regression models.

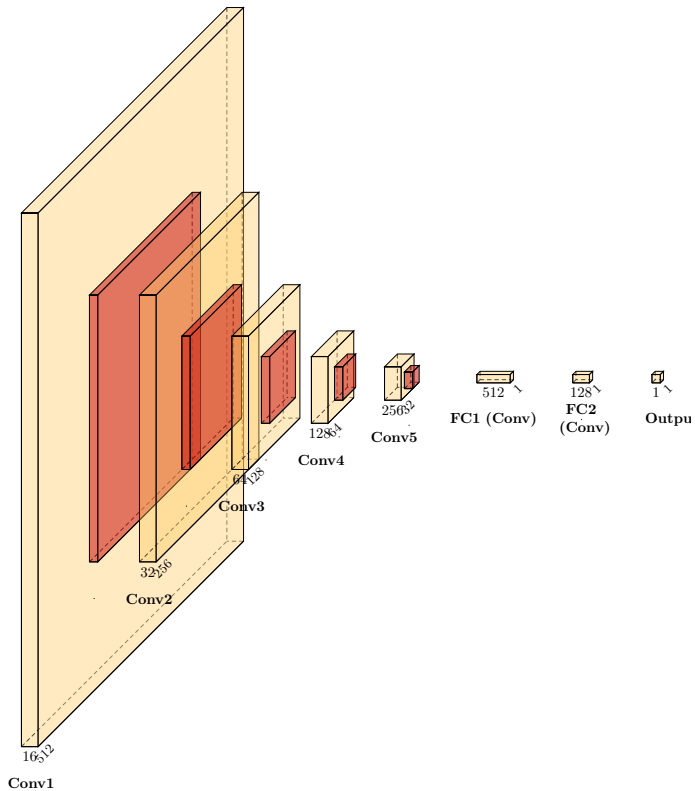


Figure: Gender Classifier

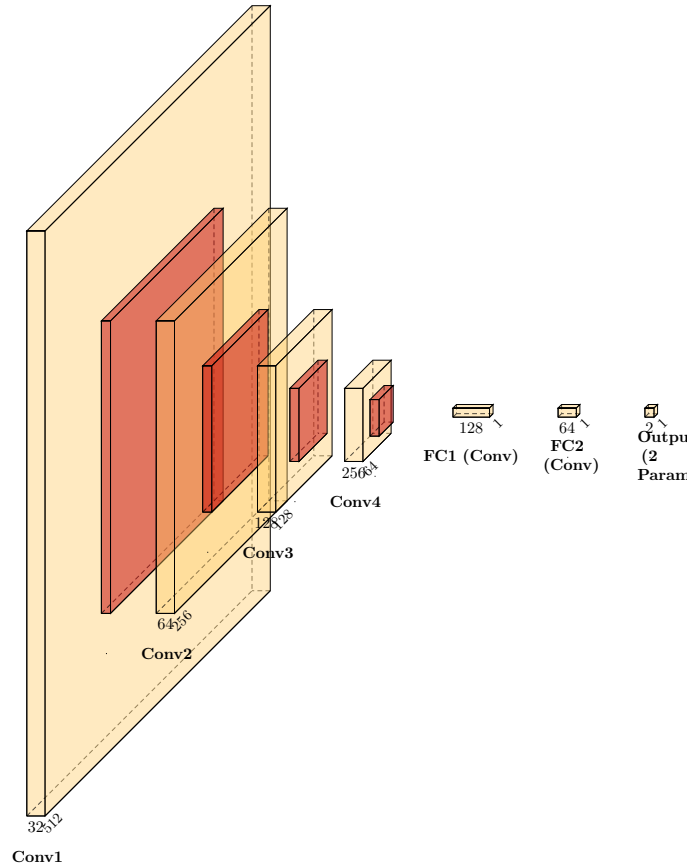


Figure: Age and Weight predictor

Methodology

- We train gender recognition and regression models.

2259	2
20	1754

Table: Confusion Matrix

- **Precision:** 0.99
- **Recall:** 0.99
- **F1 Score:** 0.99

Gender Classifier Performance Metrics Analysis

Methodology

- We train gender recognition and regression models.

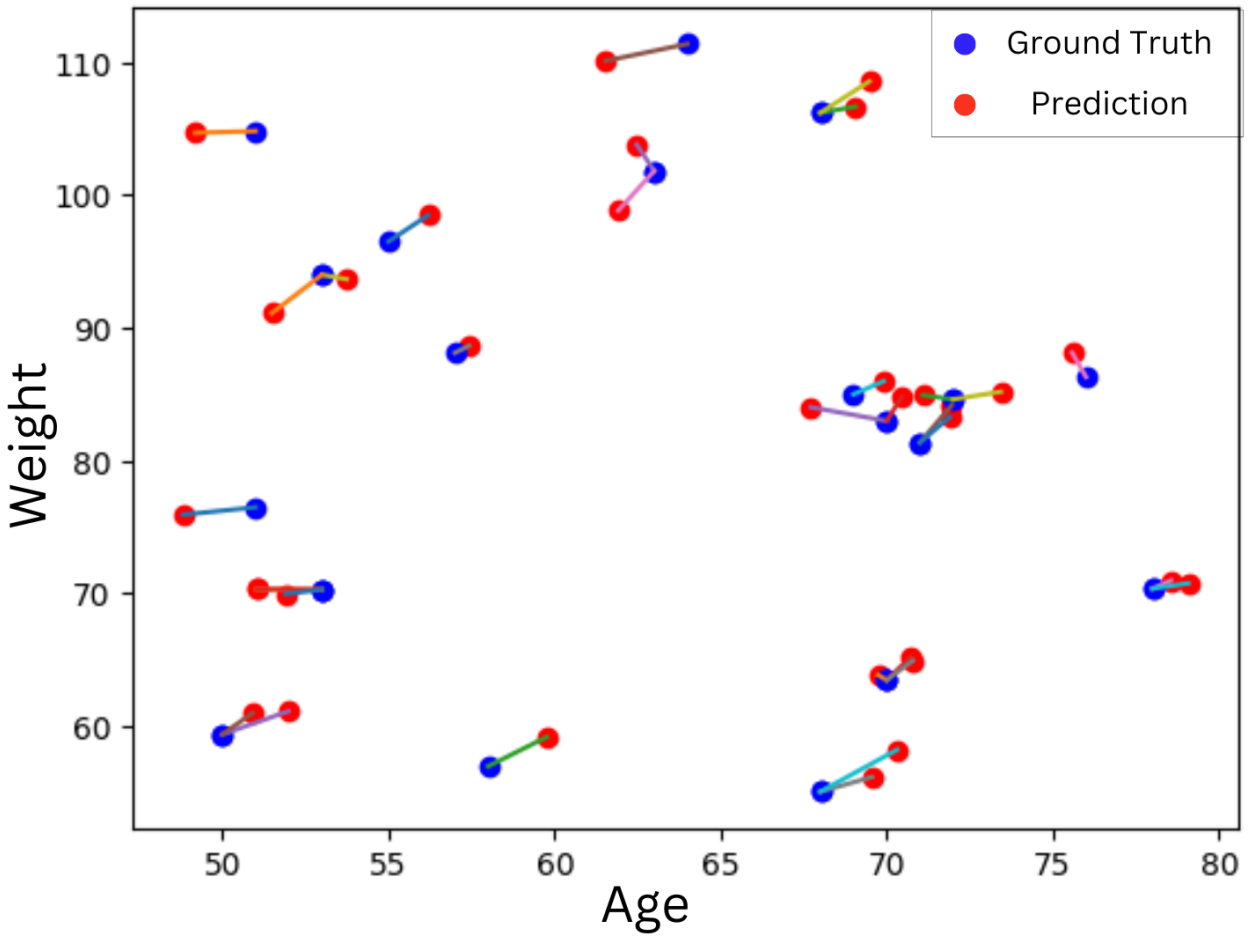


Figure: Predictor Model's Performance Analysis

We get mean squared error 2.98 for test cases.

Methodology

- We train gender recognition and regression models.
- We clone the input images.
- We set target attributes (age, weight, gender).
- We perform forward pass on the cloned images to detect attributes.
- We compute loss and backpropagate.
- We modify cloned input using Adam optimizer.
- Then, we repeat for multiple epochs.

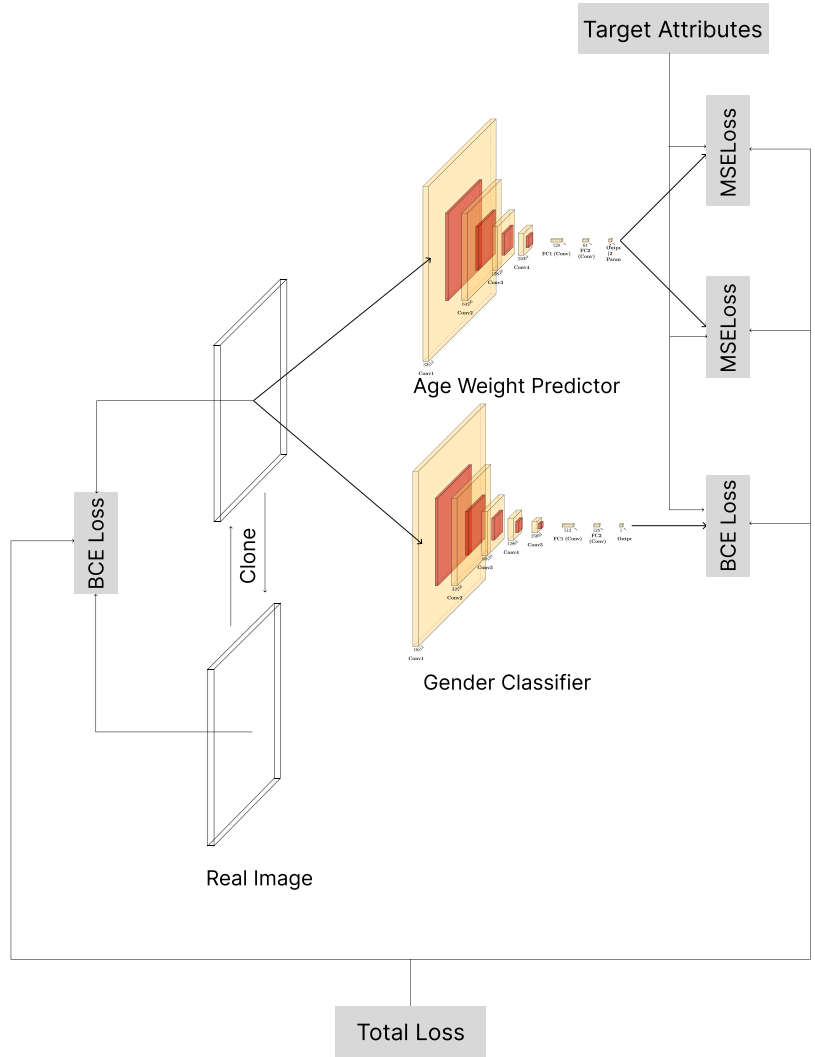
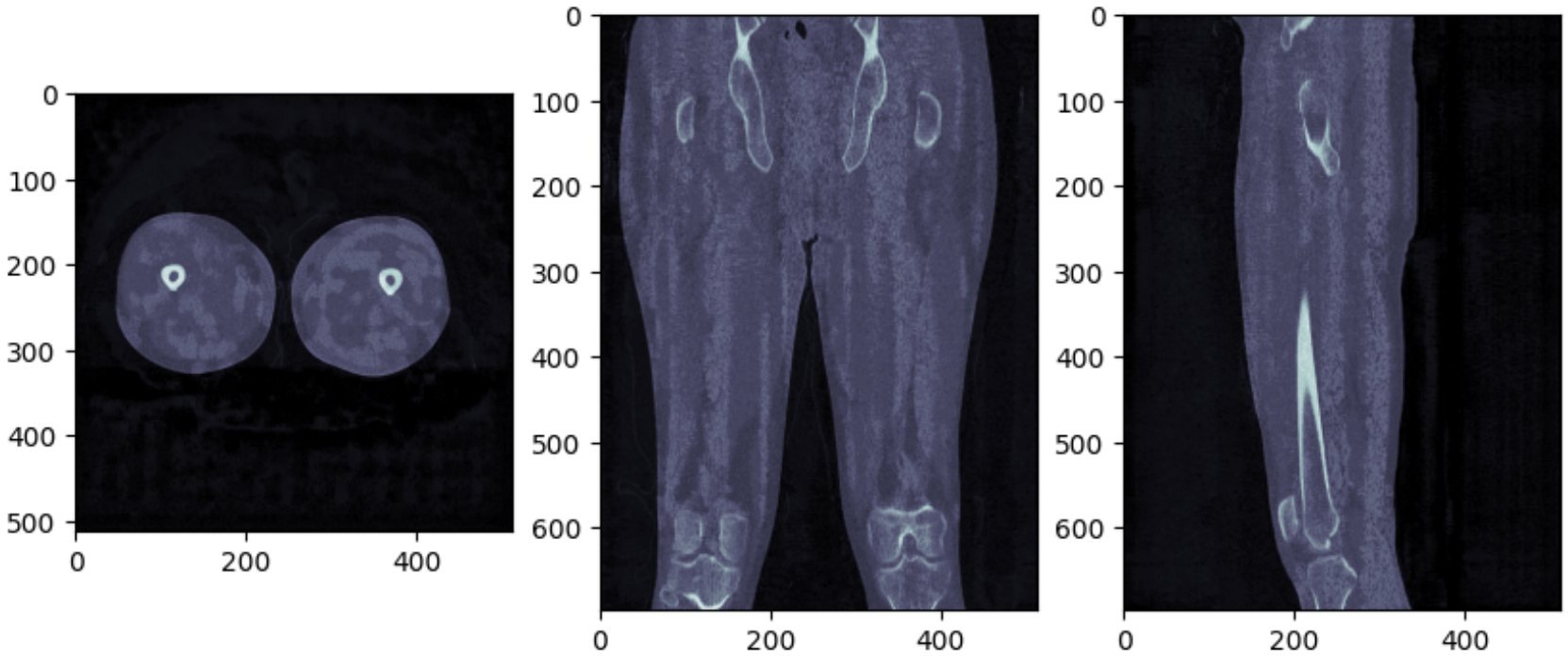


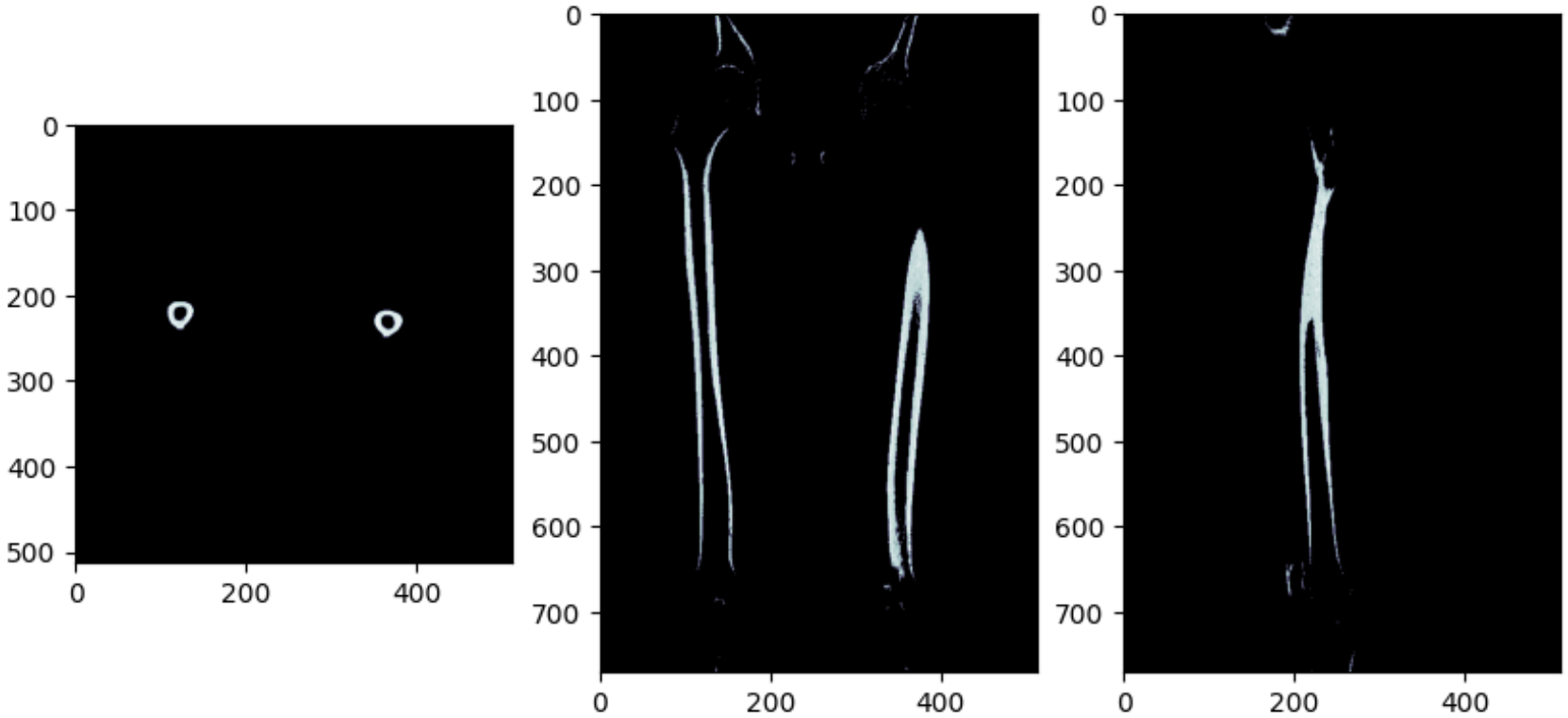
Figure: Algorithm for Input Optimization

Results



Synthetic images are evaluated for resemblance to real images.

Analysis

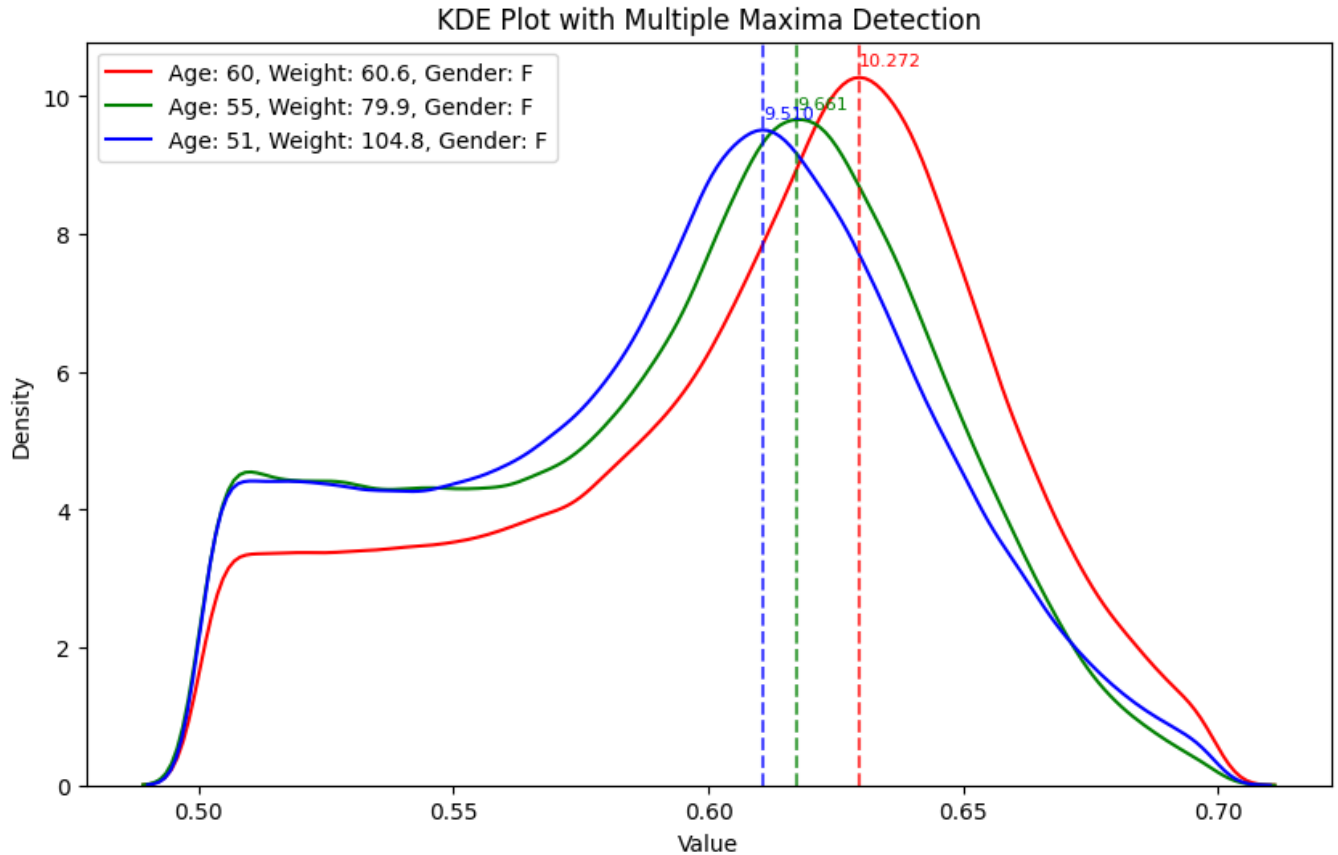


- Images normalized to range [0,1].
- Focus on voxels within the 0.5-0.7 density range representing bone.
- Peak shifting in voxel distribution shows rightward movement with decreasing weight.

Voxel Distribution Analysis

Distribution of Voxels and Peak Shifting

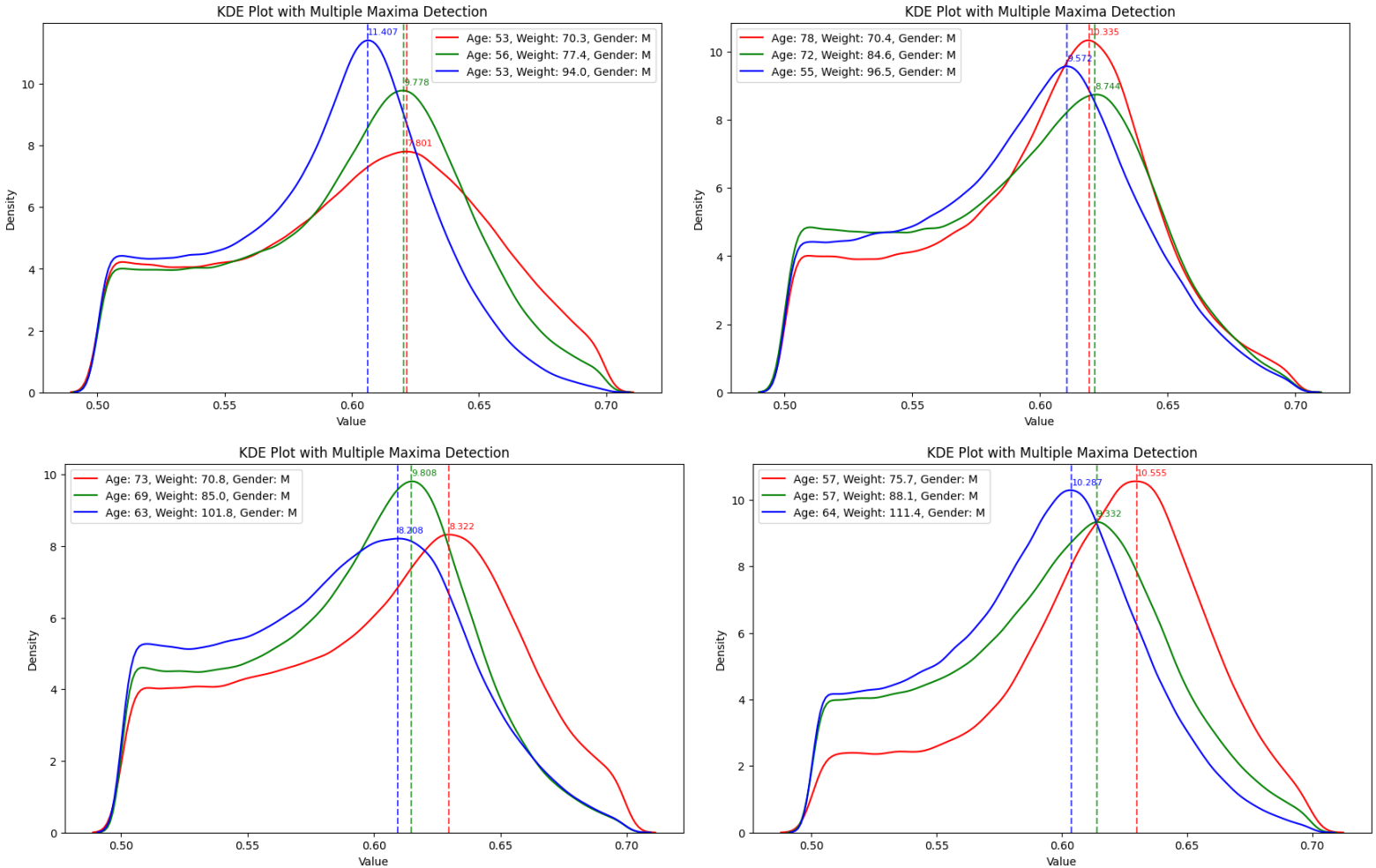
We observed a distinctive peak-shifting pattern indicating a rightward movement as weight decreased.



Voxel Distribution Analysis (Contd.)

Distribution of Voxels and Peak Shifting

We observed a distinctive peak shifting pattern that indicates a movement to the right as weight decreased.



Voxel Distribution Analysis (Contd.)

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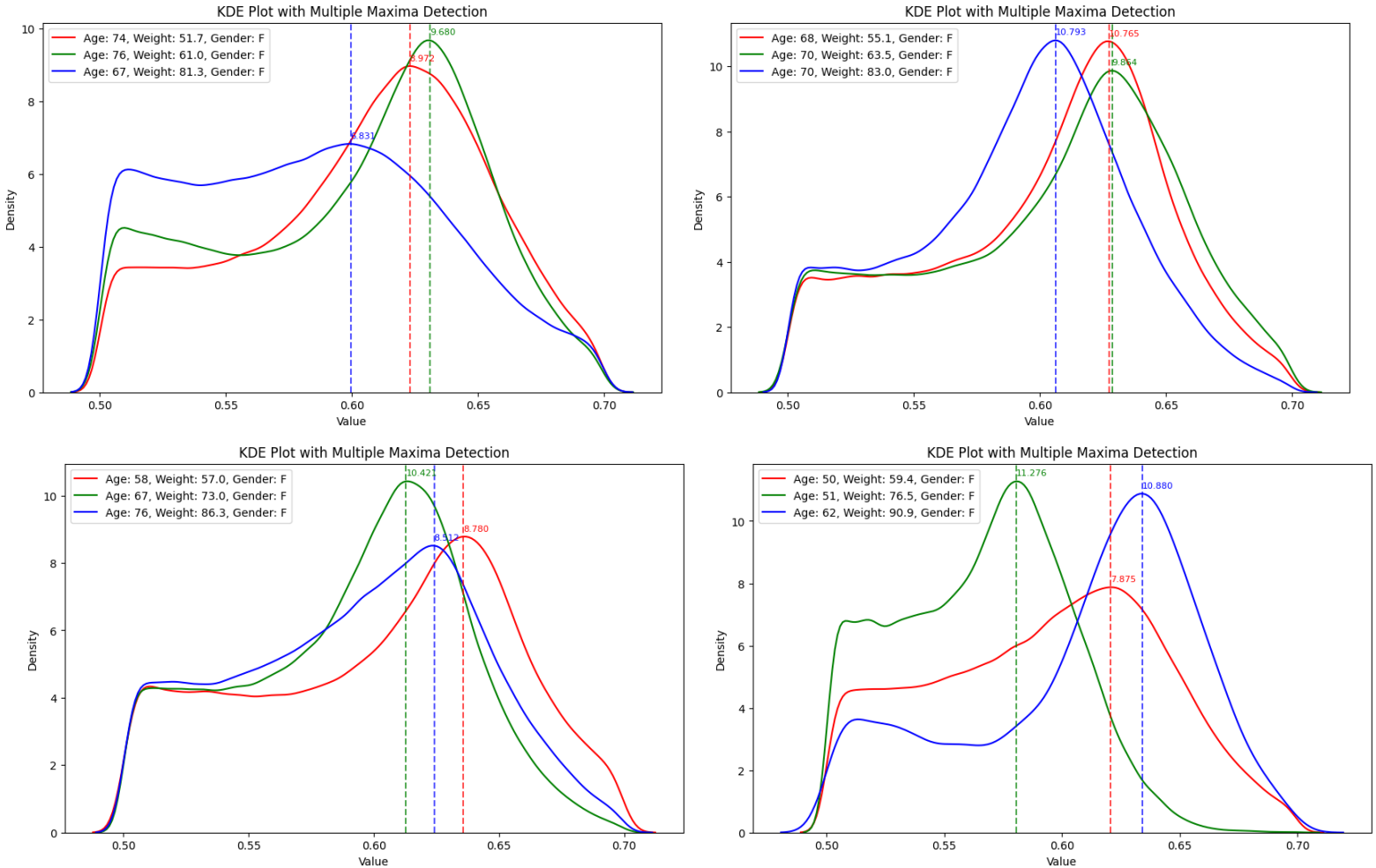

Voxel Distribution Analysis (Contd.)

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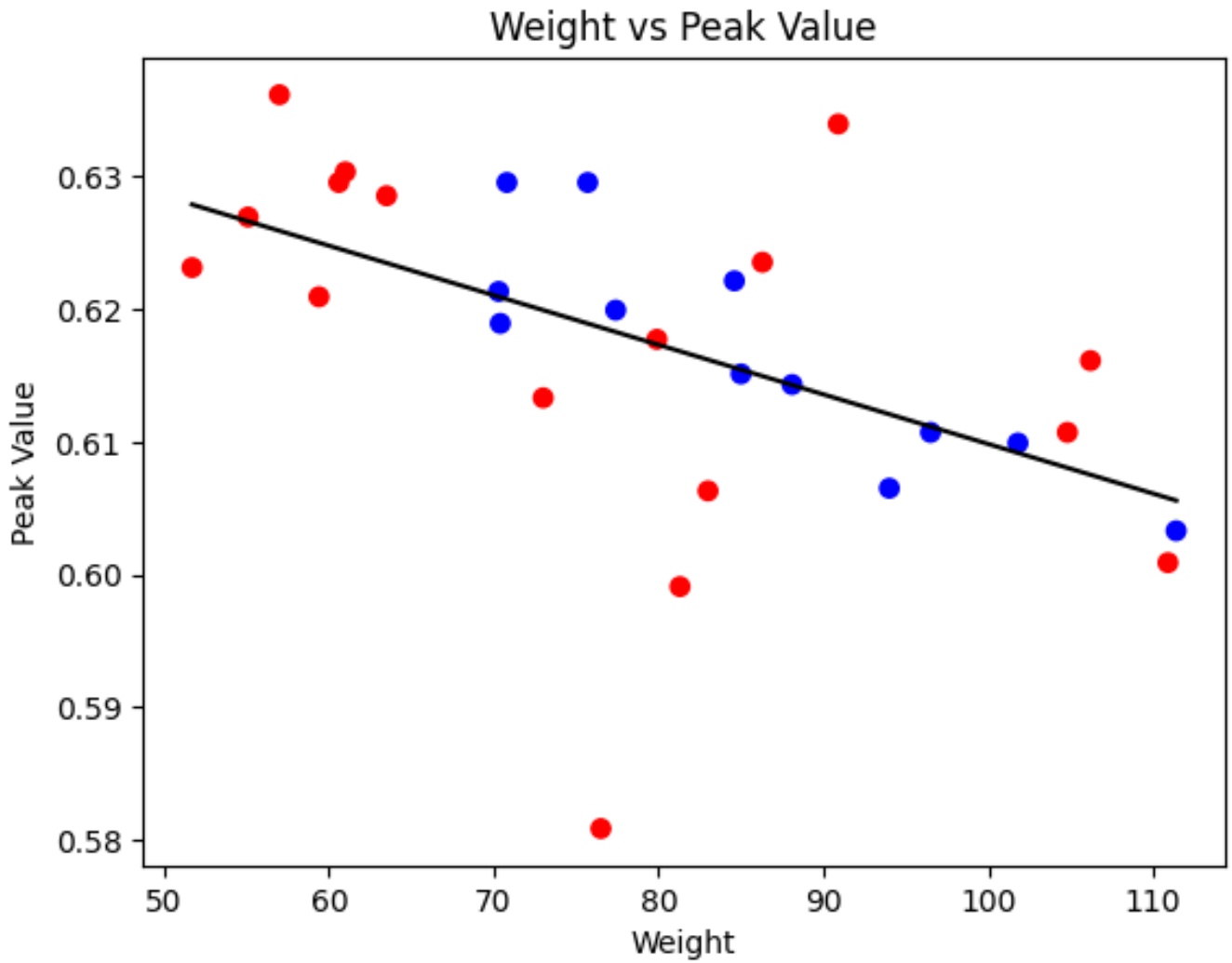

Synthetic Image Analysis

Distribution of Voxels and Peak Shifting

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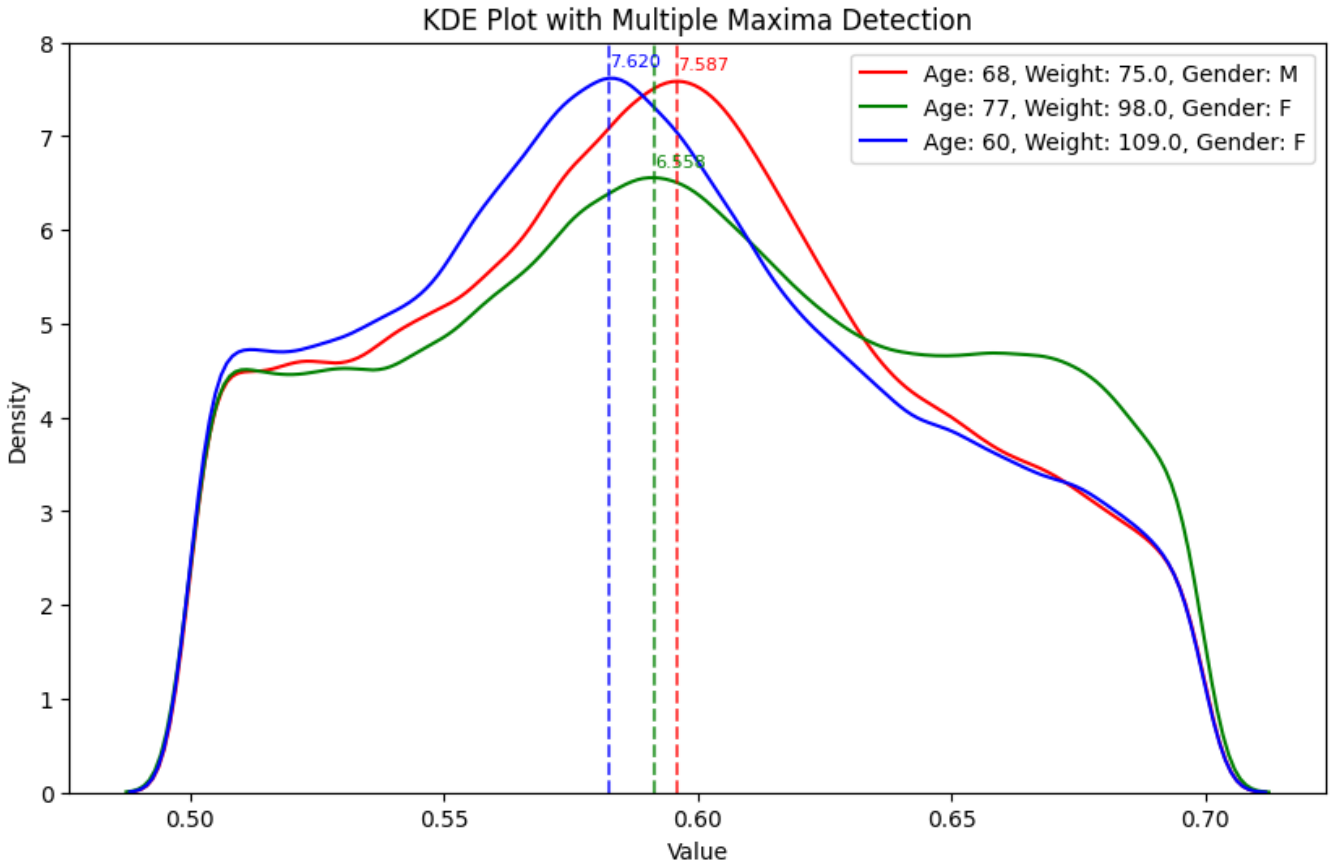
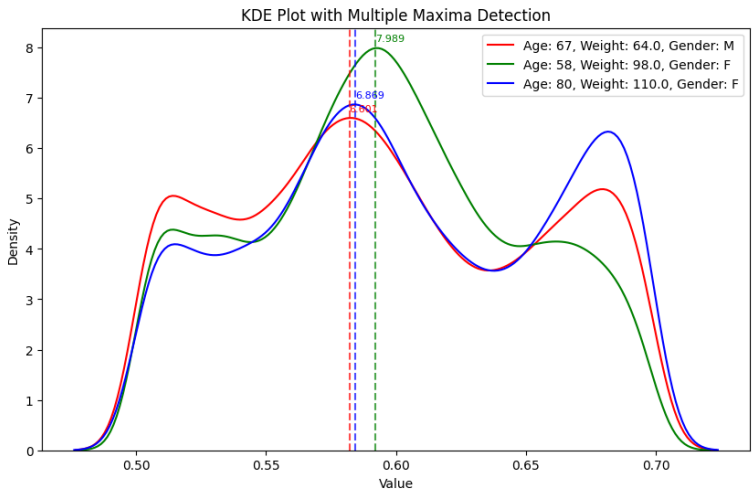
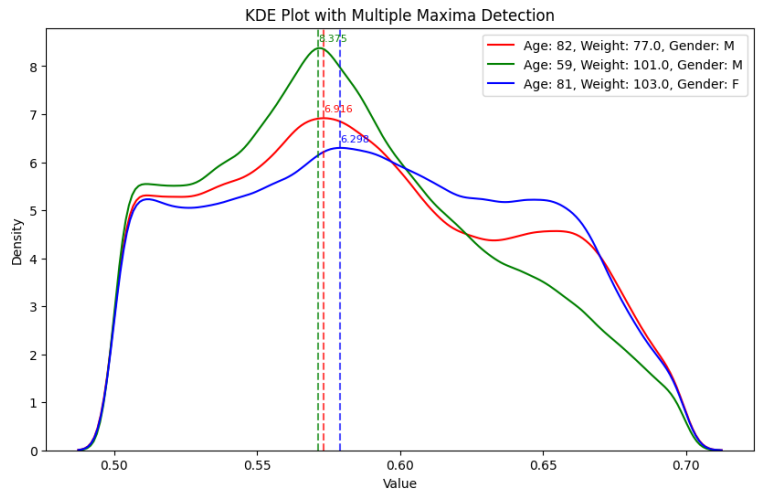


Synthetic Image Analysis (Contd.)

Comparison with Real Images

A similar peak-shifting pattern was observed in synthetic images, supporting the effectiveness of augmentation techniques.





Synthetic Image Analysis (Contd.)

Comparison with Real Images

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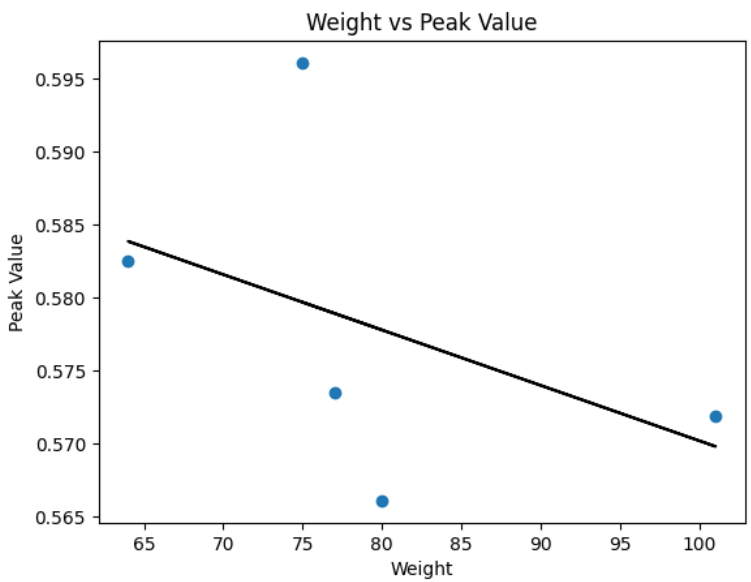
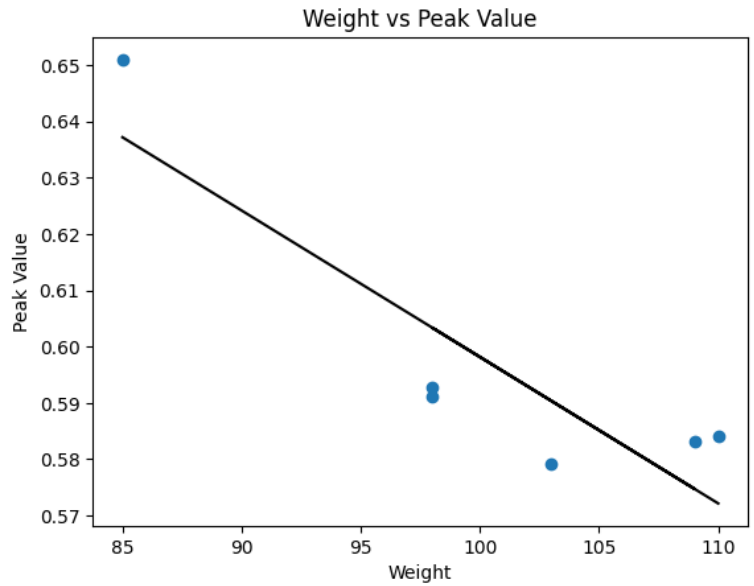




Conclusion

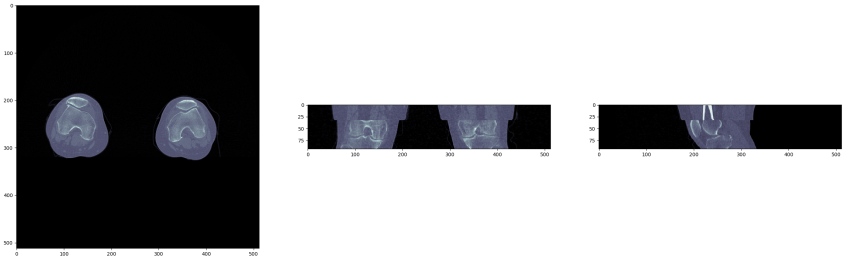
- Demonstrates effectiveness of gradient-based input optimization.
- Maintains weight-dependent intensity variations.
- Weak correlation with age suggests the need for alternative feature extraction techniques.

Recommendation

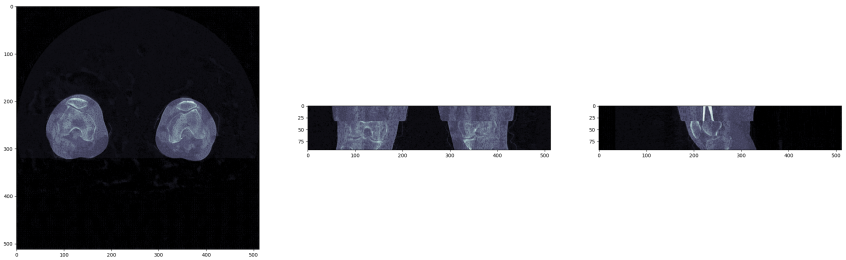
- Augmented data may be used for bone-related predictions.
- Layers may be converged to different minima.

Appendix

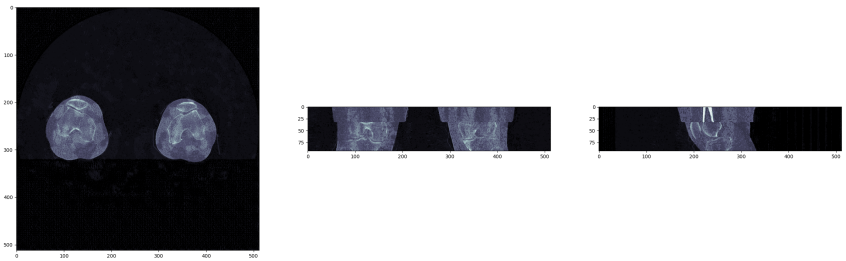
Age: 62, Weight: 90.9, Gender: F Real



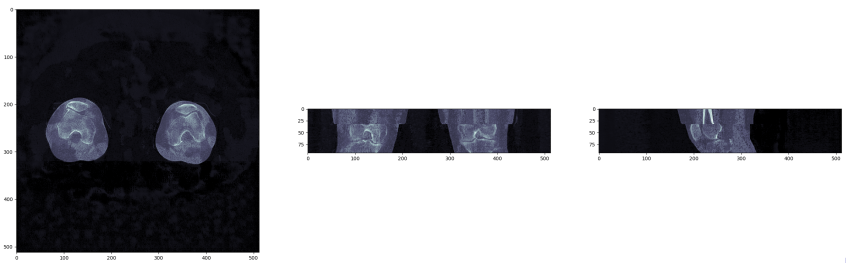
Age: 58, Weight: 98.0, Gender: F Generated



Age: 80, Weight: 110.0, Gender: F Generated

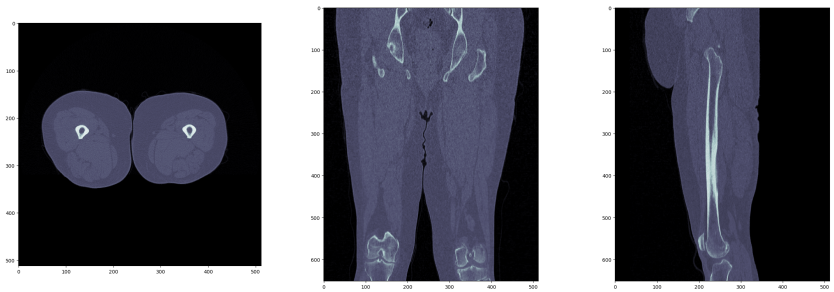


Age: 67, Weight: 64.0, Gender: M Generated

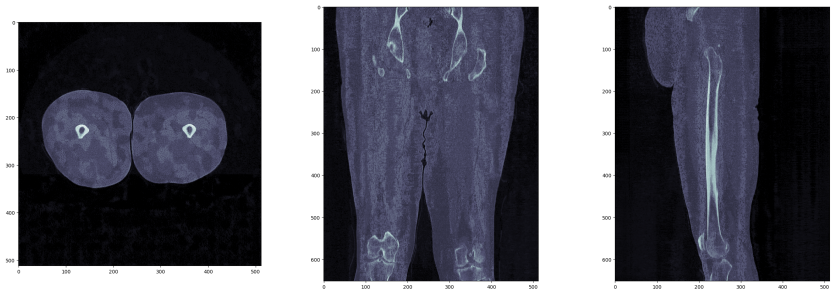


Appendix (Contd.)

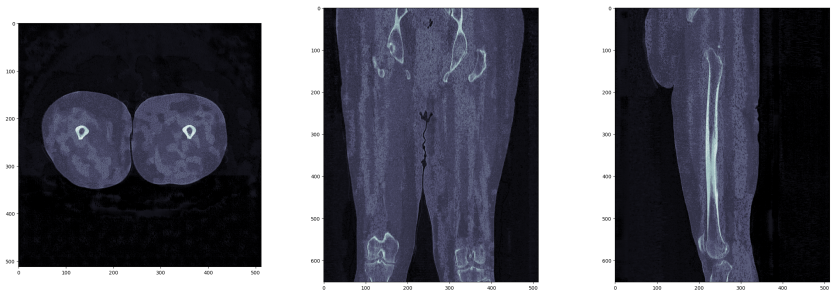
Age: 68, Weight: 106.2, Gender: F Real



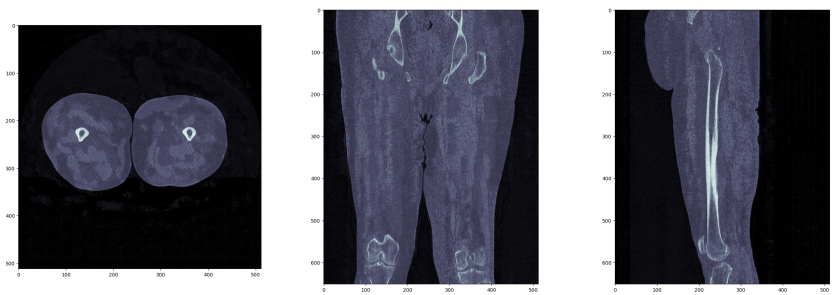
Age: 59, Weight: 101.0, Gender: M Generated



Age: 82, Weight: 77.0, Gender: M Generated

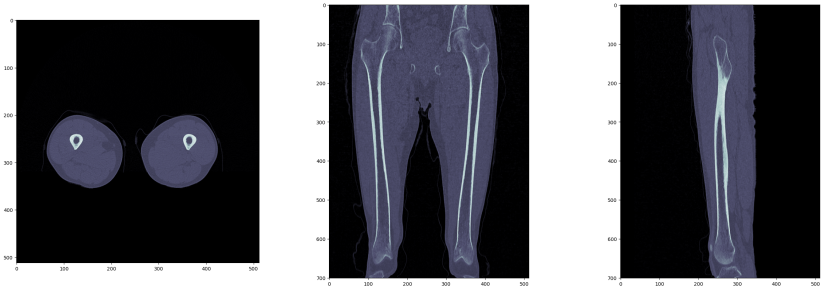


Age: 81, Weight: 103.0, Gender: F Generated

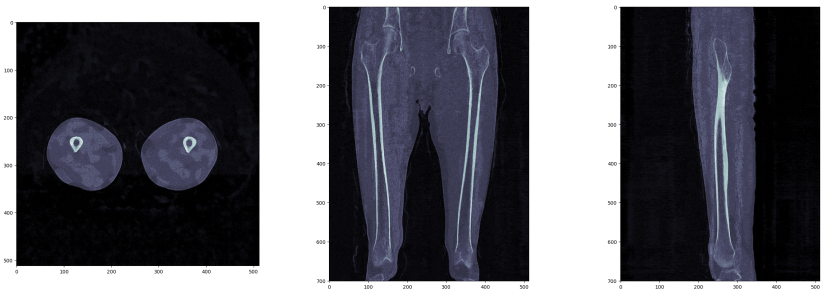


Appendix (Contd.)

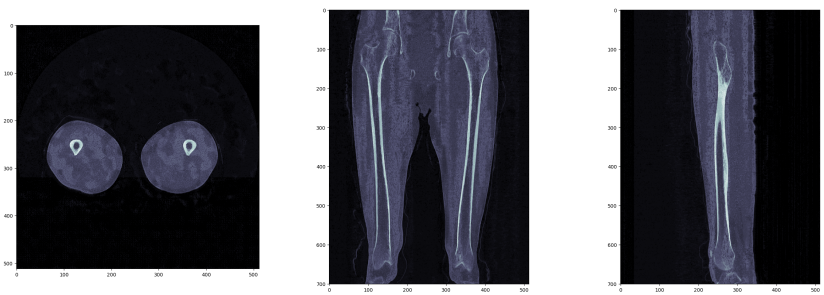
Age: 73, Weight: 70.8, Gender: M Real



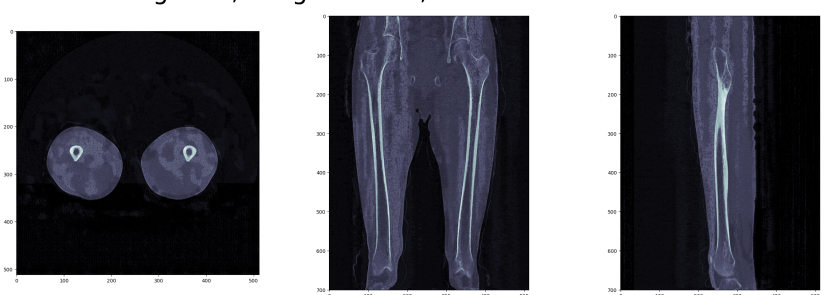
Age: 68, Weight: 75.0, Gender: M Generated



Age: 77, Weight: 98.0, Gender: F Generated



Age: 60, Weight: 109.0, Gender: F Generated



Thank You!